PREDICTION OF THE UNEMPLOYMENT RATE IN INDONESIA

ABSTRACT

The Covid-19 pandemic has had numerous detrimental effects on Indonesia's economy. One is a rising unemployment rate due to a slowing economy, resulting in fewer employment prospects. This study aims to forecast the unemployment rate in Indonesia between 2023 and 2025, explicitly following the Covid-19 pandemic. This research utilises time series data for the period 2005 to 2022. The Augmented Dickey-Fuller (ADF) test indicates that the data for the unemployment rate are stationary at the first difference. Utilising the Autoregressive Integrated Moving Average technique (ARIMA). Predictions indicate that the unemployment rate in Indonesia has increased during the Covid-19 pandemic. Important factors contributing to the high unemployment rate in Indonesia include (1) an education system that does not adequately train the younger generation in the field of entrepreneurship; (2) a large proportion of the labour force is directed to the formal sector, which has a minimal number of jobs and a high level of competition; (3) an imbalance between demand and supply in the employment market; and (4) a world of education that is less able to produce quality workers. (5) During the COVID-19 pandemic, corporations decided to employ fewer employees, resulting in many layoffs (PHK) in Indonesia. The highest unemployment rates were among people with a high school education. Moreover, among those with a college degree. Recent college and vocational school graduates are having difficulty obtaining employment.

Keywords: Unemployment Rate, Forecasting, Entrepreneurship

Background

The Covid-19 outbreak has significantly impacted the country's economic areas (Albab Al Umar et al., 2020; Susilawati et al., 2020). The rise in unemployment is a cause for concern (Rosén & Stenbeck, 2020; Su et al., 2021). Among the nations suffering similar issues is Indonesia. Where unemployment has increased in Indonesia as a result of the Covid-19 epidemic. According to data from the Central Statistics Agency (BPS, 2020), the Open Unemployment Rate (TPT) for August 2020 was 7.07 per cent, representing an increase of 1.84 per cent from August 2019. In 2020, the Covid-19 pandemic could affect as many as 29.12 million working-age persons (14.28 per cent). This includes 0.76 million unemployed due to the Covid-19 pandemic, 1.77 million unemployed due to the Covid-19 pandemic, and 24.03 million working citizens who had reduced working hours due to the Covid-19 epidemic (Badan Pusat Statistik (BPS), 2020).

During the Covid-19 outbreak, the rise in the unemployment rate in Indonesia hurt the population's well-being. During the Covid-19 outbreak, enterprises employed fewer workers, leading to numerous layoffs (PHK) in Indonesia, contributing to the unemployment rate. Where the Covid-19 epidemic caused 15,6 per cent of workers to lose their jobs (PHK), and the majority of young workers aged 15 to 24 lost their jobs (PHK), the majority of young workers between the ages of 15 and 24 were affected (Meilianna & Astrelina Purba, 2020). Therefore, the problem of rising unemployment rates has a substantial effect on economic growth (Mahmudah, 2017). Where individuals' incomes have decreased, this is evidenced by the declining PDRB per capita of the community.

The 2020 GRDP per capita was 56.9 million IDR, a reduction of IDR 2.2 million from the previous year's 59.07 million (Badan Pusat Statistik (BPS), 2020).

According to the National Statistics office (BPS), there are four types of unemployed people: those who do not have a job but are actively seeking one; those who are unemployed but are preparing for a business venture; those who are unemployed but are not looking for one because they believe it is impossible to do so; and those who have a job but have not yet started it. In the meantime, the International Labor Organization (ILO) defines unemployment as the state of not working but persistently seeking employment. The graph below depicts Indonesia's unemployment rate for 2017 to 2022 (Rosén & Stenbeck, 2020).

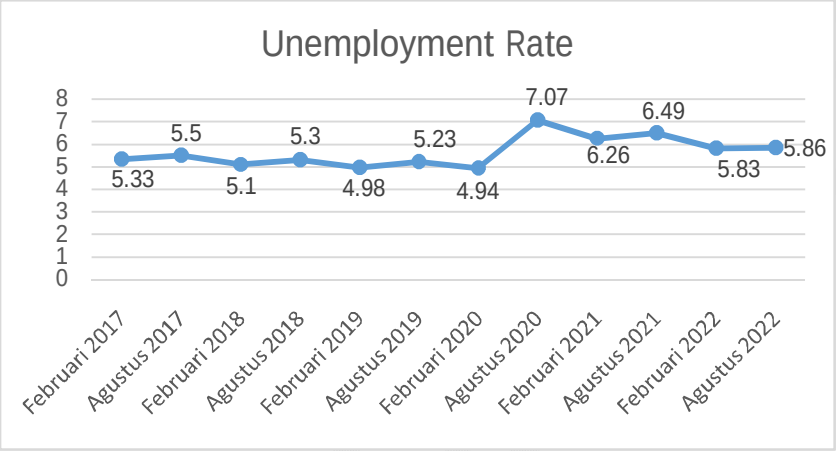

Figure 1 Unemployment rate in Indonesia 2017-2020 (Percent)

Source: Central Bureau of Statistics 2022 (data processed)

Figure 1 depicts the fluctuating unemployment rate in Indonesia. The highest rise occurred in August of 2020. This was a result of the outbreak caused by the Covid-19 virus. Effective action is required to solve the issue of unemployment. In order to reduce the problem of unemployment in the following period. This is possible if the government takes the appropriate measures to combat unemployment. Predicting the unemployment rate for subsequent years is a step that can be utilized in policy decision-making. Utilizing time series data, the ARIMA (Autoregressive Integrated Moving Average) model can be used to forecast the unemployment rate (Adhitya, 2021).

Using the Autoregressive Integrated Moving Average (ARIMA) model, the goal of this study is to forecast the unemployment rate in Indonesia. Where ARIMA is utilized for short-term forecasting utilizing past and current variable values.

The economic impact of the Covid-19 pandemic has been so significant. Since the beginning of the pandemic till now, several employees have been laid off, which has contributed to an increase in the unemployment rate and a deterioration of the household economy. Since the Covid-19 pandemic, the global labor force has suffered significantly, particularly in the service, education, reconstruction, and tourism industries. The sector that is fairly stable and even expanding is the agricultural sector. Until now, the condition has been that formerly employed individuals have lost their jobs. There are also full-time employees who work part-time or are underemployed. This contributes to the rise in unemployment.

Samuel et al research .'s is an example of the work of other academics who study the unemployment rate (2021). The study employs the ARIMA model (1,2,1) to forecast the Nigerian unemployment rate for the following four years, namely 2020 to 2024. The findings of the study indicate that the unemployment rate in Nigeria has increased (Samuel et al., 2021). In addition, Afiqah Ismail et al. (2022) conducted a study that employed the ARIMA model (2,1,2) to estimate the next two years, namely 2017 and 2018. The data indicated that the unemployment rate in Malaysia increased.

LITERATURE REVIEW

Unemployment

The National Bureau of Statistics (BPS), 2020, defines unemployment as a population aged 15 and older that is not working but is looking for work or preparing for a new enterprise, or residents who do not have a job because they have been accepted for work but have not yet begun working (Badan Pusat Statistik (BPS), 2020). Unemployment can be caused by (1) an education system that does not provide sufficient training in the field of entrepreneurship for the younger generation, (2) an excessive number of workers in the formal sector, whose number is very limited and the level of competition is very high, (3) an imbalance between demand and supply in the field of employment, (4) the education system's inability to produce quality workers in accordance with labor market demands, and (5) an imbalance between demand and supply in the field of employment. (5) During the COVID-19 epidemic, enterprises decided to employ fewer people, resulting in numerous layoffs (PHK) in Indonesia, (6) the number of workers did not correspond to the number of available jobs (Pavlopoulos & Chkalova, 2022.; (Barbieri Góes & Gallo, 2021).

During the Covid-19 epidemic, unemployment has risen. For instance, research (Rahayu & Muharam, 2021) reveals that Covid-19 linked to Termination of Employment (PHK) increased unemployment in Indonesia. Compared to the previous period, the province of DKI Jakarta saw the greatest growth in its unemployment rate, 5.80 percent. In addition, Bali Province had a 4.38 percent growth compared to the preceding period. The Riau Islands Province afterwards increased by 4.36 percent in comparison to the preceding period. Another study, specifically (Sally Jeya Singh, 2021), explains that the Covid-19 pandemic has caused many businesses to fail and consequently lay off employees, thereby increasing unemployment in Indonesia.

Unemployment is a crucial factor in defining a country's economic equilibrium (Didiharyono & Syukri, 2020). In order for unemployment to become a macroeconomic indicator that is crucial and primary for economic planning (Claveria, 2019). High unemployment has direct or indirect effects on a nation's social problems, poverty, crime, and politics. Among the causes of unemployment in Indonesia include Termination of Employment (PHK) and decreased employment as a result of the Covivirus-19 outbreak. Therefore, an estimate of the unemployment rate over the following few years is required. This is crucial for a nation's economic strategies, such as recognizing, planning, and avoiding a sustained growth in the unemployment rate in Indonesia (Didiharyono & Syukri, 2020)

Unemployment Rate Prediction

Autoregressive Integrated Moving Average (ARIMA)

ARIMA combines Autoregressive and Moving Average techniques (Adenomon, 2018). In 1976, Box-Jenkins was the creator of this model. The Box-Jenkins method has been extensively utilized to predict macroeconomic variables, such as the unemployment rate variable. The Box-Jenkins technique stresses the likelihood of time series data variables based on

the variable's own data (Adenomon, 2018). Previous studies using the ARIMA approach, such as research (Afiqah Ismail et al., 2022b), predicted future unemployment rates in Malaysia using the ARIMA method (2,1,2). Other research, especially (Samuel et al., 2021), indicates that the ARIMA approach (1,2,1) is useful for predicting the unemployment rate in Nigeria.

The Arima model is characterized by characteristics of stationary data (Mahmudah, 2017). If the data is not stationary, a differencing procedure is necessary to make it so. Data that is stationary does not fluctuate considerably. This methodology employs three models to analyze time series data: the autoregressive (AR) model, the moving average (MA) model, and previous data observations (Mahmudah, 2017). For stationary series, the ARIMA model is implemented. The ARIMA model can be represented as ARIMA (p,d,q), where p and q represent the selected AR and MA processes and q represents the differencing process in achieving stationary (Afiqah Ismail et al., 2022b).

The ARIMA method is implemented for short-term forecasting. The ARIMA approach forecasts without using independent variables. This is because ARIMA uses past and present values of the dependant variable to make accurate short-term predictions of these variables. Time series data are used by the ARIMA approach. The purpose of the ARIMA model is to forecast

In its analysis, the ARIMA model utilizes only one variable (univariate) time series data that is stationary. Data fluctuations are constant in stationary data. This suggests that there is no data increase or drop, or that variations are centered on a steady average number. When the time series data is not stationary, differencing is required. Calculating the change or difference from the observed value is known as differencing. If the data is still not stationary after differencing, the process is repeated until the data is stationary.

The ARIMA approach, often known as the Box-Jenkins method, has a model that looks like this (Harijono and Sugiarto, 2000):

1. Autoregressive (AR) is indicated by the order p

2. Differencing (difference) is indicated by the order d

3. Moving Average (MA) is indicated by order q

Model *Autoregressive* (AR)

The Autoregressive (AR) model shows that the dependent variable is affected by the dependent variable itself in the previous period. The Autoregressive Model (AR) in general is as follows:

$$Y_t = \theta_0 + \theta_1 Y_{t-1} + \theta_2 Y_{t-2} + \ldots + \theta_p Y_{t-p} + e_t$$

Where Yt is a stationary time series, θ0 is a constant, Yt-1,…,Yt-p is a related past value, θ1,…,θp is a coefficient or parameter of the autoregressive model, et is a residual at time t.

The Autoregressive (AR) model is denoted by the p order. The order is determined by the number of periods of the dependent variable used in the model. For example, an AR model that has order 1 has the equation Yt = θ0+ θ1Yt-1 which can be written using ARIMA notation (1,0,0). If the AR model has order 2 then it has the equation Yt= θ0+ θ1Yt-1 + θ2Yt-2 which can be written using ARIMA notation (2,0,0), and so on.

The Autoregressive (AR) model has similarities with the regression equation in general, but what distinguishes it is that the AR model which becomes the independent variable is the previous value (lag) of the dependent variable itself.

Moving Average (MA) Models

The Moving Average (MA) model shows that the dependent variable is affected by the residual value in the previous period. The Autoregressive Model (AR) in general is as follows:

$Y_t = ø_0 + ø_1 e_{t-1} + ø_2 e_{t-2} + ... + ø_n e_{t-q}$

Where Yt is a stationary time series, ø0 is a constant, ø1,...,øn is the moving average model coefficient, eth is the past residual at time t.

The Moving Average (MA) model has differences from the Autoregressive (AR) model. The difference lies in the independent variables used. The independent variable used in the Moving Average (MA) model is the residual value of the variable from the previous period, while the independent variable used in the Autoregressive (AR) model is the previous value (lag) of the dependent variable.

The Moving Average (MA) model is denoted by the order q. The order is determined by the number of periods of the independent variables used in the model. For example, the MA model, which has order 1, has the equation Yt = ø0 + ø1et-1, which can be written using ARIMA notation (0,0,1). If the MA model has order 2 then it has the equation Yt= ø0+ ø1et-1 + ø2et-2 which can be written using ARIMA notation (0,0,2), and so on.

Autoregressive Moving Average (ARMA) Model

The Autoregressive Moving Average (ARMA) model is a combination of the AR model and the MA model. So the ARMA model equation becomes as follows:

$Y_t = \gamma_0 + \delta_1 Y_{t-1} + \delta_2 Y_{t-2} + ... + \delta_n Y_{t-p} - \lambda_1 e_{t-1} - \lambda_2 e_{t-2} - \lambda_n e_{t-q}$

Where Yt is a stationary time series, γ0 is a constant, δ and λ are model coefficients, et is the past residual at time t. Write ARMA notation like ARMA (2,3) if the model uses two dependent variable lags and three residual lags.

Autoregressive Integrated Moving Average (ARIMA) Model

The Autoregressive Integrated Moving Average (ARIMA) model is a model combining the AR model and the MA model with stationary data that has undergone differentiation. Differencing is done by reducing the value of a period with the value of the previous period. If when performing the first differencing the data is still not stationary, then the differencing is carried out again until the data is stationary. Thus, the data used in the ARIMA model is not original data or transformed data that has been stationary. (PACF) (Didiharyono, 2020).

METHOD

The data collected for this study are secondary data. This study utilizes secondary data, Indonesia's unemployment rate. When the information is collected from the Central Bureau of Statistics (BPS). Unemployment is the proportion of jobless individuals to the labor force. In other terms, the unemployment rate is the proportion of the labor force that is unemployed or actively seeking employment. This analysis utilizes time series data between 2005 and 2022.

The ARIMA approach is used to make accurate short-term forecasts based on past, present, and stochastic error terms of the dependent variable for forecasting time series data (Nkoane & Seeletse, 2021). The ARIMA approach consists of the steps of identifying the model using the stationarity test and the correlogram test. The stationarity test is conducted because the ARIMA model can only be applied if the data are stationary or steady. In the meantime, the correlogram test is conducted to establish the differencing value (d), the lag value residual (q), and the value of

the dependent variable (p). Using a plot of the Autocorrelation Function (ACF) value and the Partial Autocorrelation Function (PACF) value, determine where to test the correlogram (2020 Didiharyono).

The ARIMA model consists of identification, estimate, Diagnostic Checking, and forecasting phases (Tufaner & Sozen, 2021). In the first step of identification, the values of p, d, and q are determined. The next phase is estimate, which involves estimating autoregressive parameters and moving averages. Third, Diagnostic Checking by identifying the suitable model based on the white noise assumptions that are satisfied. Fourth, forecast multiple future periods for which only short-term forecasting is possible (Tufaner & Sozen, 2021).

This study's primary objective is to forecast the unemployment rate following the Covid-19 epidemic. How the Covid-19 epidemic has affected Indonesia's rising jobless rate. The ARIMA method's results for predicting the unemployment rate can be used to explain the unemployment rate in the upcoming era.

The ARIMA (Autoregressive) method consists of the AR model which has order (p) and the MA model (Moving Average) which has order q (2021_Samuel). The AR model is a model that explains that the current period variable is influenced by the previous period (Tufaner & Sozen, 2021). AR models as follows:

$$Y_t = \varnothing Y_{t-1} + \ldots + \varnothing_p Y_{t-p} + a_t$$

The Yt variable is the current period variable, Yt-1 is the previous period variable value and at is the error term. Then the next model is the Moving Average (MA) model which is a model using error values in the previous period. The Moving Average (MA) model as follows:

$$Yt = at - \theta 1at\text{-}1 - \ldots - \theta qat\text{-}q$$

The ARIMA model which is a combination of AR and MA models, the model is as follows:

$$Yt = atYt\text{-}1 + \ldots apYt\text{-}p + - \theta qat\text{-}q$$

The variable Yt is the current unemployment rate, a1yt-1 is the lag from the previous period's unemployment rate, and at-1 is the residual value of the previous unemployment variable. If the ARMA model (p,q) is stationary in the difference process, it is indicated by order (d).

RESULTS AND DISCUSSION

Figure 2 depicts the unemployment rate in Indonesia for the period 2002 to 2022. Figure 2 demonstrates that the unemployment rate has fluctuated continuously, indicating that the data is not stagnant. Where during a given time period the unemployment rate in Indonesia increased. In 2020, the unemployment rate rose dramatically from 4.94 in the first semester to 7.07 in the second. Therefore, research that can predict the unemployment rate in Indonesia is necessary so that it can be predicted in advance.

Figure 2 Unemployment rate in Indonesia 2005-2022 (Percent)

Source: Central Bureau Statistics 2022 (data processed)

Figure 2 depicts the fluctuating unemployment rate in Indonesia from 2005 to 2022. The unemployment rate in Indonesia saw an upward trend in 2019. This is because to the Covid-19 pandemic, which has had a significant impact on the economy, including an increase in Indonesia's unemployment rate. From 2005 to 2022, data on the unemployment rate in Indonesia indicate that the data is not steady or constant. Therefore, testing the stationarity of the data is necessary.

First, the values of Partial Autocorrelation Function (PACF), Unit Root Test (Dickey Fuller test), and Autocorrelation Function are determined (ACF). In other words, determine p, d, and q's values. Using the Augmented Dickey Fuller Test, the value of d (stationary test) is determined to initiate the identification procedure. The data stationarity test is visible from Dicky Fuller in Augmented Reality (ADF). If the ADF value is below 0.05, then the data is stationary. Vice versa. Figure 2 illustrates that the ADF at level 0 is 0.8, indicating that the unemployment rate is not steady. Therefore, a transformation in the form of the first derivative or first difference is required. The result of the ADF test on the first derivative (first difference) is 0.00, indicating that the unemployment rate is stable. So that the value of order d, precisely d, can be written (1).

Table 1. Data Stationarity Test

Level	ADF value	Description
level 0 derivative	0,8	Not Stationer
level 1 derivative	0,0	Stationer

Source: processed data, 2022

The unemployment rate which has been stationary is then tested with a correlogram using the ACF and PACF charts. ACF is used to see the order (q) or the MA model and PACF is used to see the order (p) or AR model. The magnitude of the order q and p seen from the line that exceeds the threshold.

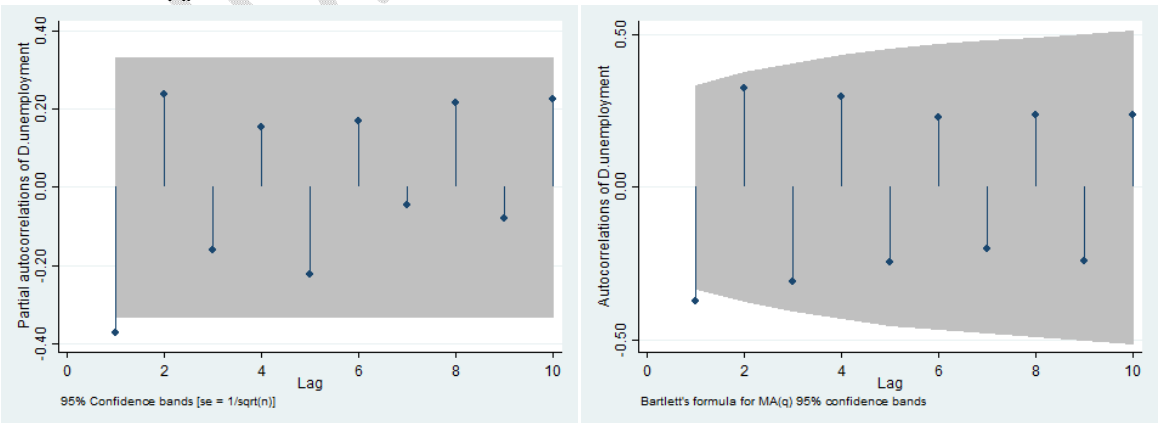

Figure 3. PACF and ACF graphs

Source: processed data, 2022

Figure 3 shows that the ACF graph exceeds the threshold at point 1. So the MA model has order q(1). While on the PACF graph that exceeds the threshold, that is at point 1. So the AR model has order p(1). The estimation results that can be used in the ARIM A model are ARIMA (1,1,1).

Estimation is carried out with the lowest ARIMA value first and is continued by carrying out Diagnostic Checking by estimating models that have residual or White Noise errors.

Table 2. White Noise Test

Portmanteau test for white noise	Value
Portmanteau (Q) statistic	2,7322
Prob > chi2 (15)	0,9998

Source: processed data, 2022

Table 2. Shows that the p-value is 0.9998. This means that it is greater than the significance of 0.05 so it can be concluded that it meets the residual or White Noise error. Thus the ARIMA model (1,1,1) can be used for forecasting.

Table 3. Forecasting Results of the Unemployment Rate in Indonesia for 2023-2025

Year	Unemployment Rate (%)	increase in unemployment rate (%)
2023 h1	5,56	-4,63
2023 h2	5,81	4,50
2024 h1	5,29	-8,95
2024 h2	5,54	4,73
2025 h1	5,02	-9,39
2025 h2	5,26	4,78

Source: processed data, 2022

The results of forecasting the unemployment rate in Indonesia from 2023 to 2025 are shown in Table 3. Where the unemployment rate for the next three years experiences a downward trend. This is due to uncertain economic conditions, one of which is due to the phenomenon of the Covid-19 pandemic. This is supported by research (Mifrahi & Darmawan, 2022) which explains that the Covid-19 pandemic has caused an increase in the unemployment rate in Indonesia. One of the reasons is because various companies in Indonesia carry out Termination of Employment (PHK) simultaneously. Thus the Covid-19 pandemic has had a major impact on the economy in Indonesia, one of which has an impact on increasing the unemployment rate in Indonesia.

The research results are in line with research (Mahmudah, 2017) which explains that forecasting results show that the unemployment rate in Indonesia tends to decrease.

CONCLUSION

The unemployment rate in Indonesia is expected to decrease between 2023 and 2025, according to the results of forecasts. This occurred as a result of the Covid-19 pandemic, which contributed to Indonesia's economic turmoil. Where the Covid-19 epidemic has caused an increase in the unemployment rate as a result of an increase in Termination of Employment (PHK) in a number of businesses. At the time of the Covid-19 epidemic, the Indonesian government was required to combat the unemployment rate. Such as creating employment opportunities and fostering MSMEs' productivity. In the future, it is hoped that the unemployment rate in Indonesia will decline.

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