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Time series approach on Philippines' three economic participation using ARIMA Model

[1]Robert Jay N. Angco, [2]Lee D. Timtim, [3]Mikee P. Ando, [4]Cathy L. Leyson, [5]Cristy Rose P. Villasin

[12345]Department of Mathematics and Statistics, Cebu Technological University

robertjay.angco@ctu.edu.ph[1], lee.timtim@ctu.edu.ph[2], mikee.ando@ctu.edu.ph[3], cathy.leyson@ctu.edu.ph[4], cristyrose.villasin@ctu.edu.ph[5]

Abstract. The main objective of this study was to predict the three economic participation's (unemployment, underemployment, employment) in the Philippines for the year 2020 progressively and respectively on a quarterly scale. With a time series approach, the researchers were able to produce ARIMA models that contribute to determining the future values using the quarterly data from the year 2005 to 2019, a total of 60 observations for each economic participation, with the help of the software R Programming. The ARIMA (2,1,0) and ARIMA (0,1,1) were the identified models that are the most adequate and appropriate used to forecast the future values of the three economic participation. These models have undergone series of diagnostics like the seasonally adjusted plot to remove the seasonality of the data, and the Augmented Dickey-Fuller test to check the stationarity which starts with differencing the data. The Augmented Dickey-Fuller test generated the p-values for each economic participation non-stationary which means that the models should undergo a first-order differencing. After differencing, these results were obtained. For the unemployment rate, the ARIMA (2,1,0) forecast the quarterly rate for the year 2020 which are 5.34, 5.29, 5.14, and 4.66. While for the underemployment rate, these values were produced, 15.90, 15.52, 16.15, and 14.90, respectively, by ARIMA (0,1,1). And for employment, ARIMA (2,1,0) was able to generate these values,94.60, 94.64, 94.89, and 95.46. The predicted quarterly values for the year 2020 show a declining trend for unemployment which consequently indicates an inclining path for employment. While the underemployment rate follows a trend from high to low for the first and second quarter, rises for the third quarter and decreases for the last quarter. The obtained results that a low percentage of unemployment and underemployment, subsequently gives employment a higher rate, and vice versa.

Keywords. ARIMA Model, Economic Participation, Time Series

Introduction

Economics is all about money and finance and problems with supply and demand. Economics also provides a framework for understanding the actions and decisions of people, businesses and governments. It provides a way to know interactions during a market-driven society and for analyzing government policies like for the reduction of poverty that affects the lives of citizens and their families. Citizens that are less affected by poverty can engage with and are empowered in a variety of ways when they gain a better grasp and understanding of economics. There is a considerable appetite for participation in initiatives they consider to be meaningful and responsive to their voices. This, in turn, strengthens their sense of power and willingness to participate in other civic initiatives (Patel & Gibbon, 2017).

Each citizen can stimulate an increase in economic growth with its economic participation. The statistics of the economically active population, employment, unemployment, and underemployment serve a large variety of purposes. They provide measures of labor supply, labor input, the structure of employment, and the extent to which the available labor time and human resources are actually utilized or not (Hussmanns, 2007).

According to Felipe & Lanzona (2006), unemployment and underemployment are the Philippines' most important problems and the key indicators of the weaknesses of the economy. The preliminary results of the Annual Labor and Employment Estimates for 2019 based on the average of the four (4) LFS rounds (January, April, July, and October) reported an annual labor force participation rate of 61.3 percent out of the 72.9 million population 15 years old and over. This is equivalent to about 44.7 million economically active people comprising either employed or unemployed persons (Labor and Employment, 2019).

The annual employment rate in 2019 was estimated at 94.9 percent; the annual unemployment rate was 5.1 percent, and the annual underemployment rate was 14.0 percent. In the 2018 final result, the annual labor force participation rate was 60.9 percent, the annual employment rate was 94.7 percent, the annual unemployment rate was 5.3 percent and the annual underemployment rate was 16.4 percent (Philippine Statistical Authority, 2019).

According to National Economic and Development Authority (NEDA), the increasing number of workers hiring in the services and agriculture sectors, the Philippines has enjoyed significantly better employment results in July 2019 as well as lower underemployment. In July 2019, the employment rate increased by 5.7 percent from 1.2 percent in July 2018, showed by the Labor Force Survey of the Philippines Statistics Authority. The increased result of 5.7 percent abruptly translates to 2.3 million jobs, almost five times the 479, 000 employment that was generated in the same period in 2018. Simultaneously, the unemployment rate remains constant at 5.4 percent. This remains to be the lowest unemployment rate recorded for all July rounds of the survey since 2009 (National Economic and Development Authority, 2019).

Despite the fact that employment in the Philippines has been growing fast for the past decade, still, many Filipinos are jobless, having 9.1 million unemployed citizens (Atienza, Tampis, & Urrutia, 2017).

Philippines, a country primarily considered as a newly industrialized which has an economy transitioning from one based on agriculture to one based more on services and manufacturing (Economy of the Philippines, 2002-2020) . The Philippines comprises seventeen regions and that we are ought to examine each regions' three-dimensional economic participation that affects the Philippines as a whole.

Therefore, the researchers aim to produce a descriptive statistical data investigating the economic participation of the different quarterly rates within the Philippines; employing a time series approach covering the years from 2005-2019. With the data collected from the Philippine Statistics Authority (PSA), the researchers ought to show a comparative analysis among the three dimensions of economic participation.

Review of Related Literature

Unemployment

Officially unemployment is defined as the situation of being without work, wanting work, and actively seeking work. It is usually measured as a percentage of the people in the total labor force or the total for some social group. The labor force is defined as those who are employed or unemployed (Villegas, 2016)

The Bureau of Labor and Statistics defined a person as unemployed if he is not working but is willing and able to work. More precisely, it stated that unemployment is when the labor force is seeking employment but cannot find it. Further defined, unemployment is a cost to the economy in terms of the deficiency in production. In other words, when people do not have jobs, those employees are not able to produce, and therefore the economy produces less. The number of unemployed persons includes people age 16 and older who are without a job but looking for work.

Underemployment

Underemployment is a measure of employment and labor utilization in the economy that looks how well the labor force is being utilized in terms of skills, experience and availability to work. It refers to a situation in which individuals are forced to work in low paying or low skill jobs.

There are two types of underemployment. Visible underemployment is underemployment in which an individual works fewer hour than is necessary for a full-time job in his or her chosen field. Due to the reduced hours, they work two or more part-time jobs in order to make ends meet. The second type of underemployment is invisible underemployment. It refers to the employment situation in which an individual is unable to find a job in his or her chosen field. A third type of underemployment refers to situations in which individuals, who are unable to find work in their chosen field, quit the workforce altogether, meaning they haven't looked for a job in the last four weeks per the Bureau of Labor Statistics' definition of labor force participation. (Villegas, 2016).

Employment

It is a relationship between two parties, usually based on a contract where work is paid for, where one party, which may be a corporation, for profit, not-for-profit organization, cooperative or other entity is the employer and the other is employee. Employees work in return for payment, which may be in the form of an hourly wage, by piecework or an annual salary, depending on the type of work an employee does or which sector they are working in. Employment is typically governed by employment laws, organization or legal contracts. (Villegas, 2016).

Time Series

One objective of analyzing economic data is to predict the future values of certain variables. Time series analysis is an alternative approach that has proved quite successful, especially for short-term forecasting. It uses only the past values of a particular variable to predict its future values (Judge & Hill, 1988).

According to Chao (1969), time series is a set of quantitative reading of some variables arranged in chronological order of their occurrences.

A time series is a sequence of data points, typically measured at uniform time intervals (Greene, 2000). Examples occur in a variety of fields ranging from economics to engineering, and methods of analyzing time series constitute an important part of Statistics. Greene (2000) added that time series analysis comprises methods for analyzing time series data in order to extract meaningful characteristics of the data and forecast future values.

A time series is a collection of observations made sequentially and typically equally spaced in time. The special feature of time series analysis is the fact that the analysis must take into account the time order because the successive observations are usually not independent observations, whereas most other statistical theory is concerned with random samples of independent observations. Methods of analyzing time series constitute an important area of statistics. Although there are several objectives that can be satisfied by analyzing a time series, they can all be classified as descriptive, explanatory, predictive, or control (Chatfield, 2000).

Components of a Time Series

In general, the fluctuations in an economic time series in which account for the changes in the series over a period of time and give the series irregular appearance are assumed to result from four different components: trend, seasonal variation, irregular variation, and cyclical variation.

1. Trend (T)

   This refers to a smooth upward or downward movement of time series over a long period of time. Such movements are thought of as requiring a minimum of about 15 or 20 years to describe, and as being attributable to factors such as population change, technological progress, and large-scale shifts in consumer tastes (Hamburg, 1983).
2. Seasonal Variations (S)

   This can be recognized by seeing the same repeating patterns over successive period of time. This type of variation is generally annual in period and arises for many series, whether weekly, monthly measured or quarterly, when similar patterns of behavior are observed at particular time of year (Chatfield, 2000).
3. Cyclical Variation (C)

   This refers to the recurring movements above and below the trend of the time series. These fluctuations last from two to ten years (or even longer) when measured from peak to peak or from trough to trough. The duration of cyclical component is more than one year (Kazmier, 1976).
4. Irregular Variation (I)

   Irregular variations are fluctuations in time series that are short in duration, erratic in nature, and follow no regularly recurrent or other discernible pattern. These movements are sometimes referred to as residual variations, since, by definition, they represent what is left over in an economic time series after trend, cyclical, and seasonal elements have been accounted for. Irregular fluctuations result from sporadic, unsystematic occurrences such as erratic shifts in purchasing habits, accidents, strikes, and the like (Hamburg, 1983).

Box-Jenkins Procedure

The Autoregressive Integrated Moving Average (ARIMA) models, or Box-Jenkins methodology, are a class of linear models that are capable of representing stationary as well as nonstationary time series. ARIMA models rely heavily on autocorrelation patterns (Brockwell & Davis, 2002).

The Box-Jenkins methodology is a five-step process for identifying, selecting, and assessing conditional mean models (for discrete, univariate time series data) (Box & Jenkins, 1994). The steps are as follows:

1. Establish the stationarity of the time series. If the series is not stationary, successively difference the series to attain stationarity. The sample autocorrelation function (ACF) and partial autocorrelation function (PACF) of stationary series decay exponentially (or cut off completely after a few lags).
2. Identify a stationary conditional mean model for the data. The sample ACF and PACF functions can help with this selection. For an autoregressive (AR) process, the sample

ACF decays gradually, but the sample PACF cuts off after a few lags. Conversely, for a moving average (MA) process, the sample ACF cuts off after a few lags, but the sample PACF decays gradually. If both the ACF and PACF decay gradually, consider an ARMA model.

3. Specify the model, and estimate the model parameters. When fitting nonstationary models, it is not necessary to manually difference the data and fit a stationary model. Instead, use the data on the original scale, and create an ARIMA model object with the desired degree of non-seasonal and seasonal differencing. Fitting an ARIMA model directly is advantageous for forecasting: forecasts are returned on the original scale (not differenced).
4. Conduct goodness-of-fit checks to ensure the model describes the data adequately. Residuals should be uncorrelated, homoscedastic, and normally distributed with constant mean and variance. If the residual are not normally distributed, one can change the innovation distribution to a Student's t.
5. After choosing a model – and checking its fit and forecasting ability – one can use the model to forecast or generate Monte Carlo simulations over a future time horizon.

Types of ARIMA Model

In theory, ARIMA models are class of models for a time series forecasting. This type of model can be stationarized by differencing and logging. The acronym ARIMA stands for "Auto-Regressive Integrated Moving Average." There are special cases of ARIMA models: random-walk and random-trend models, autoregressive models, and exponential smoothing models.

A nonseasonal ARIMA model is classified as an "ARIMA(p,d,q)" model, where:

- p is the number of autoregressive terms,
- d is the number of nonseasonal differences, and
- q is the number of lagged forecast errors in the prediction equation.

ARIMA(0,1,0) or random walk model is a type of ARIMA model with the prediction equation that can be written as:

$$\hat{Y}(t) - Y(t-1) = \mu$$

...where the constant term (here denoted by "mu") is the average difference in Y. This can be considered as a degenerate regression model in which DIFF(Y) is the dependent variable and there are no independent variables other than the constant term. Since it includes (only) a nonseasonal difference and a constant term, it is classified as an "ARIMA(0,1,0) model with constant." Of course, the random walk without growth would be just an ARIMA(0,1,0) model *without* constant.

ARIMA(1,1,0) or differenced first-order autoregressive model is a type of ARIMA model by adding one lag of the dependent variable to the prediction equation. This model has a prediction equation written as:

$$\hat{Y}(t) - Y(t-1) = \mu + \phi(Y(t-1) - Y(t-2))$$

which can be rearranged to

$$\hat{Y}(t) = \mu + Y(t-1) + \phi(Y(t-1) - Y(t-2))$$

This is a first-order autoregressive, or "AR(1)", model with one order of nonseasonal differencing and a constant term--i.e., an "ARIMA(1,1,0) model with constant." Here, the constant term is denoted by "mu" and the autoregressive coefficient is denoted by "phi", in keeping with the terminology for ARIMA models popularized by Box and Jenkins.

ARIMA(0,1,1) without constant or simple exponential smoothing is a type of model that uses exponentially weighted moving average. The prediction equation for this model can be written as:

$$\hat{Y}(t) = Y(t-1) - \theta e(t-1)$$

...where e(t-1) denotes the error at period t-1. Note that this resembles the prediction equation for the ARIMA(1,1,0) model, except that instead of a multiple of the lagged difference it includes *a multiple of the lagged forecast error.* (It also does not include a constant term--yet.) The coefficient of the lagged forecast error is denoted by the Greek letter "theta" (again following Box and Jenkins) and it is conventionally written with a *negative* sign for reasons of mathematical symmetry.

When a lagged forecast error is included in the prediction equation as shown above, it is referred to as a "moving average" (MA) term. The simple exponential smoothing model is therefore a first-order moving average ("MA(1)") model with one order of nonseasonal differencing and no constant term --i.e., an "ARIMA(0,1,1) model without constant." This means that in Statgraphics (or any other statistical software that supports ARIMA models) you can actually fit a simple exponential smoothing by specifying it as an ARIMA(0,1,1) model without constant, and the estimated MA(1) coefficient corresponds to "1-minus-alpha" in the SES formula.

ARIMA(0,1,1) with constant or simple exponential smoothing with growth has the prediction equation written as:

$$\hat{Y}(t) = \mu + Y(t-1) - \theta e(t-1)$$

ARIMA(0,2,1) or (0,2,2) without constant or linear exponential smoothing is a type of model which uses two nonseasonal differences with MA terms. This model has a prediction equation written as:

$$\hat{Y}(t) - 2Y(t-1) + Y(t-2) = -\theta_1 e(t-1) - \theta_2 e(t-2)$$

which can be rearranged as:

$$\hat{Y}(t) = 2Y(t-1) - Y(t-2) - \theta_1 e(t-1) - \theta_2 e(t-2)$$

where theta-1 and theta-2 are the MA(1) and MA(2) coefficients. This is essentially the same as Brown's linear exponential smoothing model, with the MA(1) coefficient corresponding to the quantity 2*(1-alpha) in the LES model. To see this connection, recall that forecasting equation for the LES model is:

$$\hat{Y}(t) = 2Y(t-1) - Y(t-2) - 2(1-\alpha)e(t-1) + (1-\alpha)^2 e(t-2)$$

Upon comparing terms, we see that the MA(1) coefficient corresponds to the quantity 2*(1-alpha) and the MA(2) coefficient corresponds to the quantity -(1-alpha)^2 (i.e., "minus (1-alpha) squared"). If alpha is larger than 0.7, the corresponding MA(2) term would be less than 0.09, which might not be significantly different from zero, in which case an ARIMA(0,2,1) model probably would be identified.

A "mixed" model--ARIMA(1,1,1): The features of autoregressive and moving average models can be "mixed" in the same model. For example, an ARIMA(1,1,1) model with constant would have the prediction equation:

$$\hat{Y}(t) = \mu + Y(t-1) + \phi(Y(t-1) - Y(t-2)) - \theta e(t-1)$$

Normally, though, we will try to stick to "unmixed" models with either only-AR or only-MA terms, because including both kinds of terms in the same model sometimes leads to overfitting of the data and non-uniqueness of the coefficients (Introduction to ARIMA: nonseasonal models, n.d.).

Time Plot

The first step in any time series analysis or forecasting exercise is to plot observations against time to give what is called a time plot. The graph should show important features such as trend, seasonality, outliers, smooth changes in structure, turning points discontinuities, and is vital, both in describing the data, in helping to formulate a sensible model and in choosing an appropriate forecasting method (Chatfield, 2000).

Autocorrelation and Partial Autocorrelation

Models are identified through patterns in their autocorrelation functions (ACFs) and partial autocorrelation functions (PACFs) (Box & Jenkins, 1976). Box and Jenkins further added that both autocorrelation and partial autocorrelations are computed for sequential lags in the series. The first lag has an autocorrelation between y_{t-1} and y_t, the second lag has both an autocorrelation and partial autocorrelation between y_{t-2} and y_t, and so on. ACFs and PACFs are the function across all the lags. Autocorrelation function measures the correlation between y_t and y_{t-1} in which the impact of intermediate lags is retained and not assumed to be constant. Thus, the correlation between y_t and y_{t-2} includes the effects of the correlation between y_t and y_{t-1} and y_t, y_{t-2}, and so on. On the other hand, the partial autocorrelation function measures the correlation between y_t and y_{t-1} in which intermediate correlation is held constant. The correlation between y_t and y_{t-3} is not impacted by that between y_t and y_{t-2}, which is effective removed (Yaffee and McGee, 1999). The following table summarizes the general shape of autocorrelation function for model identification.

Model Identification

The identification stage is the most important and also the most difficult; it consists to determine the adequate model from ARIMA family models. The most general Box-Jenkins model includes difference operators, autoregressive terms, moving average terms, seasonal difference operators, seasonal autoregressive terms and seasonal moving average terms. This phase is founded on the study of autocorrelation and partial autocorrelation (Box & Jenkins, 1976).

Box and Jenkins (1976) further added that the first step in developing a Box-Jenkins model is to determine if the series is stationary and if there is any significant seasonality that needs to be modelled.

Stationarity

The Box-Jenkins model assumes that the time series is stationary. A stationary series has constant mean, constant variance and constant autocorrelation structure (Dobre & Alexandru, 2008).

Dobre and Alexandru (2008) added that regression with nonstationary variables is a spurious correlation. Stationary can be assessed from a run sequence plot. The run sequence plot should show constant location and scale. It can also be detected from an autocorrelation plot. Specifically, non-stationarity is often indicated by an autocorrelation plot with very slow decay.

Box and Jenkins (1976) recommended differencing non-stationary series one or more times to achieve stationarity. They further added that doing so produces an ARIMA model, with the "I" standing for "Integrated". But its first difference $Dy_t = y_{t-1=}$ $u_t$is stationary, so y is "integrated of order 1", or y ~ I (1).

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The Box-Jenkins approach suggests short and seasonal (long) differencing to achieve stationarity in the mean, and logarithmic or power transformation to achieve stationarity in the variance (Box & Jenkins, 1976). Furthermore, the value of both differencing and transformations has been questioned. Pierce (1971) argued that differencing was not an appropriate way of making the data stationary and instead he proposed linear de-trend. However, Nelson and Plosser (1982) argued that some series could be better made stationary through differencing while others through linear de-trending.

The following ways are used to determine if the series is stationary or not.

1. Autocorrelation function

   If autocorrelations start high and decline slowly, then series is nonstationary, and should be differenced (Dickey & Fuller, 1979). Box and Jenkins (1976) defines autocorrelation as the linear dependence of a variable with itself at two points in time. For stationary process, autocorrelation between any two observations only depends on the time lag between them.
2. Dickey-Fuller Test

   Dickey and Fuller (1979) developed a procedure for testing whether a variable has a unit root or, equivalently, that the variable follows a random walk. It tests to determine whether a time series is stationary or, specifically, whether the null hypothesis of a unit root can be rejected.

Autoregressive (AR) Progress (p)

According to Brockwell and Davis (2002), specifically, for an AR (1) process, the sample autocorrelation function should have an exponentially decreasing appearance. However, Brockwell and Davis (2002) added that higher-order AR processes are often a mixture of exponentially decreasing and damped sinusoidal components. For higher-order autoregressive processes, the sample autocorrelation needs to be supplemented with a partial autocorrelation plot. The partial autocorrelation of an AR (p) process becomes zero at log p+1 and greater, so we examine the sample partial autocorrelation function to see if there is evidence of a departure from zero. This is usually determined by placing a 95% confidence interval on the sample partial autocorrelation plot (most software programs that generate same autocorrelation plots will also plot this confidence interval). If the software program does not generate the confidence band, it is approximately $\pm 2/\sqrt{N}$, with N denoting the sample size.

The data is AR (p) if: ACF will decline steadily, or follow a damped cycle and PACF will cut off suddenly after p lags (Dobre & Alexandru, 2008).

Moving Average (MA) Process (q)

The autocorrelation of a MA (q) process becomes zero at lag q+1 and greater, so we examine the sample correlation function to see where it essentially becomes zero (Dobre & Alexandru, 2008).

Dobre and Alexandru (2008) further added that the data is MA (q) if: ACF will cut off suddenly after q lags and PACF will decline steadily, or follow a damped cycle. It is not stated to build models with large numbers of MA terms and large numbers of AR and MA terms together.

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Model Estimation

Dobre and Alexandru (2008) stated that the main approaches to fitting Box-Jenkins models are non-linear least squares and maximum likelihood estimation. Maximum likelihood estimation is generally the preferred technique.

Model estimation means finding the values of the model coefficients which provide the best fit to the data. At the identification state one or more models are tentatively chosen that seen to provide statistically adequate representations of the available data. At this stage we get precise estimates of the coefficients of the model chosen at the identification stage. That is we fit the chosen model to our time series data to get estimates of the coefficients. This stage provides some warning signals about the adequacy of our model. In particular, if the estimated coefficients do not satisfy certain mathematical inequality conditions, that model is rejected (Ofori & Ephraim, 2012).

Model Diagnostics

Model diagnostics for Box-Jenkins models is similar to model validation for non-linear least squares fitting (Dobre & Alexandru, 2008).

A diagnostic check is carried out to validate the model, or possibly realize that the tentative model may need to be modified. For a model to be considered "good" it should have the following properties: the residuals should be approximately Normal, all the parameter estimates should have significant p-values, and the model should contain as few parameters as possible (Greene, 2000).

Box et al. (1994) states that if Box-Jenkins model is a good model for the data, the residuals should satisfy these assumptions. If these assumptions are not satisfied, we need to fit a more appropriate model. That is, we go back to the model identification step and try to develop a better model. Hopefully the analysis of the residuals can provide some clues as to a more appropriate model. The residual analysis as cited by Box et al. (1994) is based on:

1. Random residuals: the Box-Pierce Q-statistic: $Q(s) = n \sum r(k)^2 \approx \chi^2(s)$ where r (k) is the k-th residual autocorrelation and summation is over first autocorrelations.
2. Fit versus parsimony: the Schwartz Bayesian Criterion (SBC):
   SBC = ln {RSS/n} + (p+d+q) ln (n)/n, where RSS = residual sum of squares, n is sample size, and (p+d+q) the number of parameters.

Model Selection Criteria

The final model can be selected using a penalty function statistics such as Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC). The AIC and BIC are a measure of goodness of fit of an estimated statistical model. Given a data set, several competing models may be ranked according to their AIC or BIC with the one having the lowest information criterion value being the best. These information criterion judges a model by how close its fitted values tend to be to the true values, in terms of certain expected value. The criterion value assigned to a model is only meant to rank competing models and tell which the best among the given alternative is. The criterion attempts to find the model that best explains the data with a minimum of free parameters but also includes a penalty that is increasing function of the number of estimated parameters (Akaike, 1974); (Schwarz, 1978); and (Sakamoto, Ishiguro, & Kitagawa, 1986). (Ofori & Ephraim, 2012) Cited that in the general case, the AIC and BIC take the form as shown below:

$$AIC = 2k - 2\log(L) or\ 2k + n log\left(\frac{RSS}{n}\right)$$

$$BIC = -2\log(L) + k\,log(n) or \log(\sigma_e^2) + \frac{k}{n}\log(n)$$

Where

k = number of parameters in the statistical model
L = maximized value of the likelihood function for the estimated model
RSS = residual sum of squares of the estimated model
n = number of observations, or equivalently, the sample size
σ_e^2 = variance of the residuals

Limitations

There are few limitations to the Box-Jenkins models. If there are not enough data, they may be no better at forecasting then the decomposition or exponential smoothing techniques. Box-Jenkins models usually are based on stochastic rather than deterministic or axiomatic processes. Much depends on the proper temporal focus. These models are better at formulating incremental rather than structural change (Mccleary, R. Hay, & Mcdowell, 1980).

The ARIMA method is appropriate only for a time series that is stationary and it is recommended that there are at least 50 observations in the input data; however, more history is advantageous in the model identification. It is also assumed that the values of the estimated parameters are constant throughout the series (Hillier & Lieberman, 1986).

Statistical Forecasting

Statistical forecasting concentrates on using the past to predict the future by identifying trends, patterns, and business drives within the data to develop a forecast. The forecast is referred to as statistical forecast because it uses mathematical formulas to identify the patterns and trends while testing the results for mathematical reasonableness and confidence (Villegas, 2006).

The ARIMA models have proved to be excellent short-term forecasting models for a wide variety of time series (Levenbach, 2015). Levenbach (2015) further added that a major drawback of the pure ARIMA models is that they are based only on historical data and thus have limited explanatory usefulness. ARIMA models are essentially sophisticated extrapolative devices that are of greatest use when it is expected that the underlying factors causing demand for products, services, revenues, and so on, will behave in the future in much the same way as in the past. In the short term, this is often a reasonable expectation, however, because these factors tend to change slowly; data tend to show inertia in the short term. However, there are extensions of the ARIMA approach that incorporate explanatory factors for including information such as price, promotions, strikes, and holiday effects.

Methodology

This study is non-experimental quantitative design using time-series approach. Time series is a technique in Statistics concerning time-series data or trend analysis. Its models anticipate future values using the previously observed values as the basis for the prediction. The said design is used to prove some factors affecting the three dimensions: Unemployment, Underemployment and Employment rate within the year 2005 – 2019 and predicting the economic status for the year 2020.

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Results and Discussion
Yearly Rates of the Three Economic Participation

Table 1 shows the different quarterly rate of unemployment in the Philippines from the year 2005 until 2019.

Table 1: Quarterly Rate of Unemployment in the Philippines from 2005-2019

YEAR	UNEMPLOYMENT RATE			
	Quarter 1	Quarter 2	Quarter 3	Quarter 4
2005	11.3	8.3	7.7	7.4
2006	8.1	8.2	8	7.3
2007	7.8	7.4	7.8	6.3
2008	7.4	8.0	7.4	6.8
2009	7.7	7.5	7.6	7.1
2010	7.3	8.0	6.9	7.1
2011	7.4	7.2	7.1	6.4
2012	7.2	6.9	7.0	6.8
2013	7.1	7.5	7.3	6.4
2014	7.5	7.0	6.7	6.0
2015	6.6	6.4	6.5	5.6
2016	5.8	6.1	5.4	4.7
2017	6.6	5.7	5.7	5.0
2018	5.3	5.5	5.4	5.1
2019	5.2	5.1	5.4	4.5

Table 1 shows the different quarterly rate of unemployment in the Philippines from the year 2005 until 2019. Among all the years, the highest unemployment rate during this period is 2005 which is the first quarter with the percentage of 11.3. While during the year of 2019, as tabulated above has the lowest rate from all the years in the data with the percentage of 4.5 in the fourth quarter.

The worsening joblessness reflect the backward and crisis-ridden state of the economy. The Arroyo administration has the worst sustained joblessness rates compared to previous administrations that was revealed by a study of Ibon Foundation after registering an 11.4 percent unemployment rate in 2005 (Olliveros, 2006).

Table 2 shows the different quarterly underemployment rate of the Philippines from 2005 until 2019.

Table 2: Quarterly Rate of Underemployment in the Philippines from 2005-2019

YEAR	UNDEREMPLOYMENT RATE			
	Quarter 1	Quarter 2	Quarter 3	Quarter 4
2005	16.1	26.1	20.5	21.2
2006	21.3	25.4	23.5	20.4
2007	21.5	18.9	22.0	18.1
2008	18.9	19.8	21.0	17.5
2009	18.2	18.9	19.8	19.4
2010	19.7	17.8	17.9	19.6
2011	19.4	19.4	19.1	19.1
2012	18.8	19.3	22.8	19.0

2013	20.9	19.2	19.2	18.1
2014	19.5	18.2	18.3	18.7
2015	17.5	17.8	21	17.7
2016	19.7	18.4	17.3	18.0
2017	16.3	16.1	16.3	15.9
2018	18.0	17.0	17.2	13.3
2019	15.6	13.5	13.9	13.0

Table 2 shows the different quarterly underemployment rate of the Philippines from 2005 until 2019. The highest tabulated value among all the years was from 2006 in the second quarter with the percentage rate of 25.4. Meanwhile, the year 2019 recorded as the lowest underemployment rate with 13.0 in the fourth quarter.

According to National Economic and Development Authority, the Philippine labor market continued to record positive gains as underemployment rate fell to its lowest. The January round of the Labor Force Survey (LFS) of the Philippine Statistics Authority showed that the country's underemployment rate – the proportion of those already employed but still wanting more work – dropped further to 14.8 percent, from 15.6 percent in January 2019.This is the lowest underemployment rate recorded for all January rounds in the last ten years (NEDA, 2020).

Table 3 shows the different quarterly employment rate in the Philippines from 2005-2019.

Table 3: Quarterly Rate of Employment in the Philippines from 2005-2019

YEAR	EMPLOYMENT RATE			
	Quarter 1	Quarter 2	Quarter 3	Quarter 4
2005	88.7	91.7	92.3	92.6
2006	91.9	91.8	92	92.7
2007	92.2	92.6	92.2	93.7
2008	92.6	92	92.6	93.2
2009	92.3	92.5	92.4	92.9
2010	92.7	92	93.1	92.9
2011	92.6	92.8	92.9	93.6
2012	92.8	93.1	93	93.2
2013	92.9	92.5	92.7	93.6
2014	92.5	93.0	93.3	94.0
2015	93.4	93.6	93.5	94.4
2016	94.2	93.9	94.6	95.3
2017	93.4	94.3	94.4	95.0
2018	94.7	94.5	94.6	94.9
2019	94.8	94.9	94.6	95.5

Table 3 shows the different quarterly employment rate in the Philippines from 2005-2019. The highest calculated result was from the year 2019 in the last quarter with the percentage of 95.5. Meanwhile, the first quarter in the year 2005 was recorded as the lowest with 88.7 employment rate.

The July round of the Labor Force Survey (LFS) of the Philippine Statistics Authority showed that employment growth rate increased by 5.7 percent in July 2019, from 1.2 percent in July 2018. This translates to 2.3 million additional employment, almost five times the 479,000-employment generated in the same period last year (NEDA, 2019).

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Estimated Quarterly Seasonal Indices Using the Central Moving Average of the Three Economic Participation

Figure 1 shows the quarterly unemployment rate in the Philippines from 2005 to 2019.

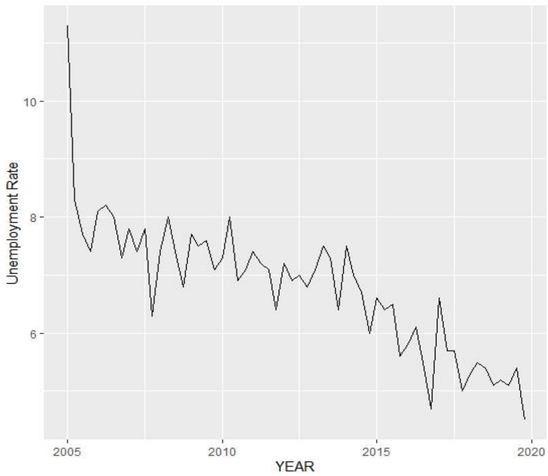

Figure 1. Quarterly Unemployment Rate in the Philippines: 2005-2019

There are 60 quarterly observations of the unemployment rate in the Philippines from 2005-2019 (Figure1). The graph showed a large rate of unemployment in the first quarter of year 2005 while the smallest recorded unemployment rate is in the last quarter of 2019. It also showed a decreasing trend in which the series slowly decrease in value over time.

Figure 2 shows the seasonally adjusted unemployment rate.

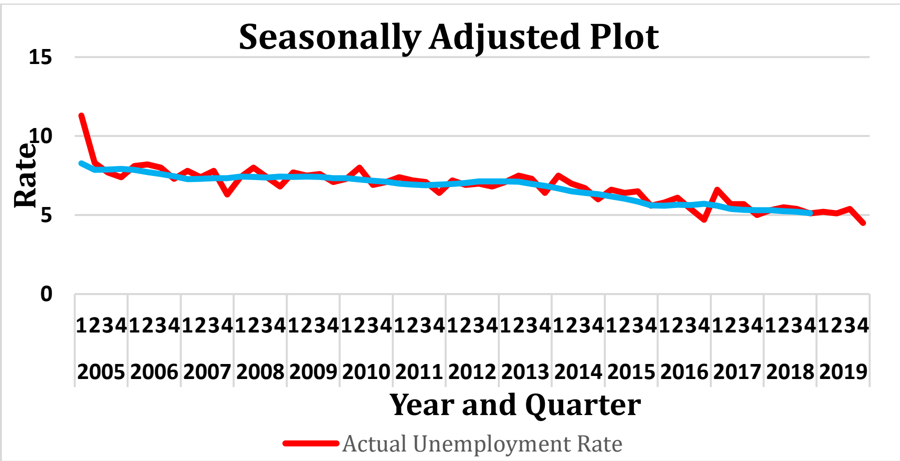

Figure 2. The Unemployment rate and the unemployment seasonally adjusted

Figure 2 shows the unemployment rate and seasonally adjusted unemployment rate. This is done to remove the seasonal component of the time series that exhibit a seasonal pattern; although the data presented shown to be non-seasonal (see Figure 1). Moreover, seasonal adjusted unemployment rate data is done to reveal its underlying trends.

Checking Stationarity for Unemployment

The first step of Box-Jenkins approach is to plot the data. The graph suggests that the data is non-stationary (see Figure 1,). The unemployment rate in the Philippines exhibits no

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distinct pattern over the years. This can be due to the decreasing unemployment rate, causing irregular fluctuations the irregular change signifies non-stationarity of the series.

Table 4: Augmented Dicky-Fuller Test result for the stationarity of the original data for Unemployment

Augmented Dicky-Fuller Test	
Test Statistic	-1.9094
p-value	0.6114

The result of the Augmented Dicky-Fuller Test (Table 4) suggests that the series is non-stationary since the p-value is greater than 0.05. At 5% level of significance, the null hypothesis, the series not stationary, is accepted. This implies that the data has a unit root and must be difference at least once to make it stationary.

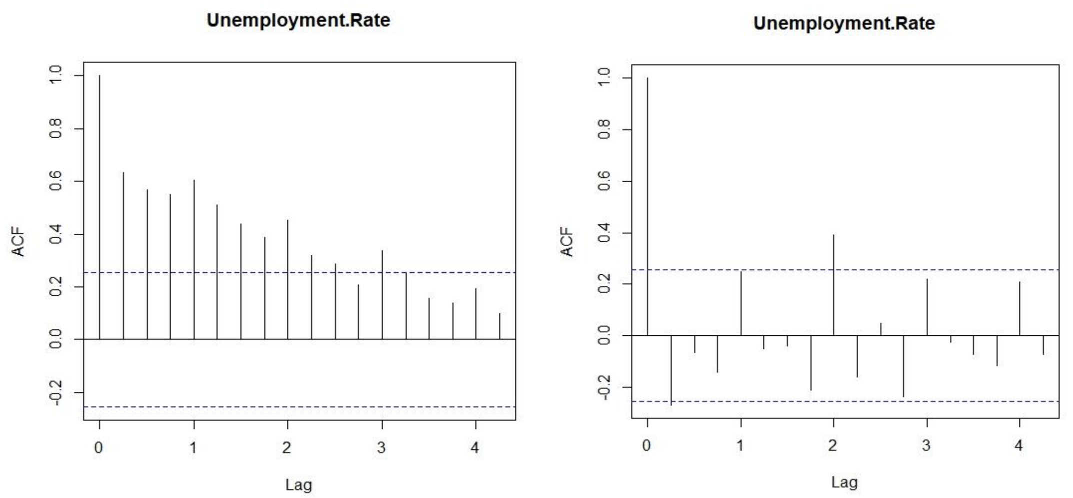

Figure 3. Actual Autocorrelation Function (ACF) and first order difference of the quarterly unemployment rate in the Philippines: 2005-2019

The correlogram (Figure 3) indicates that the sample autocorrelations are strong and positive and decayed slowly over time. The blue breaking lines indicate the upper and lower limits of the autocorrelation. Those lines that lie beyond the blue lines are considered significant. The autocorrelation plot of the differenced data (Figure 3) shows that the autocorrelation is highly significant at lag 8. The autocorrelation plot suggests that difference data are now stationary. The significant lags are lesser than the autocorrelation function of the actual data.

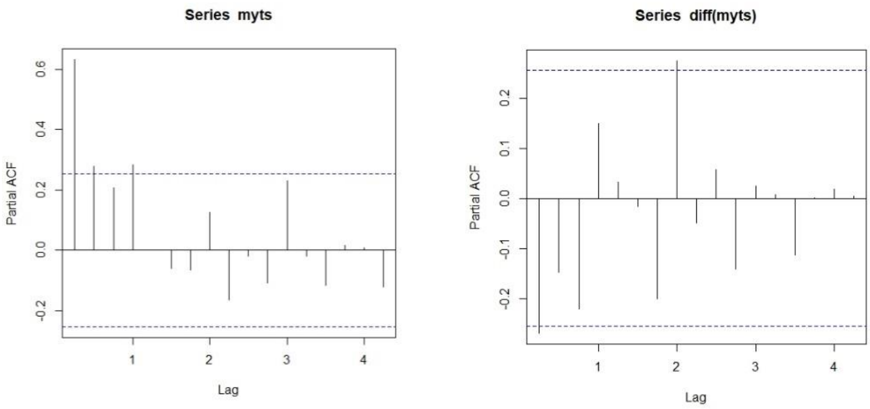

Figure 4. Actual Partial Autocorrelation Function (PACF) and first order difference of the quarterly unemployment rate in the Philippines: 2005- 2019

The Partial Autocorrelation Function (PACF) plot (Figure 4) shows that there are significant partial autocorrelations. These significant autocorrelations are those lines that exceed the lower and upper limits represented by the blue broken lines. The plot further shows that highly significant partial autocorrelations occurred at lag 7. Meanwhile the partial autocorrelation plot of the differenced data (Figure 4) indicates that the only highly significant partial autocorrelations are found in the first and third lags.

Figure 5 shows the quarterly underemployment rate in the Philippines from 2005 to 2019.

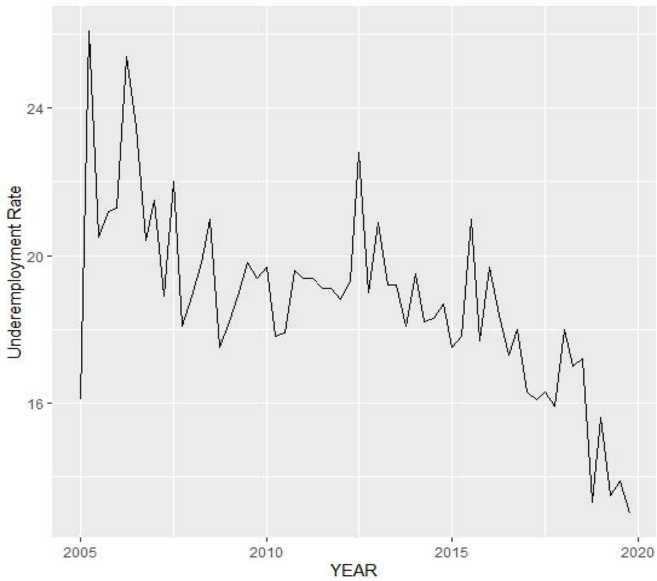

Figure 5. Quarterly Underemployment Rate in the Philippines: 2005-2019

There are 60 quarterly observations of the underemployment rate in the Philippines from 2005-2019 (Figure5). The graph showed a large rate of underemployment in both the second quarter of year 2005 and 2006 while the smallest recorded underemployment rate is in the last quarter of 2019. It also showed a decreasing trend in which the series slowly decrease in value over time.

Figure 6 shows the seasonally adjusted underemployment rate.

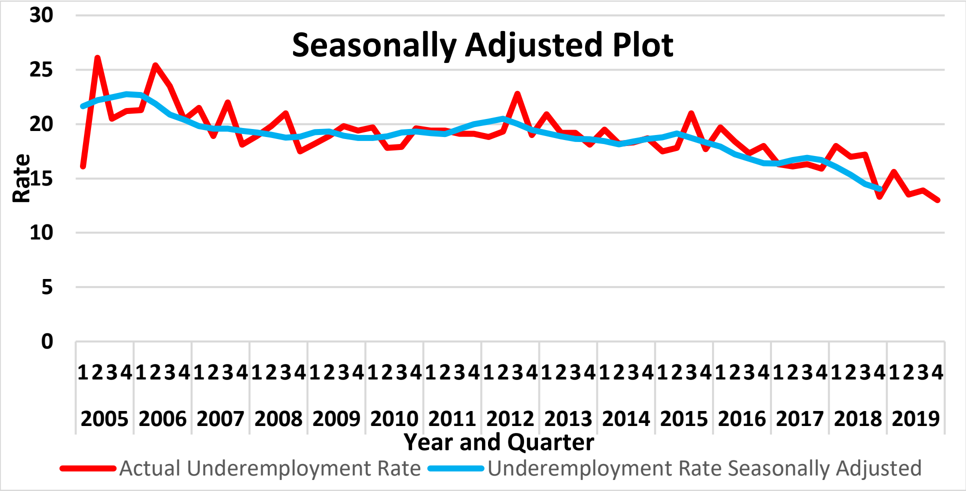

Figure 6. The Underemployment rate and the underemployment seasonally adjusted

Figure 6 shows the underemployment rate and seasonally adjusted underemployment rate. This is done to remove the seasonal component of the time series that exhibit a seasonal pattern; although the data presented shown to be non-seasonal (see Figure 5,) moreover seasonal adjusted underemployment rate data is done to reveal its underlying trends.

Checking Stationarity for Underemployment

The first step of Box-Jenkins approach is to plot the data. The graph suggests that the data is non-stationary (see Figure 5). The underemployment rate in the Philippines exhibits no distinct pattern over the years. This can be due to the decreasing underemployment rate, causing irregular fluctuations the irregular change signifies non-stationarity of the series.

Table 5: Augmented Dicky-Fuller Test result for the stationarity of the original data for Underemployment.

Augmented Dicky-Fuller Test	
Test Statistic	-1.7599
p-value	0.6718

The result of the Augmented Dicky-Fuller Test (Table 5) suggests that the series is non-stationary since the p-value is greater than 0.05. At 5% level of significance, the null hypothesis, the series not stationary, is accepted. This implies that the data has a unit root and must be difference at least once to make it stationary.

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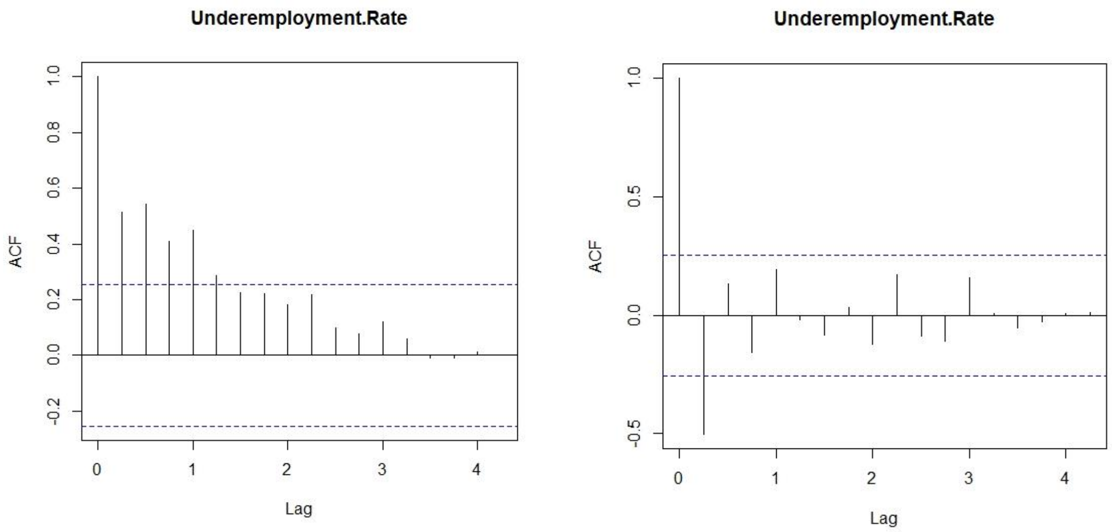

Figure 7. Actual Autocorrelation Function (ACF) and first order difference of the quarterly underemployment rate in the Philippines: 2005-2019

The correlogram (Figure 7) indicates that the sample autocorrelations are strong and positive and decayed slowly over time. The blue breaking lines indicate the upper and lower limits of the autocorrelation. Those lines that lie beyond the blue lines are considered significant. The autocorrelation plot of the differenced data (Figure 7) shows that the autocorrelation is highly significant at lag 1. The autocorrelation plot suggests that difference data are now stationary. The significant lags are lesser than the autocorrelation function of the actual data.

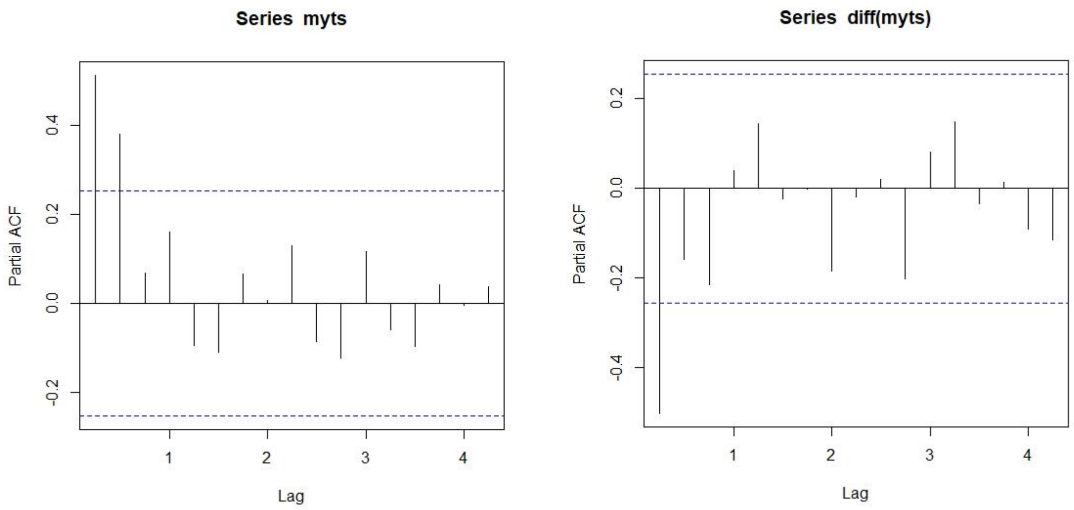

Figure 8. Actual Partial Autocorrelation Function (PACF) and first order difference of the quarterly underemployment rate in the Philippines: 2005-2019

The Partial Autocorrelation Function (PACF) plot (Figure 8) shows that there are significant partial autocorrelations. These significant autocorrelations are those lines that exceed the lower and upper limits represented by the blue broken lines. The plot further shows that highly significant partial autocorrelations occurred at lag 1. Meanwhile the partial autocorrelation plot of the differenced data (Figure 8) indicates that the only highly significant partial autocorrelations are found in the first lags.

Figure 9 shows the quarterly employment rate in the Philippines from 2005 to 2019.

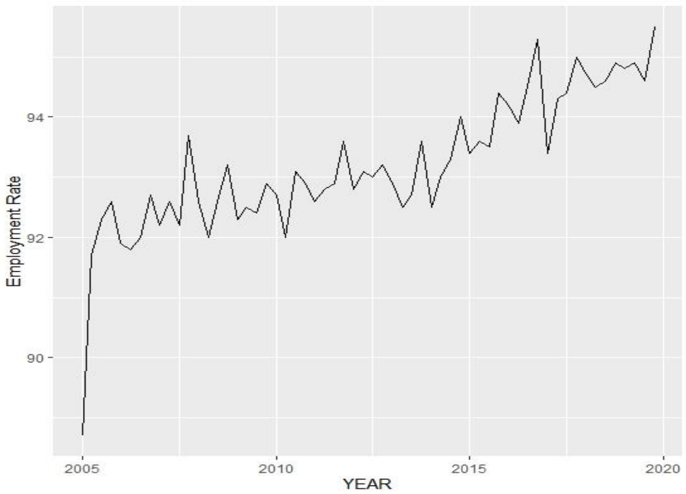

Figure 9. Quarterly Employment Rate in the Philippines: 2005-2019

There are 60 quarterly observations of the employment rate in the Philippines from 2005-2019 (Figure 9). The graph showed a large rate of employment in both the last quarter of year 2018 and 2019, and the second quarter of year 2019 while the smallest recorded employment rate is in the first quarter of year 2005. It also showed an increasing trend in which the series slowly increase in value over time.

Figure 6 shows the seasonally adjusted employment rate.

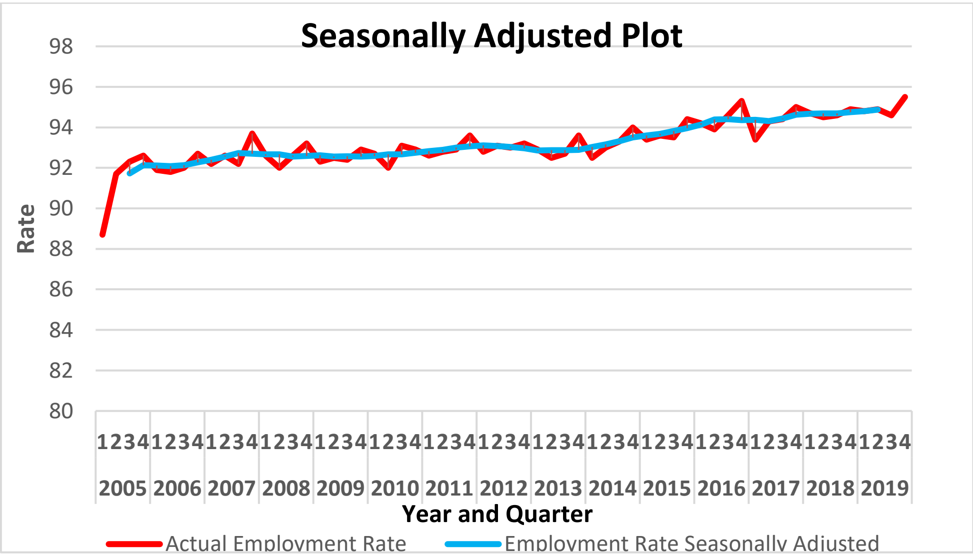

Figure 10. The employment rate and the employment seasonally adjusted

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Figure 10 shows the employment rate and seasonally adjusted employment rate. This is done to remove the seasonal component of the time series that exhibit a seasonal pattern; although the data presented shown to be non-seasonal (see Figure 9). Moreover, seasonal adjusted employment rate data is done to reveal its underlying trends.

Checking Stationarity for Employment

The first step of Box-Jenkins approach is to plot the data. The graph suggests that the data is non-stationary (see Figure 9). The employment rate in the Philippines exhibits no distinct pattern over the years. This can be due to the increasing employment rate, causing irregular fluctuations the irregular change signifies non-stationarity of the series.

Table 6: **Augmented Dicky-Fuller Test result for the stationarity of the original data for employment.**

Augmented Dicky-Fuller Test	
Test Statistic	-1.8945
p-value	0.6174

The result of the Augmented Dicky-Fuller Test (Table 6) suggests that the series is non-stationary since the p-value is greater than 0.05. At 5% level of significance, the null hypothesis, the series not stationary, is accepted. This implies that the data has a unit root and must be difference at least once to make it stationary.

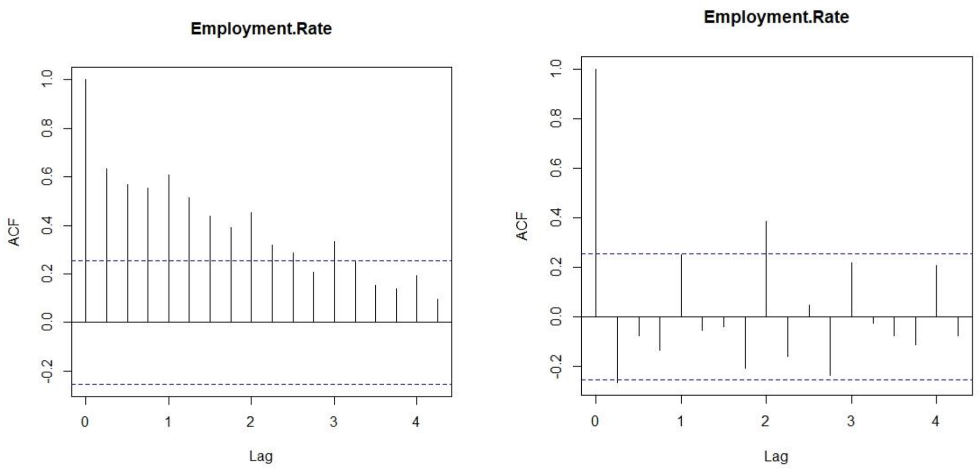

Figure 11. Actual Autocorrelation Function (ACF) and first order difference of the quarterly employment rate in the Philippines: 2005-2019

The correlogram (Figure 11) indicates that the sample autocorrelations are strong and positive and decayed slowly over time. The blue breaking lines indicate the upper and lower limits of the autocorrelation. Those lines that lie beyond the blue lines are considered significant. The autocorrelation plot of the differenced data (Figure 11) shows that the autocorrelation is highly significant at lag 8. The autocorrelation plot suggests that difference data are now stationary. The significant lags are lesser than the autocorrelation function of the actual data.

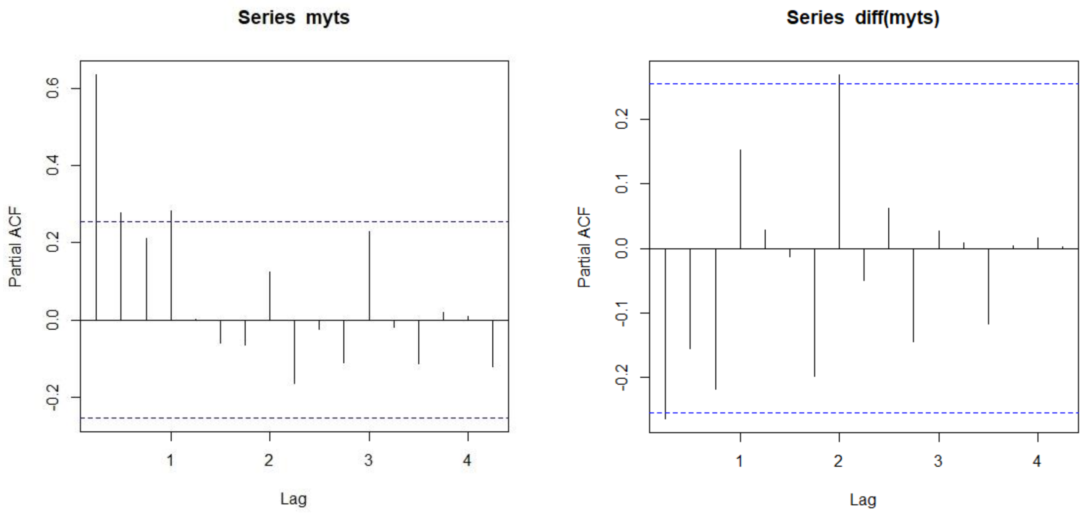

Figure 12. Actual Partial Autocorrelation Function (PACF) and first order difference of the quarterly employment rate in the Philippines: 2005-2019

The Partial Autocorrelation Function (PACF) plot (Figure 12) shows that there are significant partial autocorrelations. These significant autocorrelations are those lines that exceed the lower and upper limits represented by the blue broken lines. The plot further shows that highly significant partial autocorrelations occurred at lag 3. Meanwhile the partial autocorrelation plot of the differenced data (Figure 12) indicates that the only highly significant partial autocorrelations are found at lag 8.

Forecasted Value in the year 2020 of the Three Economic Participation

Table 7 shows the forecasted unemployment value for the year 2020.

Table 7: Forecasted Unemployment Rate for the Four Quarters of the Year 2020

Year	Quarter	Forecast	LCL (95%)	UCL (95%)
2020	1st	5.34	3.70	5.95
	2nd	5.29	3.83	6.23
	3rd	5.14	3.66	6.15
	4th	4.66	3.12	5.99

Table 7 shows the year 2020 forecasted quarterly unemployment rate in the Philippines. All the forecasted values lie between the confidence limits implying that all the forecasts are reliable. The first quarter was predicted with an unemployment rate of 5.34, and it decreased in the second quarter down to 5. 29 percent. It continued to decrease in the third quarter to 5.14 and as well as on the last quarter to 4.66 percent. The model that was used to forecast the four quarters of 2020 was ARIMA(2,1,0), since it was the most appropriate model the R Programming Software suggested. Many models are mixed models in reality. Some of these models need to be differenced before being analyze and ARIMA(2,1,0) is one of them and so if the series is not stationary, successively difference the series to attain stationarity.

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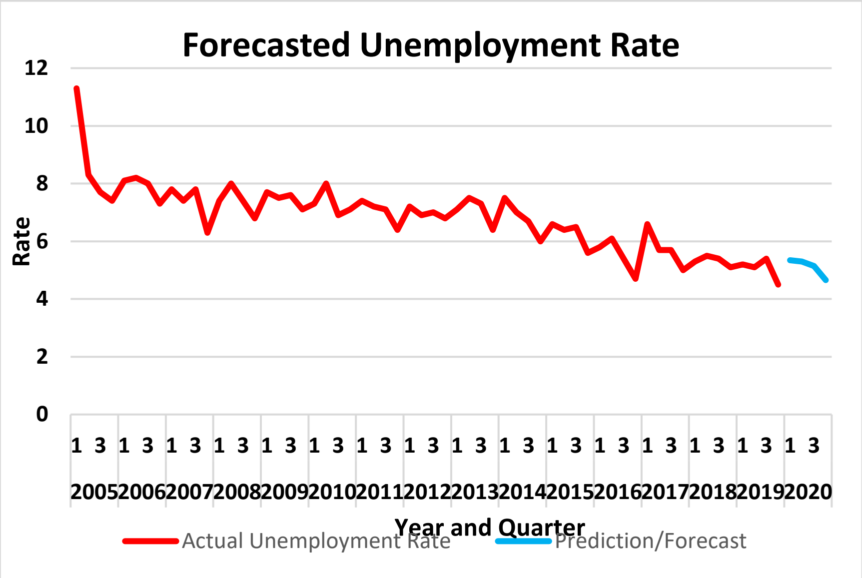

Figure 13 shows the time plot of the unemployment rate actual data and the forecasted unemployment rate for the year 2020.

Figure 13. Actual Rate and Forecasted Unemployment Rate in the Philippines: 2005-2020

Table 8 shows the forecasted underemployment value for the year 2020.

Table 8: Forecasted Underemployment Rate for the Four Quarters of the Year 2020

Year	Quarter	Forecast	LCL (95%)	UCL (95%)
2020	1st	15.90	10.60	17.59
	2nd	15.52	9.86	16.94
	3rd	16.15	9.89	17.07
	4th	14.90	9.88	17.15

Table 8 shows the year 2020 forecasted quarterly underemployment rate in the Philippines. All the forecasted values lie between the confidence limits implying that all the forecasts are reliable. The first quarter was predicted with an underemployment rate of 15.90 percent, and it continued to decrease in the second quarter down to 15.52. However, it increased to 16.15 percent in the third quarter and decreased to 14.90 percent in the last quarter.

The model that was used to forecast the four quarters of 2020 was ARIMA(0,1,1) with drift, since it was the most appropriate model the R Programming Software suggested. Many models are mixed models in reality. Some of these models need to be differenced before being analyze and ARIMA (0,1,1) with drift is one of them and so if the series is not stationary, successively difference the series to attain stationarity.

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Figure 14 shows the time plot of the underemployment rate actual data and the forecasted underemployment rate for the year 2020.

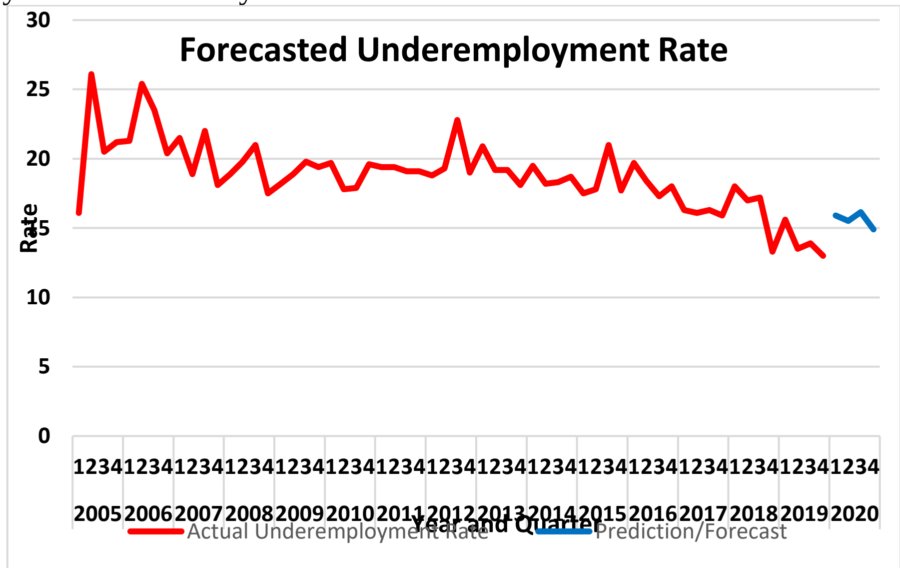

Figure 14. Actual Rate and Forecasted Underemployment Rate in the Philippines: 2005-2020

Table 9 shows the forecasted employment value for the year 2020.

Table 9: Forecasted Employment Rate for the Four Quarters of the Year 2020

Year	Quarter	Forecast	LCL (95%)	UCL (95%)
2020	1st	94.60	94.05	96.30
	2nd	94.64	93.74	96.14
	3rd	94.89	93.85	96.32
	4th	95.46	94.00	96.87

Table 9 shows the year 2020 forecasted quarterly employment rate in the Philippines. All the forecasted values lie between the confidence limits implying that all the forecasts are reliable.

In the first quarter, the employment rate was predicted to 94.60 percent, and it decrease in the second quarter down to 94.64 percent. However, it increased to 94.89 percent in the third quarter and continued to increase to 95.46 percent.

The model that was used to forecast the four quarters of 2020 was ARIMA(2,1,0), since it was the most appropriate model the R Programming Software suggested. Many models are mixed models in reality. Some of these models need to be differenced before being analyze and ARIMA(2,1,0) is one of them and so if the series is not stationary, successively difference the series to attain stationarity.

Figure 15 shows the time plot of the employment rate actual data and the forecasted employment rate for the year 2020.

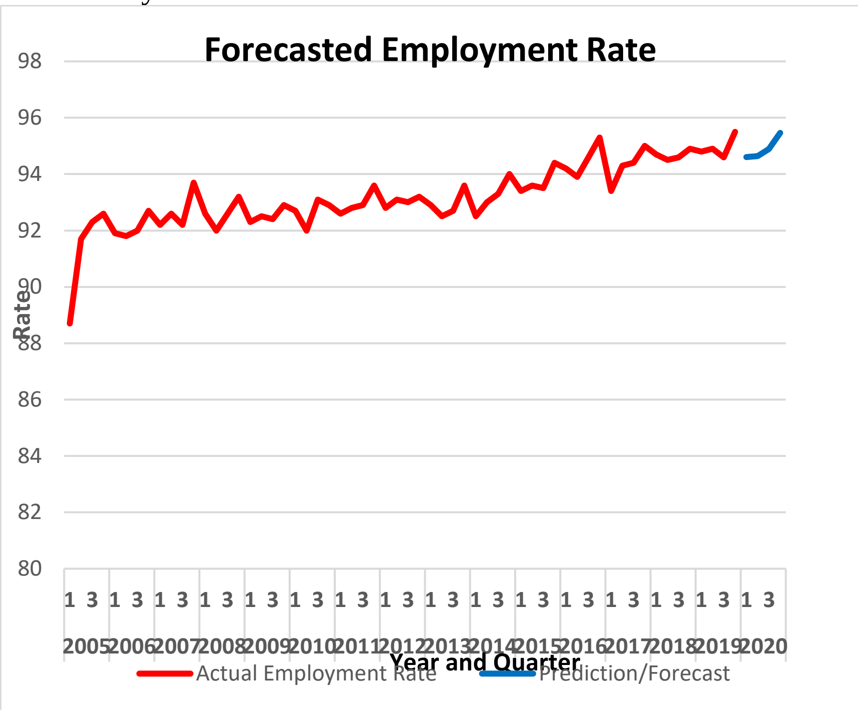

Figure 15. Actual Rate and Forecasted Employment Rate in the Philippines: 2005-2020

Actual Value and the Forecasted Value of the Three Economic Participation

Table 10: Results of the two-sample t-test for the accuracy and identicality of the actual and forecasted value of Unemployment Rate

T- test: Two Paired Sample	
Test Statistic	-0.00058
P-value	0.99542

The table shows the test statistics with the value of -0.00058 and its corresponding p-value equals to 0.99542. Since the p-value is greater than the alpha which is equal to 0.05, we failed to reject our null hypothesis. This means that there is no significant difference between the actual value and the forecasted value of unemployment rate. This implies that the forecasted value is accurate and identical to the actual value.

Table 11: Results of the two-sample t-test for the accuracy and identicality of the actual and forecasted value of Underemployment Rate

T- test: Two Paired Sample	
Test Statistic	-0.05697
P-value	0.954763

The table shows the test statistics with the value of -0.05697 and its corresponding p-value equals to 0.945763. Since the p-value is greater than the alpha which is equal to 0.05, we failed to reject our null hypothesis. This means that there is no significant difference between the actual value and the forecasted value of underemployment rate. This implies that the forecasted value is accurate and identical to the actual value.

Table 12: Results of the two-sample t-test for the accuracy and identicality of the actual and forecasted value of Employment Rate

T- test: Two Paired Sample	
Test Statistic	0.00408
P-value	0.99676

The table shows the test statistics with the value of 0.00408 and its corresponding p-value equals to 0.99676. Since the p-value is greater than the alpha which is equal to 0.05, we failed to reject our null hypothesis. This means that there is no significant difference between the actual value and the forecasted value of employment rate. This implies that the forecasted value is accurate and identical to the actual value.

Conclusion

As the economy of the Philippines continuously grows, it is important to investigate the trend of the three economic participation as it is considered an assumption of a growth or progression. With the aide of the best fitted and appropriate ARIMA model, the forecasted values were generated.

Overall, the unemployment rate in the Philippines from 2005 to 2019 and the forecasted year as well is visibly declining as the findings had shown. This means that for over 15 years, the unemployment situation in the Philippines has been decreasing, consequently, the employment rate rises higher from its previous values. This declining situation is also reflected in the underemployment rate as millions of underemployed individuals in the Philippines were lessening for the past 5 years. The pattern of the trend shows and adept result wherefore makes the state of the economy surge.

While the ARIMA models which were used in forecasting the 2020 results were the best fitted and appropriate model for the data since it has undergone a diagnostics test. Furthermore, the forecasted values of the three economic participation are accurate and identical to the actual values. Therefore, these models can be utilized in predicting future unemployment, underemployment, and employment (the three economic participation) rates in the Philippines.

Recommendations

Based on the results of the study, the following recommendations are formulated:

1. The government promotes and continues on making more livelihood programs for the people especially those unprofessional, skilled and unskilled individuals.
2. LGU's provide more job opportunities in their areas.
3. Businesses promote programs to accept and will train fresh graduates based on their fields.
4. The government focused on livelihood that will grow, continue and help our economy despite the pandemic and natural disasters.
5. The government, businesses and LGU's might be encouraged to know what programs and opportunities for them to promote for present and future job seekers.

6. The individuals might inspire and motivate to find a job and to help our economy.

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