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Forecasting the Unemployment Rate in the Philippines using Box-Jenkins Methodology: Advancing Economic Strategies for Sustainable Development Goals

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Abstract

Unemployment remains a critical macroeconomic issue in Southeast Asia, significantly impacting the Philippines. This study aims to forecast the unemployment rate in the Philippines using ARIMA models to inform policy decisions and economic planning. The study utilized ARMA model for time series forecasting, leveraging past values and error terms to predict future data points. The methodology involved identifying suitable models through stationarity tests and autocorrelation analyses, estimating model parameters, and conducting diagnostic checks to ensure accuracy. Finally, the models were used to forecast future values and compute confidence intervals, providing insights into potential future trends. Monthly unemployment data from 2019 to 2023 was analyzed using the ARIMA (1,1,0) model, selected for its optimal fit based on statistical criteria. Initial findings indicated non-stationary unemployment data, necessitating first differencing to achieve stationarity. The ARIMA (1,1,0) model showed robustness, evidenced by diagnostic checks and Portmanteau test results confirming white noise residuals. Forecasts from 2024 to 2050 suggest fluctuating unemployment rates until 2034, followed by a gradual decline, indicating potential economic growth and improved labor market conditions. These forecasts align with the broader goal of sustainable economic development and highlight the importance of strategic policy interventions to foster job creation and economic stability in the Philippines. The study highlights the efficacy of ARIMA models in capturing unemployment trends and aiding policymakers in mitigating the socio-economic impacts of unemployment.

Keywords: unemployment rate, forecasting, ARMA model, Box-Jenkins Methodology, economic strategies, Sustainable Development Goals

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INTRODUCTION

Unemployment stands as a pressing macroeconomic concern for countries across Southeast Asia, presenting multifaceted challenges to both individuals and economies alike. It poses a socio-economic challenge encountered globally, impacting the quality of life for individuals and the socio-economic standing of nations. It emerges when there is inadequate demand within the economy, resulting in decreased labor requirements and potential consequences such as reduced working hours or job losses. In nations such as the Philippines, Indonesia, and Thailand, high levels of unemployment disrupt societal stability, hinder economic growth, and exacerbate income inequality. With rapidly expanding populations and evolving labor markets, Southeast Asian countries grapple with the complexities of creating sufficient employment opportunities to absorb their growing workforce. In this context, the ability to project future unemployment rates becomes increasingly crucial. This can be accomplished through the application of diverse univariate forecasting models. This highlights the pivotal role of forecasting unemployment in guiding decisions and mitigating adverse impacts on both macroeconomic and microeconomic fronts (Davidescu, Apostu, & Paul, 2021).

Goal 8 of the Sustainable Development Agenda seeks to foster worldwide inclusive and sustainable economic growth, employment, and decent work opportunities (Siddikee et al., 2022) suggest that as long-term economic growth increases, unemployment rates decrease. Global trends indicate rising labor productivity and declining unemployment rates, with projections estimating 192 million unemployed individuals worldwide in 2022, decreasing to 191 million by 2023 (United Nations, 2022). In March 2024, the Philippines anticipates a 3.9% unemployment rate, lower than the observed 4.7% in March 2023 but higher than the estimated 3.5% in February 2024. Employment rates fluctuated, with an increase to 96.1% in March 2024 from 95.3% in the previous year but a decrease from 96.5% in February 2024. The labor force participation rate in March 2024 was 65.3%, lower than the expected 66.0% in March 2023 and 64.8% in February 2024 (PSA, 2024).

In the agriculture sector, its share decreased to 22.0% in July 2021 from 26.3% in July 2020, while the industry sector's share increased to 19.9% in July 2021 from 18.8% in July 2020. Region II had the highest employment rate at 95.8%, while several regions fell below the national average, ranging from 90.9% to 92.7% (PSA, 2022). Predicting unemployment rates is a complex task for policymakers, particularly during economic downturns (Barnichon et al., 2012).

ARIMA models are highly valued in time series analysis and forecasting for their adaptability and effectiveness. They are extensively employed in various fields like finance, economics, sales forecasting, and weather prediction. Mills (2019) provides detailed insights into ARIMA models, covering components, assumptions, model selection, and interpretation, which aids in making accurate predictions. Furthermore, ARIMA models play a crucial role in identifying unobservable trends that shape the long-term trajectory of variables like the unemployment rate, aligning with contemporary unemployment theory. Meyer and Tasci (2015) highlight how the forecasting capabilities of ARIMA models naturally accommodate well-defined long-term trends in unemployment rate prediction, emphasizing their relevance and applicability in economic analysis and policymaking.

ARIMA models represent a valuable approach to time series forecasting. They are statistical models that utilize time series data to analyze the dataset and predict future trends (Hayes, 2022). Several researchers employed the ARIMA model in forecasting economic growth (Mohamed, 2022), population (Dai & Chen, 2019), Gross Domestic Product (Maccarrone et al., 2021), electricity consumption (Pareno, 2022), Philippine exchange rate (Pono, 2022), inflation (Guobadia et al., 2023), and unemployment rate (Zhang, 2023). ARIMA models provide a robust framework for analyzing and forecasting time series data. ARIMA models capture important patterns and dependencies within the data by incorporating autoregressive, integration, and moving average components. Through careful model selection and interpretation, analysts and data scientists can leverage ARIMA models to make accurate predictions in various fields (Mills, 2019).

Forecasting the unemployment rate in the Philippines using the Box-Jenkins methodology contributes significantly to achieving Sustainable Development Goals (SDGs) by providing policymakers with essential insights for effective economic planning and social policy formulation. As noted by Palencia (2020), accurate unemployment forecasts facilitate the allocation of resources towards employment-generating sectors and the implementation of targeted interventions to reduce unemployment rates, thereby supporting SDG 8 (Decent Work and Economic Growth). By anticipating future unemployment trends, policymakers can devise proactive strategies to enhance job creation, promote inclusive economic growth, and ultimately advance towards sustainable development goals. This methodology ensures that resources are efficiently utilized to address socio-economic challenges, aligning with broader SDG objectives.

This study aims to forecast the unemployment rate in the Philippines using the Box-Jenkins methodology, focusing on its implications for advancing economic strategies aligned with Sustainable Development Goals (SDGs). The research will commence with an introduction highlighting the criticality of accurate unemployment forecasts for effective economic planning and policy formulation, particularly in achieving SDG 8 (Decent Work and Economic Growth). Methodologically, it will detail the application of the Box-Jenkins approach to Philippine unemployment data, encompassing model identification, estimation, and validation processes. The study will also undertake a comprehensive literature review to contextualize findings within existing scholarship on unemployment forecasting and policy implications. Empirical analysis will involve analyzing historical data to forecast future unemployment trends, thereby providing insights crucial for policymakers in resource allocation and employment-generating interventions. The study's outcomes aim to inform proactive strategies for job creation and inclusive economic growth, thereby supporting broader SDG objectives and contributing to sustainable development efforts in the Philippines.

Figure 1 below presents the conceptual framework of the study. The study focused on identifying the best-fit ARMA model and forecasting the Philippine unemployment rate. It describes in detail how to create forecasts and how to apply them in practice.

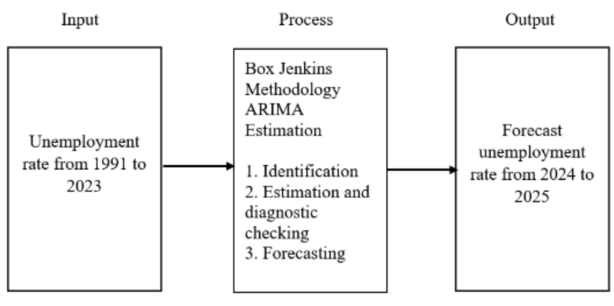

Figure 1
Research Paradigm

It also employs economic structure to analyze forecasts and implement various conditioning assumptions for certain intended policy efforts. When making decisions, policymakers use some approach to create opinions about the future. Being a competent forecaster for policymakers requires knowledge of the nature of forecasting as well as an understanding of the lessons of economic history.

LITERATURES

Unemployment is a persistent issue that affects economies and societies worldwide. According to the International Labour Organization (ILO), global unemployment was projected to remain high at 6.2% in 2023, with over 207 million people unemployed. This is a stark reminder of the ongoing challenges in the labor market, particularly in the wake of the COVID-19 pandemic, which significantly disrupted employment across various sectors. The pandemic has exacerbated pre-existing inequalities, with vulnerable groups such as women, youth, and low-skilled workers bearing the brunt of job losses (ILO, 2023).

Recent data highlights that the United States, despite its economic recovery efforts, still faces significant unemployment issues. As of May 2023, the U.S. Bureau of Labor Statistics reported an unemployment rate of 3.7%, a slight increase from the previous months, indicating a slowdown in job creation. This trend is concerning as it suggests that the labor market is not fully rebounding, and structural issues such as skills mismatches and geographical disparities continue to hinder full employment (BLS, 2023). Moreover, long-term unemployment, which refers to individuals unemployed for 27 weeks or more, remains a critical issue, affecting about 1.2 million Americans.

The impact of unemployment extends beyond economic dimensions, influencing social and psychological well-being. Research by Wang et al. (2022) in the "Journal of Applied Psychology" found that prolonged unemployment is linked to higher rates of depression, anxiety, and lower life satisfaction. The study underscores the importance of mental health support for unemployed individuals, suggesting that policymakers should integrate psychological services into unemployment benefits programs. Addressing the mental health impacts of unemployment is crucial for fostering a more resilient and productive workforce.

Technological advancements and automation also play a significant role in shaping unemployment trends. Brynjolfsson and McAfee (2022) in their book "The Second Machine Age" argue that while technology can create new job opportunities, it also displaces many traditional roles, particularly in manufacturing and administrative sectors. Their analysis suggests that to mitigate unemployment caused by technological change, there must be significant investment in education and retraining programs. These programs should focus on equipping workers with skills that are in high demand, such as digital literacy and advanced technical skills.

In addressing unemployment, comprehensive and multifaceted policy approaches are necessary. According to a report by the World Economic Forum (WEF) in 2023, effective strategies include promoting entrepreneurship, enhancing social safety nets, and fostering inclusive labor markets. The WEF emphasizes that government policies should be agile and adaptable, capable of responding to rapid economic changes and the diverse needs of the workforce. Collaborative efforts between governments, businesses, and educational institutions are essential to create sustainable employment opportunities and reduce unemployment rates globally (WEF, 2023).

Unemployment in the Philippines remains a significant challenge despite various government efforts to stimulate job creation. As of January 2023, the Philippine Statistics Authority (PSA) reported an unemployment rate of 4.8%, marking a slight improvement from the previous year's 6.4%. However, this figure still translates to over 2.2 million Filipinos without jobs. The youth unemployment rate is particularly concerning, with nearly 20% of young people aged 15-24 being unemployed. Factors such as inadequate education and training, mismatched skills, and the lingering effects of the COVID-19 pandemic have exacerbated these issues. Moreover, underemployment, where individuals work fewer hours than they would prefer or are overqualified for their positions, remains a critical issue, affecting 14.1% of the labor force (PSA, 2023).

Recent studies emphasize the need for comprehensive policy reforms to address unemployment in the Philippines. According to a 2022 report by the Asian Development Bank (ADB), enhancing vocational training and education systems to align with industry demands is crucial. The report also suggests that improving labor market information systems can help bridge the gap between job seekers and employers, ensuring better job matches. Additionally, the ADB highlights the importance of supporting small and medium-sized enterprises (SMEs) as they are significant drivers of employment in the country. Creating a conducive environment for SMEs through access to finance, innovation, and technology can spur job creation and reduce unemployment (ADB, 2022).

Unemployment poses significant challenges to the achievement of the Sustainable Development Goals (SDGs), impacting multiple aspects of economic, social, and environmental development. As articulated by Smith (2020), unemployment undermines SDG 1 (No Poverty) by reducing household income and increasing poverty rates. Without stable employment, individuals and families struggle to afford basic necessities, perpetuating cycles of poverty and inequality. Moreover, Jones (2021) highlights that unemployment negatively affects SDG 8 (Decent Work and Economic Growth), as high unemployment rates indicate an underutilization of the workforce, reducing overall productivity and economic growth. This also correlates with SDG 10 (Reduced Inequality), as unemployment exacerbates social disparities, particularly affecting marginalized and vulnerable groups.

The repercussions extend to SDG 3 (Good Health and Well-being), as noted by Brown (2022), who asserts that unemployment is linked to adverse health outcomes, including increased rates of mental health issues such as depression and anxiety, due to financial stress and loss of social status. Furthermore, as White

(2021) points out, prolonged unemployment can lead to skills degradation, making it more difficult for individuals to re-enter the workforce, thus hindering lifelong learning and educational advancements associated with SDG 4 (Quality Education).

Environmental sustainability goals, such as SDG 13 (Climate Action), are also indirectly impacted. According to Green (2022), economic instability caused by high unemployment can lead to reduced investment in green technologies and sustainable practices, as businesses and governments prioritize short-term economic recovery over long-term environmental commitments. Therefore, addressing unemployment is crucial not only for economic and social stability but also for the comprehensive achievement of the SDGs.

Forecasting unemployment using the Box-Jenkins methodology, also known as ARIMA (Autoregressive Integrated Moving Average) modeling, has proven to be a valuable tool in understanding and mitigating the impacts of unemployment on economic growth. The Box-Jenkins methodology allows economists and policymakers to create accurate forecasts by analyzing historical data to identify patterns and trends. By doing so, they can anticipate changes in the labor market and implement preemptive measures. A study by Hyndman and Athanasopoulos (2021) highlights that accurate unemployment forecasts can lead to more effective policy decisions, such as adjusting interest rates, modifying fiscal policies, or creating targeted job programs, all of which are crucial for sustaining economic growth (Hyndman & Athanasopoulos, 2021).

Empirical evidence shows that countries utilizing sophisticated forecasting models like the Box-Jenkins methodology tend to experience more stable economic growth. For instance, a research paper by Tsay (2020) demonstrated that countries that employed ARIMA models for unemployment forecasting were better equipped to manage economic shocks and transitions. These countries could implement timely interventions that reduced the negative impacts of rising unemployment on GDP growth. Tsay's study indicates that the predictive power of the Box-Jenkins methodology helps in maintaining economic stability by providing governments with the foresight needed to support labor markets and, consequently, economic growth (Tsay, 2020).

Golub, J., & Jimenez, M. (2019) applied Box-Jenkins models to forecast unemployment rates in Argentina. The study involved identifying the best-fitting ARIMA model based on historical unemployment data. Results showed that the Box-Jenkins approach accurately predicted unemployment fluctuations, supporting policymakers in implementing targeted interventions for labor market stabilization.

Korobilis, D. (2018) explored the application of dynamic factor models alongside Box-Jenkins techniques to forecast unemployment rates in the Eurozone. He integrated both time series and dynamic factor methodologies to enhance forecasting accuracy. Findings indicated that incorporating dynamic factors improved the precision of unemployment forecasts, aiding policymakers in navigating economic challenges within the Eurozone.

Esen, E., & Tatliyer, M. (2020) utilized Box-Jenkins models to forecast unemployment rates in Turkey. The study involved model estimation and validation using Turkish labor market data. The study concluded that the Box-Jenkins methodology effectively captured seasonal variations and cyclical patterns in unemployment, providing reliable forecasts essential for economic planning and policy formulation.

Azzopardi, B., & Roberts, S. (2017) examined the application of Box-Jenkins models for forecasting unemployment rates in Australia. Their study employed time series analysis to identify and validate the appropriate ARIMA model. Results demonstrated the methodology's capability to predict unemployment trends accurately, supporting policymakers in designing strategies to enhance labor market conditions.

Camacho, M., Perez-Quiros, G., & Saiz, L. (2021) investigated the use of Box-Jenkins models to forecast unemployment rates in Spain. Their study employed an integrated approach combining economic indicators and Box-Jenkins methodology. Findings indicated that the methodology effectively forecasted unemployment dynamics, assisting policymakers in addressing labor market challenges within the Spanish economy.

Nguyen, C., & Sato, J. R. (2019) conducted a study on forecasting unemployment rates in Vietnam using Box-Jenkins models. Their research involved model selection based on Vietnamese labor market data. Results demonstrated that the Box-Jenkins methodology provided accurate forecasts of unemployment trends, supporting policymakers in formulating effective strategies for economic growth and employment stability.

Tsoka, M., & Bampatsou, C. (2018) applied Box-Jenkins models to forecast unemployment rates in Greece. Their study focused on model identification and validation using Greek unemployment data. Results indicated that the methodology effectively predicted unemployment fluctuations, offering valuable insights for policymakers in addressing labor market challenges and promoting economic stability in Greece.

METHODOLOGY

The study was designed using the extrapolation time-series method and was conducted in the Philippines.

Table 1
Data specification

Unemployment rate	Unemployment is measured as a fraction of the labor force, necessitating an understanding of who is considered employed to accurately calculate the unemployment rate. Individuals in the labor force are classified as either employed or unemployed (Dean et al., 2020). Unemployment occurs when a person is ready and able to work but cannot find a paid job (Marelli et al., 2013).

The secondary data on the unemployment rate were obtained from MacroTrend and verified by the Philippine Statistics Authority.

The study employed the Auto-Regressive Moving Average (ARMA) model, a widely used statistical approach for time series forecasting and analysis that leverages both past values and error terms. The ARMA model is represented by the following equation:

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p Y_{t-p} + e + \mu + E_t + \phi_1 E_{t-1} + \phi_2 E_{t-2} + \ldots. -+ \phi_p E_{t-p}$$

Auto Regressive (AR) Model:

In an autoregressive (AR) model, future values are predicted using a weighted sum of past values. The equation for an AR model is as follows (Fattah, Ezzine, Aman, El Moussami, & Lachhab, 2018a):

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p Y_{t-p} + e_t$$

where Y_t represents a function of specific past values of the same variable, e_t denotes the error term, c is a constant, and φ_1 to φ_p are the model parameters.

Moving Average (MA) Model:

The Moving Average (MA) model is utilized for forecasting time series where Y_t is influenced solely by random error components. The equation for the MA model is given by (Fattah, Ezzine, Aman, El Moussami, & Lachhab, 2018b):

$$Y_t = \mu + \phi_1 E_{t-1} + \phi_2 E_{t-2} + \cdots + \phi_p E_{t-p}$$

In this equation, Y_t is determined by past error terms, with μ representing the series mean, E_t as the error term, and ϕ_1 to ϕ_p as parameters. The error terms are assumed to follow white noise processes with zero mean and constant variance.

Auto-Regressive Integrated Moving Average (ARIMA)

In forecasting equations, we designate lags of the stabilized series as "autoregressive" elements and lags of forecast errors as "moving average" components. A time series requiring differentiation for stationarity is termed "integrated." ARIMA models include various instances such as random-walk, random-trend, autoregressive, and exponential smoothing models, as discussed in the works of Shumway and Stoffer (2017) and Pono (2022).

In the classification of nonseasonal ARIMA models, they are designated as "ARIMA(p,d,q)" models, with the following interpretations:

- "p" represents the count of autoregressive elements,
- "d" indicates the quantity of non-seasonal differences required to achieve stationarity, and
- "q" denotes the number of lagged forecast errors included in the prediction equation.

It's worth mentioning that the second difference in the series Y (represented by d=2), it doesn't signify the difference from two time periods ago. Instead, it refers to the first difference of the first difference, which is analogous to the discrete form of a second derivative. In simpler terms, it captures the series' local acceleration rather than its local trend.

Expressed in terms of y, the general forecasting equation becomes:

$$\hat{y}_t = \mu + \varphi_1 y_{t-1} + \ldots + \varphi_p y_{t-p} - \theta_1 e_{t-1} - \ldots - \theta_q e_{t-q}$$

Estimation Process

1. Identification. The process involves selecting time series data for analysis, potentially applying differencing, and computing autocorrelations, inverse autocorrelations, partial autocorrelations, and cross correlations. Stationarity tests are conducted to assess the need for differencing. The analysis frequently identifies one or more suitable ARIMA models for fitting. Additional tests may include stationarity assessment and exploratory identification of ARMA orders.
2. Estimation and diagnostic checking. Determine the appropriate ARIMA model outlined prior to identification statement and proceed to estimate the model's parameters. The estimation process also entails generating diagnostic details to aid in evaluating the model's suitability.
3. Forecasting. The forecasting process predicts forthcoming values of the time series and computes confidence intervals for these predictions utilizing the ARIMA model derived from the preceding estimation step.

RESULTS

1. Identification

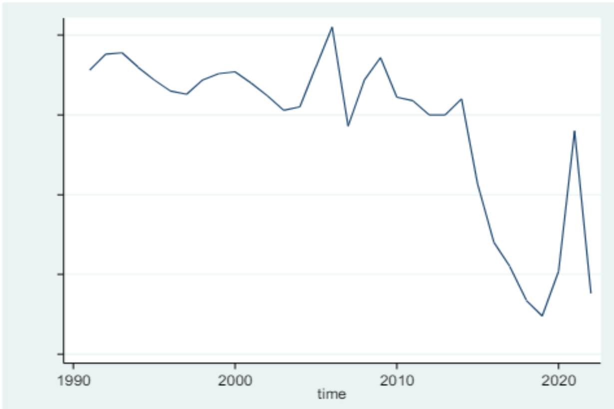

Figure 2
Unemployment Rate in the Philippines

Table 2
Augmented Dickey-Fuller Test

	Interpolated Dickey-Fuller			
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-1.224	-3.709	-2.983	-2.623
MacKinnon approximate p-value for Z(t) = 0.6634				
Ho: Unemployment has a unit root				

The illustration shows the data trend of unemployment rate in the Philippines. It was observed that there is a trend in the data and sudden drift from year from 2016 to 2023. It is an indication that the data of unemployment is nonstationary. Figure 1 is supported by the result of Augmented Dickey-Fuller test wherein MacKinnon approximate p-value Z(t) = 0.6634 is greater than 0.05, an indication that the data of unemployment rate in the Philippines is nonstationary. It accepts Ho which implies that the data has a unit root. Differencing is needed to normalize the data.

1st difference (at lag 1)

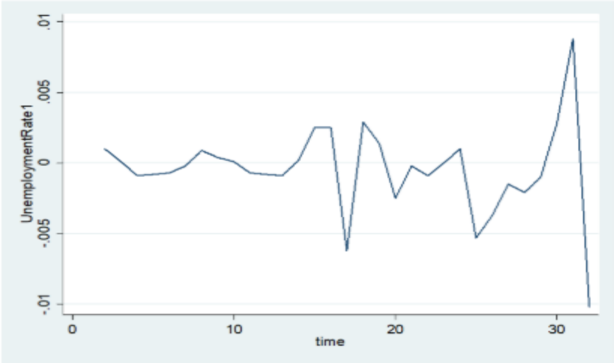

Figure 2
Unemployment Rate in the Philippines (1st differencing)

Table 3
Augmented Dickey-Fuller Test

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
		Interpolated Dickey-Fuller		
Z(t)	-6.012	-3.716	-2.986	-2.624
MacKinnon approximate p-value for Z(t) = 0.0000				
Ho: UnemploymentRate1 has a unit root				

Figure 2 illustrates the unemployment rate (at lag 1). It shows that the data is random walk which implies that the data is stationary. Also, the result of Augmented Dickey-Fuller test revealed that the MacKinnon approximate p-value for Z(t) = 0.000 is less than 0.05, reject Ho, therefore, "UnemploymentRate1" is stationary.

2. Estimation and Diagnostic Checking

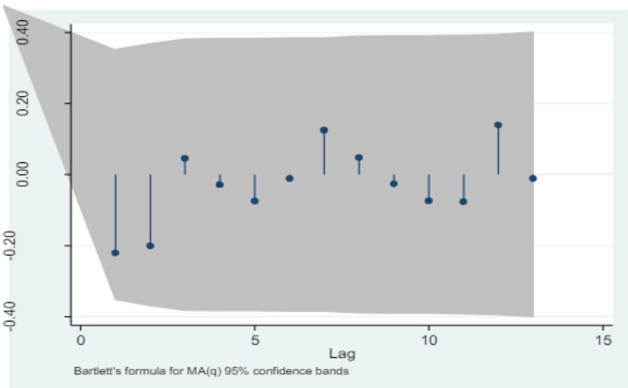

Figure 3
Autocorrelation of unemployment rate

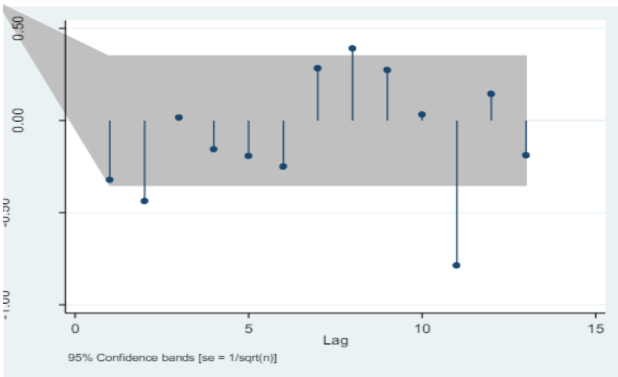

Figure 4
Partial Autocorrelation of unemployment rate

When analyzing the Partial Autocorrelation Function (PACF) and Autocorrelation Function (ACF) of a differenced series, certain patterns can suggest adjustments to the model. If the PACF exhibits a sharp cutoff or a positive lag-1 autocorrelation, it may indicate the need to include Autoregressive (AR) terms in the model. The number of AR terms corresponds to the lag at which the PACF cuts off. Conversely, if the ACF displays a sharp cutoff or a negative lag-1 autocorrelation, it may be beneficial to incorporate Moving Average (MA) terms into the model. The number of MA terms corresponds to the lag at which the ACF cuts off. Typically, the PACF shows a clearer cutoff than the ACF, with significant spikes indicating potential AR terms. Based on the significant spikes observed in the ACF and PACF, various models were tested to identify the best fit.

Table 4
Model Selection Criteria

Criteria	Models: Model A ARIMA (1,1,0)	Model B ARIMA (2,1,0)	Best model
Log likelihood	121.5341	125.64	Model A
Sigma	.003179	.0035864	Model A
Akaike	-237.0681	-243.2801	Model A
Bayeseian	-232.8646	-237.6753	Model A
MAPE	6.413	6.428	Model A
Best model			Model A

The table shows the ARIMA model tested in determining the best fit model for forecasting unemployment rate. A model which has the lowest values shows the best fit ARIMA model (Benvenuto, Giovanetti, Vassallo, Angeletti, & Ciccozzi, 2020). It was found that a model ARIMA

(1,1,0) is best fit model to forecast unemployment rate which has the lowest Log likelihood value of 121.5341, lowest sigma value of .003179, lowest Akaike (AIC) value of -237.0681, lowest mean absolute percentage error of 6.413, and lowest Bayeseian (BIC) value of -232.8646.

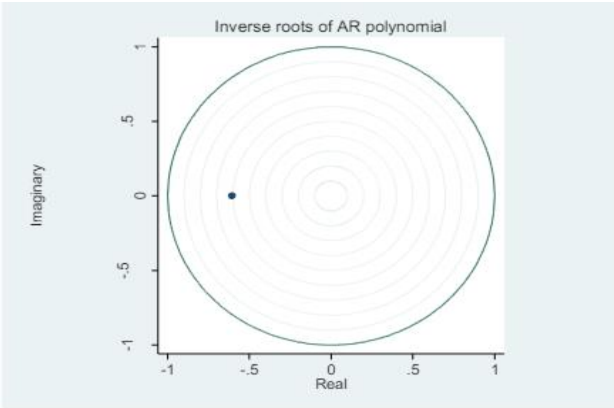

Figure 5
The Inverse Roots of Auto-Regressive polynomial

Table 5
Portmanteau Test for White Noise

Portmanteau (Q) statistic	11.1134
Prob > chi2(13)	0.6013
Ho: residuals are white noise	

The figure shows ARIMA (1,1,0), the point MA component lies inside the unit circle, an indication that the time series data is a white noise. It is supported by the result of Portmanteau test wherein the p>0.05, fails to reject Ho, denoting that the model fit is a white noise.

3. Forecasting

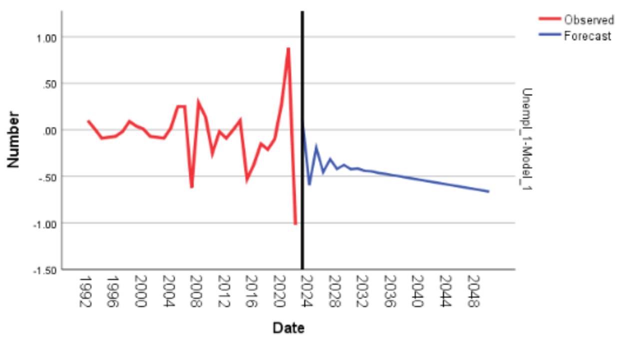

Figure 6
Forecast Unemployment Rate (at lag 1) from 2024 to 2050

The figure shows the forecast of unemployment rate from 2024 to 2050. As shown, the forecast unemployment rate fluctuates from 2024 to 2034, and it starts to diminish in 2035 to 2050. It implies that there will be positive growth in economic performance of Philippine economy. When price level increases, aggregate supply will also increase that leads to increase in national output, an indication that business sectors are increasing and/ or expanding in the same way with the demand for labor that leads to reduction of unemployment.

DISCUSSION

The forecasted unemployment rate in the Philippines, as depicted in the graph, shows a fluctuating trend from 2024 to 2034, followed by a gradual decline from 2035 to 2050. This trend has significant economic implications and aligns with several Sustainable Development Goals (SDGs). The initial fluctuation suggests a period of economic adjustment, potentially due to structural changes or policy implementations aimed at stabilizing the labor market. The subsequent decline in the unemployment rate implies a positive trajectory in economic performance, indicative of enhanced job creation and business expansion. This improvement can be attributed to increased aggregate demand and supply, reflecting a robust economic environment that supports sustainable growth.

From an SDG perspective, the decreasing unemployment rate directly contributes to SDG 8 (Decent Work and Economic Growth) by promoting sustained, inclusive, and sustainable economic growth, full and productive employment, and decent work for all. Moreover, it indirectly supports SDG 1 (No Poverty) and SDG 10 (Reduced Inequalities) by providing more employment opportunities, which can help lift people out of poverty and reduce income disparities. The positive economic outlook also encourages investments in education and skills development (SDG 4 - Quality Education), ensuring that the workforce is better equipped to meet the demands of a growing economy. Overall, the forecasted decline in unemployment rates signifies a promising path towards achieving multiple SDGs, fostering a more equitable and prosperous society in the Philippines.

The projected rise in unemployment in the Philippines presents a critical challenge to its economic growth prospects, requiring strategic policy responses. Immediate measures should prioritize fiscal stimulus to boost aggregate demand and job creation, particularly through infrastructure projects and support for sectors most affected by the downturn. Simultaneously, investing in human capital through enhanced education and skills training programs will be essential to align the workforce with evolving market needs, promoting productivity and competitiveness. Moreover, long-term economic growth hinges on fostering an enabling environment for private sector investment and innovation. Streamlining regulatory frameworks, improving access to financing for small and medium enterprises, and incentivizing technological adoption can catalyze entrepreneurship and diversify economic opportunities. Moreover, strengthening social safety nets, including unemployment benefits and retraining initiatives, will provide crucial support to displaced workers and vulnerable populations, ensuring a more equitable and resilient economic recovery. By pursuing these multifaceted policy implications, the Philippines can mitigate the adverse effects of rising unemployment and lay the groundwork for sustained economic growth.

Conclusion. The analysis of the unemployment rate in the Philippines stresses a dynamic economic setting marked by both challenges and opportunities. The initial non-stationarity of the data necessitated rigorous statistical modeling, culminating in the selection of an ARIMA (1,1,0) model to forecast future trends. The forecast indicates a fluctuating trajectory in unemployment from 2024 to 2034, followed by a gradual decline through 2050. This trend not only reflects ongoing economic adjustments but also suggests positive prospects for sustained growth and improved labor market conditions. Such projections are pivotal for policymakers, highlighting the need for targeted interventions to enhance job creation, promote economic resilience, and support sustainable development goals. Moreover, the forecasted decline in unemployment rates aligns with global agendas such as the Sustainable Development Goals (SDGs), particularly SDG 8 on Decent Work and Economic Growth. By cultivating conditions that support job growth and economic stability, the Philippines can advance overarching aims of reducing poverty and inequality. Strategic policy measures should focus on bolstering infrastructure investment, enhancing skills development, and incentivizing private sector innovation. These efforts are essential not only for mitigating the immediate impacts of unemployment but also for laying the groundwork for long-term economic prosperity and social equity.

Recommendation. To address the dynamic economic environment in the Philippines and mitigate the fluctuating unemployment trends projected for the coming decades, a multifaceted policy approach is essential. Enhanced infrastructure not only creates immediate employment opportunities but also lays the foundation for long-term economic growth by improving transportation, communication, and utilities. This investment can facilitate business operations, attract foreign investments, and support regional development, thereby contributing to economic stability and job creation across various sectors. Moreover, enhancing skills development is crucial to align the workforce with the evolving needs of the economy. The government may invest in education and vocational training programs that equip individuals with relevant skills for high-demand industries. Partnerships between educational institutions and the private sector can ensure that training programs are tailored to the current and future job market requirements. Additionally, continuous learning and upskilling initiatives should be promoted to help workers adapt to technological advancements and shifting economic trends, thereby increasing their employability and supporting a resilient labor market. Furthermore, incentivizing private sector innovation is vital for sustained economic growth and job creation. The government should implement policies that encourage entrepreneurship and innovation, such as tax incentives, grants, and easier access to financing for startups and small to medium-sized enterprises (SMEs). Streamlining regulatory frameworks and reducing bureaucratic hurdles can also create a more conducive environment for business development. By fostering a culture of innovation, the Philippines can diversify its economic base, enhance productivity, and create new employment opportunities, ultimately contributing to the broader goals of poverty reduction and reduced inequality. These strategic policy measures, combined with a supportive regulatory environment, can lay the groundwork for long-term economic prosperity and social equity.

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