FORECASTING THE VOLATILITY
OF PHILIPPINE INFLATION
USING EGARCH MODEL

A Final Course Project

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ABSTRACT

In recent happenings, rising inflation has become one of the major economic challenges faced by one of the developing country, the Philippines. The objective of the study is to forecast the Philippine Inflation rate using monthly inflation rate. The models applied were Seasonal Autoregressive Moving Average (SARIMA) for the mean component and EGARCH model for the error variance component. The data used by the researchers were Philippine Inflation rate from January 2000 until March 2019 in order to have a forecasting model. The researchers found out that SARIMA (1,1,1) x (0,0,1)12 – EGARCH (3, 4) would be the best fit forecasting model with normal error distribution for measuring the predictive accuracy of the model. The researchers also estimated a GARCH model for the error variance, model used by Haydee Lopez (2008) that is further issued by *Bangko Sentral ng Pilipinas* (BSP). SARIMA (1,1,1) x (0,0,1)12 – GARCH (0, 1) with Generalized Error Distribution with fixed parameter r = 1.5 drawn as adequate model using GARCH as error variance. Between the two error variance models used, EGARCH model out performed GARCH after EGARCH have a lower AIC value compare to GARCH.

Keywords: *Inflation Rates, Mean Component, SARIMA, Error Variance, EGARCH, GARCH, AIC*

CHAPTER I

RATIONALE AND BACKGROUND OF THE STUDY

Introduction

In economics, inflation is one of the most important issues and has been one of the most researched topics in macroeconomics. Inflation is used to denote an ongoing rise in the general level of prices with what is the power of currency. Inflation is an economic term that refers to an environment of generally rising prices of goods and services within a particular economy. In addition, it is a general and progressive increase in prices, with this inflation, everything gets more valuable except money. Many people may refer inflation as “the cost of living”.

Inflation is the persistent increase in the general level of prices of goods and services in an economy. Aside from this, it is the indicator of the country's price stability. A stable inflation is one of the main objectives of every government as it is an important economic indicator. Price stability in an economy means that the general price level in an economy does not change much over time. This is the long-term targets of monetary policy.

The BSP is mandated to promote price stability that will be possible to economic growth. According to *Bangko Sentral ng Pilipinas* (BSP), there is price stability when the general price level of goods and services in the country moves at a low and predictable rate thus preserving the value of your money. On the contrary, when prices rise substantially and unpredictably your money buys fewer goods and services.

In recent happenings, rising inflation became one of the major economic challenges faced by one of the developing country, the Philippines. According to the Philippine Statistics Authority (PSA) the country's inflation rate rose from 6.4% in August 2018 to 6.7% in September 2018. The inflation rate in September is the highest rate in over 9 years. It was also the 9th consecutive monthly inflation rate increase, which started in January 2018. The government's economic managers and some businessmen have said the recent inflation levels are "mere hiccups" and are "manageable."

Inflation is undoubtedly one of the most largely observed and tested economic variables both theoretically and empirically. It causes impacts on other economic variables and cost to the overall economy is well known and understood.

According to the study published by Eric Reed (2017) there are effects of inflation you need to know.

It reduces purchasing power. Inflation is defined as the erosion in purchasing power per unit of currency. In layman's terms, this means that each dollar can buy fewer goods and services than it could before.

It incentivizes spending and deters saving. Inflation punishes savers and encourages spending and investment, it pushed people away from hoarding cash and into more productive uses of their capital. Even a savings bank account will have interest rates that reflect the inflation rate to some degree, as that money goes to productive use. Generally speaking, encouraging consumers to spend is, too, a good thing for the economy.

It helps debtors and harms lenders. Inflation works in favor of people who borrow money. The borrower might still struggle depending on how their income kept up with inflation. Currently, most professional lending institutions account for inflation in their interest rates. Whether fixed or variable, lenders expect a certain erosion of the dollar over the lifetime of the loan. Some inflation is certainly better for a debtor than none, but in practical terms the effect is minor.

It helps and hurts groups depending on income. Inflation affects and hurts anyone who earns a salary or who lives on a fixed income, such as the principal of a retirement account or a pension. The person's annual income stays the same while its purchasing power steadily vanishes. For workers with good bargaining power, inflation can actually cause real incomes to rise faster than debts and existing obligations.

It is correlated with higher wages and increased hiring. Strong economy leads to lots of people who hold well-paying jobs. Then create a large consumer base with money to spend. However, employers can't easily hire in a tight labor market. They have to raise wages to compete for scarce workers, increasing their costs which they pass along to the consumer market. As a result, prices rise, producing inflation. It leads to rising wages as workers need more money to afford the same standard of living, pushing employer costs higher and perpetuating the cycle.

It leads to higher interest rates. Inflation causes interest rates to rise. First, interest rates tend to rise as banks and lenders adjust for the new value of the dollar. They build this erosion of value into their model, so if the dollar will be worth 2 percent less next year, they ask for 2 percent on top of their profit margin. When that inflation rate goes up, so does their math. Second, interest rates tend to rise as the government deliberately begins trying to cool down the economy.

It is better to have a better forecasting about inflation since it has something to do with all the aspects of the economy. Consumer spending, business investment, employment rates to government programs, tax policies, interest rate on our savings, the level of pensions and benefits and even with the price of our train tickets, inflation affects and influences all of these.

Inflation is a major monetary policy performance indicator and is useful in informing the investors, the general public and government about the trends in movement of the currency. A better and clear understanding of inflation forecasting technique is at stake for the success of monetary policy in tracking the movement of macroeconomic aggregates and in maintaining stable and sustainable economic growth. The level of inflation is an important indicator of a country's economic and financial situation.

In business, forecasting is a common statistical task. Predicting the future as accurately as possible is what forecasting is about. It can play an important role as the integral part of the decision-making activities. Inflation levels affect all the sectors of the economy especially business transactions, it is important to be able to forecast or estimate the value of inflation. A great deal of data in business, economics, engineering and natural sciences occur in the form of the time series. Time series is a series or sequence of data points measured typically at a successive time.

Inflation is so volatile. There is a degree of change in price over a time period. It is just the variance and standard deviation of the rate. In finance, volatility refers to the variation of financial asset returns over time. It is used to quantify the risk associated with a financial instrument. In many cases, volatility itself is a risk measure. Therefore, volatility is a key concept in financial economics. Inflation rate volatility affects policy makers as well as investors, hence the need to study volatility pattern which can be an aid in financial decision making. Historical data or values of inflation can be used to construct such model for volatility.

The researchers integrated the Exponential Generalized Conditional Heteroskedasticity (EGARH) model to represent the volatility. This model differed from the traditional GARCH model due to the log of variance. Proposed by Nelson (1991), EGARCH implies that the leverage effect is exponential. The EGARCH model was developed to allow for asymmetric effect between positive and negative shocks on the conditional variance of the future observations. In addition, the advantage of EGARCH model is that there is no restriction in the parameters and can fit the characteristics of the daily data used.

This model was recommended in the study of Forecasting the Volatility of Philippine Inflation using GARCH model by Haydee Lopez published by the BSP. The researchers gave a massive research effort to find out why EGARCH model was recommended. The findings are that the EGARCH model was a better model compare to GARCH model and it was tested in other study.

According to Okeyo Johnson Otieno (2016), EGARCH model provides a better fit than the GARCH model. It was tested in the inflation rate of Kenya by fitting various models such as GARCH, GJR-GARCH and EGARCH. It is also observed by Mbeah-Baiden Benedict (2013) to his study that the EGARCH was appropriate for modelling Ghana's monthly rates of inflation after being compared to other models such as the ARCH and GARCH.

The researchers gained enough evidence citing related studies to use further the EGARCH model with this study because of the empirical results already shown by the past studies that used EGARCH. Therefore, the researchers come up with this study and have the better fit model, using EGARCH model, in forecasting the volatility of Philippine Inflation.

Statement of the Problem

The general problem of the study is to forecast the volatility of the Philippine Inflation using the Exponential Generalized Autoregressive Conditional Heteroskedasticity model. This study explored EGARCH models to further understand the inflation process. Specifically, the paper sought answer the following:

1. Is time-varying variance exhibited in the data of inflation rate to be used?
2. Is EGARCH (p, q) model reliable in forecasting a short-term volatility?
3. What will be the predicted movement of Philippine Inflation in the forecasting months such as April and May using the EGARCH model?
4. Compare the forecasted volatility of Philippine inflation using EGARCH model to the GARCH model.

Significance of the Study

The researchers wanted to study and forecast the volatility of Philippine Inflation using EGARCH model. This paper will give an idea and awareness to the public on how to develop a short-term forecast model that explores the volatility of the Philippine Inflation and to know the future movement of our inflation. The end-goal of the study is to develop a model that could help quantify the possibility of the future occurrence of high inflation. The empirical results and findings from this study will be significant to the following:

To the policy makers. This will provide a reliable model to policymakers to help them anticipate the danger of financial markets and the economy. It will bring about an understanding of the behavior of inflation.

To industry practitioners. This research will contribute to the economy by developing a short-term forecasting model for the occurrence of high inflation in the Philippines.

To the investors. This kind of research about inflation rate will have a huge support to macro-variable like interest rate and exchange rate.

To the public. The forecasting model will be a great help to know the current situation of the general price index.

Scope and Delimitation

This research was conducted to determine the forecasted volatility of the Philippine Inflation using EGARCH model. The data used to forecast the Inflation rate of the Philippines were based on the monthly data released by Philippine Statistical Authority (PSA). The researchers sent a request message through email to info@psa.gov.ph that stated that the data requested is going to be used for educational purpose only. PSA then replied that the monthly data can be downloaded through their website. That is why the researchers did download the data they requested.

The researchers utilized the EGARCH model against the GARCH model that is being used in the study of Ms. Haydee Lopez published in the BSP. The researchers would like to come up with a better model to be utilized in the data of Philippine Inflation.

CHAPTER II

REVIEW OF RELATED STUDIES AND LITERATURES

This chapter includes ideas, finished studies, generalizations, literature, theories and conclusions that will help in familiarizing information that are relevant to the present study.

Relevant Theories

Market-Power Theory of Inflation. The market power theory of inflation represents one extreme end of inflation. According to this theory inflation exists even when there is no excess in demand. This theory is based on new price that is different from the competitive price and it was decided together by the group of sellers. Such groups keep prices at the level wherein they can earn maximum profit without concerning for the purchasing power of consumers.

Oligopolies can increase the price to any level even if the demand does not rise, according to the advanced version of market power theory of inflation. Due to the increase in wages in the oligopolistic industry, the hike in price level occurs. The increase in wages is compensated with the hike in prices of products. When the purchasing power increases, the increase in the income of individuals also increases, which further results in inflation.

Conventional Demand-Pull Inflation. The conventional demand-pull theorists said that the only cause of inflation is the excess of aggregate demand over aggregate supply. In full employment equilibrium condition, when inflation becomes unavoidable the demand increases. In addition, the economy reaches to its maximum production capacity. At this point, the supply of goods and services cannot be increased while the demand of products and services increases rapidly. Inflation takes place in the economy, due to this imbalance between the demand and supply.

Structural Theories of Inflation. There is a middle group of economists called structural economists believed that market power is one of the factors that cause inflation, but it is not the only factor. The supporters of structural theories agreed that due to the maladjustments in the country or some of the institutional features of business environment, inflation arises.

Mark-up Theory. The Mark-up theory of inflation was proposed by Prof Gardner Ackley. He said that the inflation cannot occur alone by demand and cost factors, but it is the cumulative effect of demand-pull inflation that occurs due to excess of aggregate demand, which further results in the increases in price level and cost-push activities. According to Prof Gardner, due to excess of demand or increases in wage rates, inflation occurs.

Bottle-Neck Inflation. Professor Otto Eckstein is the one who introduced the bottle-neck inflation. According to him, the main cause of inflation is the direct relationship between wages and prices of products. In other words, inflation takes place when there is a simultaneous increase in wages and prices of products. However, he accepted that wage push or market-power theories alone are not able to provide a clear explanation of inflation. Professor Eckstein says that the inflation occurs due to the boom in capital goods and wage-price spiral, after analysis of inflationary situation. Furthermore, he also advocated that during inflation prices in every industry is higher, but few industries show a very high price hike than rest of the industries. These industries are termed as bottle-neck industries, which are responsible for increase in prices of goods and services wherein the concentration of demand for products results in inflation.

Foreign Related Studies

Performance of EGARCH.

The data used to test the inflation rate in Ghana by Mbeah-Baiden Benedict in this research are from January 1965 to December 2002 which they obtained from Ghana Statistical Service. The ARCH family type models (traditional ARCH, GARCH, and EGARCH) was being used for this study. The Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) were being used in this research to assess the performance of each of the fitted models such that the model with the minimum value of AIC and BIC to determine the best model. The results of the study show that they use the

ARCH (2) model for predicting the monthly rate of inflation amongst the ARCH (m) models. The GARCH (1,2) and EGARCH (1,2) models were selected as the best fit models amongst the GARCH (p, q) and EGARCH (p, q) models. The ARIMA (2, 1, 1) model was determined the best fit model for modelling monthly rates of inflation in Ghana Subsequently, the three selected Autoregressive Heteroscedastic best fit models are AR (2), GARCH (2, 1) and EGARCH (2, 1) and being compared based on their forecast performances. The goodness of fit models that were used included the root mean squared error, mean absolute error, mean absolute percent error and the Theil's Inequality coefficient. The EGARCH (2, 1) was determined as the most appropriate model amongst the three best fit models in modelling the monthly rates of inflation in Ghana. As the result, the EGARCH (2, 1) was the superior in modelling the inflation rate in Ghana after being compared to the ARIMA (2, 1, 1) model.

Okeyo Johnson Otieno (2016) published a study that describes financial time series modelling with special application to modelling inflation data for Kenya. To forecast the gathered data, this study revealed that ARCH –family type models, particularly, the EGARCH (1, 1) with generalized error distribution (GED), the outcome of the study was that the E-GARCH model provides a better fit than the GARCH model because for once it can capture leverage effects and there is no restriction that the parameters $\alpha 1$ and $\beta 1$ must be positive. Therefore, this research concluded that this study finds strong evidence that the inflation monthly returns could be best represent with the above specified model.

EGARCH in forecasting the volatility of inflation

Forecasting volatility of monthly inflation rate in Nigeria has been focused and investigated in this study. In this research, they used the application of GARCH model to know its ability in volatility. But according to this research, one of the limitations is that these models produce better results in relatively stable markets and could not capture violent volatilities and fluctuations. That's why they recommend that these models must be combined with the other models when applied it to the violent markets as also suggested by Gourieroux (1997). The best model that turns out is EGARCH model and used to test the forecast volatility of Inflation rate in Nigeria. To enhance the forecasting power of the EGARCH model, a hybrid model was suggested based on EGARCH and has been constructed using the Artificial Neural Networks. Using EGARCH model the estimates obtained volatility are being forwarded to Neural Networks while the forecast obtained by the hybrid models have been compared with EGARCH models in terms of their closeness to the standard deviation of the monthly return. Based on the results of the study, the computational results say that hybrid model provides the better volatility forecasts. (S. Suleiman and M.S. Burodo, 2017)

Other uses of EGARCH

The volatility dynamics of Istanbul Gold Exchange were being assessed in this research via different GARCH models to incorporate asymmetry and long range dependence in the conditional volatility. The data used in this research, were daily spot prices of the gold exchange from January 4, 2006 to November 20, 2013. The models used were EGARCH AND CGARCH. While the EGARCH and APARCH were suggest the presence of asymmetry, unlike the equity markets. As the results of this study, it says that GARCH model shows a short term component of volatility is weaker than the permanent component. The study shows that the forecasting results of models reveal that the EGARCH and CGARCH models are superior to other GARCH family models. And the findings of this study show that the models which include asymmetry and long-range dependence produce the lowest error measures in the forecasting procedure. (Gaye HaticeGencer and ZaferMusoglu, 2014)

Chang Su (2010) describes the behaviour of risk in the Chinese stock markets and examines the predictability of the stock market returns by analyzing the long term volatility. The researchers apply the daily data from January 2000 to April 2010. This study wants to prove which is more extensive to analyze long term volatility, it is during the crisis period or before the crisis. The researchers use GARCH and EGARCH models. To compare the uses and the performance of the two models, the researcher used two distribunal assumptions, the first assumption is the Gaussian and the other one is the student's t-distribution. All in all, this research found out the EGARCH model is more preferable model that may use to estimate the financial volatility of daily returns in China. The result shows that EGARCH is much better to use rather than the GARCH model because EGARCH can fit to the characteristics of the daily data used. On the other hand, the result also shows that the stimulus policies by Chinese government lead the price of stock increase again.

Other models for volatility of inflation

The prediction of inflation and volatility inflation in Turkey prove that the Dynamic Stochastic General Equilibrium model (DSGE) and Bayesian VAR model are poor and do not give insights for policy making and show an alternative technique. The estimated inflation and volatility of Turkey using Stochastic Differential Equation (SDE) under mathematical simulation, as the results of the inflation volatility behavior they discover that it follows systematic pattern ex-ante to ex-post period of the Turkey. SDE's explain that the systematic pattern ex-ante and ex post inflation is foreseeable for Turkey. The predicted inflation using SDE's under Ito's process, Weiner process, Vasicek model and Ornstein-Uhlenbeck process can provide better forecasting. By this it can easily realize the mathematical techniques can also give clues for inflation uncertainty and for inflation predictability also. But Euler Discretization and Unbiased Discretization process can explain that the intensity of the inflation volatility is recovered in the long run and it will take 4 to 5 years. And Euler Discretization can help in the future for calculating the time span for inflation. (Hakan Eygü, 2016)

Performance of GARCH models

The U.S inflation data are used in this research based on the out of sample forecasting test. It used empirical comparisons to study the advantages and disadvantages of the models they will use. The models that were used are ARIMA-GARCH, ARIMA, neural networks, median method of autoregressive model, least squares method of autoregressive model and exponential smoothing to investigate the inflation forecasting and it was ranked according to the superior to inferior. The ARIMA-GARCH methods are used to forecast the inflation level in the USA and the sophisticated methods such as neural networks cannot improve the forecasting results sometimes. According to the out of sample forecasting, the directions of forecasting error of methods used are almost the same indicating that these forecasts have under estimated the inflation level in USA. (Qizhi He, Hong Shen and Zhongwen Tong, 2012)

The generalized autoregressive conditional heteroscedasticity (GARCH) models have been used to forecast both the economic and financial time series data. GARCH model was augmented with the Billinear model in order to make more relevant in forecasting both in economic and financial time series data also. Also, the model Billinear-GARCH shows a better performance than GARCH model based on the performance of measures indices, models variances and out of samples forecast performances. GARCH model and Billinear-GARCH (BL-GARCH) were illustrated with the Botswana inflation rates. It observed that the model Billinear GARCH outperformed than the classical GARCH model. (Akintunde Mutairu Oyewale, D. K. Shangodoyin and P. M Kgosi, 2013)

The comparison of the extension of ARCH model was applied for the Thailand Volatility Index. The SET50 Index option was applied as a Thailand Volatility Index (TVIX). The ARMA- GARCH, -EGARCH, -GJR and -PGARCH models are used for Thailand Volatility Index (TVIX). These are the extension of ARCH model process with the various features to explain the characteristics of financial time series such as asymmetric and leverage effect. After applying the TVIX with these models, they performed the comparison and forecast. The ARMA-PGARCH is found to be the best model with the lowest AIC criteria values but the EGARCH model has the lowest SBIC criteria value. The second moment condition, MAPE and RMSE, GJR-GARCH is the best fitting model for TVIX. (Chatayan Wiphatthanananthakula, and Songsak Sriboonchittab, 2010)

From year 1970 to 2014, find out that the inflation and inflation uncertainty in Sweden used GARCH model to measure the inflation. The primary goal was to find out an applicable model for the inflation series in a GARCH model wherein it allows for the non-normal errors. The secondary goal is to relate the results of the model in two competing hypotheses. The most applicable and appropriate distributional assumption is Student's t-distribution and the GED (Generalized error distribution). Also, EGARCH (1, 1) and TGARCH (1, 1) models that is take asymmetry into account. In particular, the preferable model to estimate the inflation in Sweden is EGARCH (1, 1) that is evaluate with student's t-distribution. Therefore, there is another approach that is to consider other long memory GARCH-model. (Anna Akesson, 2016)

Performance AIC test

Forecasting Kenya's inflation determine an effective Arch-type model. Using Kenya monthly inflation data from January 1990 to December 2015, the performance of GARCH and EGARCH type models were analyzed to come up with the best model for forecasting Kenyan inflation data. Since the inflation series is non-stationary, the Consumer Price Index (CPI) was first transformed to return series by logarithmic transformation. Afterwards, the data was tested for the presence of ARCH effects and serial correlation using both Ljung Box Pierce Q test and Engle Arch test. It showed presence of heteroscedasticity and correlation in the inflation return series which is a key feature of a financial time series data. The project adopted AIC and BIC approach in selecting the best model. From the fitted models EGARCH (1,1) had the smallest AIC and BIC values followed by the GARCH (1,1) model. Model diagnostic test was conducted on the selected model EGARCH (1,1) to determine its adequacy and goodness of fit. QQ plot was fitted to the residuals of the model and fairly straight line was produced looking roughly linear. Furthermore, weighted Ljung Box Test on standard squared residuals showed the absence of correlation in the model. EGARCH (1,1) model is the best model for forecasting Kenyan inflation data. EGARCH (1,1) model has the smallest AIC and BIC compared to various GARCH models. The AIC and BIC criteria are used to determine the best model. Kenyan inflation rate data series is characterized with spikes, variations and trends, hence EGARCH model serves as the best in forecasting Kenyan inflation data. (Sammy Oketch Fwaga, 2014)

In forecasting exchange rate volatility of Canadian dollar, Euro, British Pound, Swiss Franc and Japanese Yen using the US dollar as the base currency tests the predictive power of ARCH, GARCH and EGARCH models. Both in-sample and out-of-sample performance of the volatility models using loss functions were investigated. Moreover, it examines if the best model for the in-sample forecast will emerge as the best model for the out-of-sample forecast. AIC was being adopted to determine the best error distribution for the various exchange rate series and concludes that assuming a student-t distribution provides a better in-sample and out-of-sample fit than the normal distribution. The result is unambiguous and expected considering the q-q plots in addition to the

Jarque-Bera test which find that the empirical distribution of the return series of the various exchange rate series display significantly heavier tails than the normal distribution. The GARCH (1,1) model outperforms all the other volatility models during the in-sample period. However, in terms of the out-of-sample performance of the volatility models, the results are inconclusive, even though the ARCH model performed better most of the time than the complex models. Therefore, the simple models should be given special consideration in terms of forecasting. (Obeng Prince, 2016)

Local Related Studies

Haydee Lopez (2008) published a study where the goal is to develop a short term forecasting model that explores the volatility feature of Philippine inflation from 1995 up to August 2007. To build such model, it specifies first an ARMA model, and then consider the SARMA model, if seasonality is present, to represent the mean component using the past values of inflation. It performs the actual forecast building using GARCH models to represent its volatility by completing and implementing the identification of as stationary series, estimation of GARCH models, examination of forecast accuracy measures, and dynamic forecasting. After the models with significant terms had been derived, the models were evaluated using static forecasting, and were then evaluated further with respect to predictive accuracy using the Diebold-Mariano (DM) test statistic. GARCH models are essentially limited to short-term forecasting only, up to about a two-month horizon. This suggests that a GARCH model would have to be continually re-estimated to consider the most recent observations. For now, the author hopes that this paper will serve as a guide for future studies in studying the volatility of Philippine inflation including other economic variables of interest. One may wish to consider other variance models such as TARCH, EGARCH, PARCH, and component GARCH.

Foreign Related Literature

Inflation

To understand what inflation is all about here are some related literatures;

The word inflation owes its origin to the Latin word in flare, which literally means “to blow into”, from flare, “to blow”. This is an accurate description of the current understanding of inflation. Inflation is also an unsubstantiated increase in prices. Over many centuries unsubstantiated increase in price occurred, with the related problems of containing such increases. In this sense, inflation is both a very old problem and a very new one. (Murali, 2004)

According to Bryan (1997) the current understanding of the world inflation is contrasted with its earlier meanings that for many years, the word inflation was not a statement about prices but a condition of paper money, a specific description of a monetary policy. Today, inflation is synonymous with a rise in prices, and its connection to money is often overlooked. In addition, Friedman (1972) states that the inflation origin in modern times from the actions of legislators and central banks, rather than from such acts of God as a specie discovery, implying that inflations is not likely to proceed very long without anticipated, and perhaps, over-anticipated. The implication is therefore that inflation experienced by modern economies is inevitably linked to bad policies in one way or another.

EGARCH model

Here are some related literatures for the better understanding of Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model.

As pointed out by Nelson and Cao (1992), the EGARCH model was developed to allow for asymmetric effects between positive and negative shocks on the conditional variance of future observations. Another advantage of EGARCH model is that there are no restrictions on the parameters. Nelson (1991) also brought out exponential GARCH (EGARCH) model with a conditional variance formulation that successfully captured asymmetric response in the conditional variance. Also, EGARCH model implies that the leverage effect is exponential, rather than quadratic, and the forecasts of the conditional variance are guaranteed to be non-negative and it had been demonstrated to be superior compare to other competing asymmetric conditional variance.

Local Related Literature

Inflation

In recent happenings in the Philippine economy, rising inflation has become one of the major economic problems facing each individual. The Philippines remains one of Asia's best-performing economies and one of the countries that has high inflation rate in Asia.

As said in the article of Ralf Rivas published in 2018, the movement of prices of goods and services over time is referred to as inflation. Statisticians and experts measure inflation by looking at a "basket of goods" which "contains" what the typical Filipino consumes on a regular basis. According to Reyes (1996), inflation can be influenced by several factors. First, it can rise as a result of the oversupply of money, or when the national bank prints money beyond demand. Disturbances in the prices of basic commodities, such as rice, can also affect the general prices of goods. Aside from these factors, market responses to economic uncertainties can also cause the inflation to rise. For instance, the propose increase in oil prices in 1995 induced traders and retailers to stock up on basic commodities, thereby driving their prices up due to artificial shortages.

Moreover, Caparas (2002) stated that the inflation has two major types. The first one is the demand-pull inflation, or when the consumers demand more goods and services than available. The other one is the cost-push inflation, which results from the rise in the cost of inputs in the production process.

As Reyes (1996) claimed that inflation affects mostly the poor. According to the 2015 Family Income and Expenditure Survey, for instance, the poorest Filipinos spend at least 60 percent of their earnings on food, whose prices usually increase faster than other commodities except oil. Meanwhile, Son (2008) stated that the no poor may even benefit from such increase in prices of commodities as it may lead to their income gains.

Synthesis of the Review

It is indeed that EGARCH model is way better than the GARCH model and a more preferable model to use to fit and forecast the volatility of inflation. There is a lot of evidences that show the performance of EGARCH compare with other model. Different studies agree that it is a good model to use when forecasting. Also, EGARCH perform well in forecasting not only with inflation but also with the daily returns, gold exchange and in the stock market.

According to the study of Mbeah Baiden Benedict (2013), the EGARCH model was determined as the most appropriate model in modelling the monthly rates of inflation in Ghana, the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) were being used in the study to assess the performance of each of the fitted models such that the model with the minimum value of AIC and BIC to determine the best model. Okeyo Johnson Otieno (2016) agrees that the EGARCH model provides a better fit than the GARCH model because for once it can capture leverage effects and there is no restriction that the parameters α_1 and β_1 must be positive. Chang Su (2010) found out the EGARCH model is more preferable model that may use to estimate the financial volatility of daily returns in China. The result shows that EGARCH is much better to use rather than the GARCH model because EGARCH can fit to the characteristics of the daily data used.

On the other hand, there are some studies that used other model besides EGARCH model, Charline Uwilingiyimana, et al (2015) said that the empirical results of 180 monthly data series indicate that the combination between ARIMA (1,1,12) and GARCH (1,2) model provide the optimum result and effectively improved estimating and forecasting accuracy compared to the other previous methods of forecasting.

The researchers gain an enough evidence to use further the EGARCH model in this study because of the empirical results already shown by the past studies that used EGARCH. Since, the study of Haydee Lopez (2008) published by the BSP used GARCH model in Forecasting the volatility of Philippine Inflation, the researchers want to use EGARCH model because it outperformed other model in forecasting. Also, the researchers want to prove that there is a better model other than GARCH model that must be tried in Philippine inflation. The Philippine government should have a control in behavior of the inflation. In addition, this study shows how inflation affects and influences in the economy, industries and in everyday lives. Thus, the researchers came up with this study to capture the ever changing nature of inflation and to contribute to the economy.

Conceptual Framework of the Study

The Conceptual Framework was hypothetically designed to carry out the entire process of the study. It shows the flow of the study.

The figure shows the concept of the study the researchers aimed to conduct. As shown on Input, the researcher used the monthly Philippine Inflation rate from January 2012 to October 2018. For process, the researchers performed the analysis and forecasting using EGARCH model. There was a process of five stages before coming up to the output and the main objective of the study, to have the forecasted volatility of Philippine Inflation using EGARCH model.

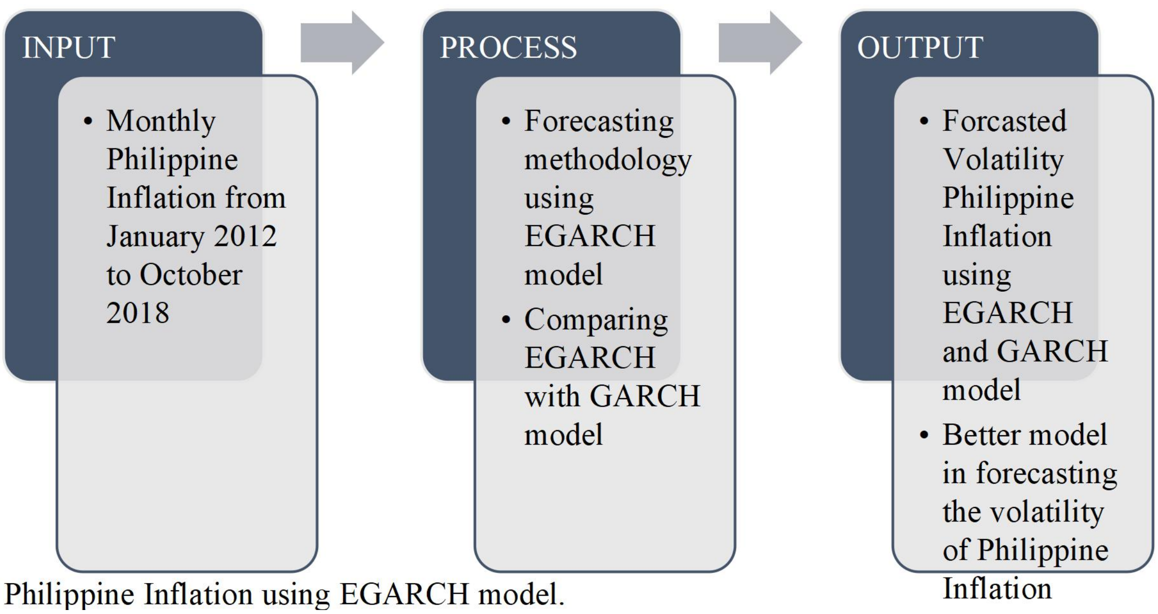


FIGURE 2.1 Conceptual Framework of the study

Definition of Terms

The following terms are listed to assist for better understanding commonly used terms and concepts when reading, interpreting, and evaluating the study:

Heteroskedasticity. It refers to the time varying variance of the inflation data under study.

Inflation. It is the persistent increase in the general price level. It measures the percentage increase in the general prices of goods and services.

Time Series. It is a series of data recorded over time. It is a set of observations on the values that a variable takes at different times.

Volatility. This is the degree of variation of inflation series over time measured by the standard deviation of returns. It is a measure of how much an underlying value of the variable fluctuations over a period of time. It is often expressed as statistical measure such as the error, standard deviation or variance.

CHAPTER III

RESEARCH METHODOLOGY

This chapter describes the methodology that the researchers used in conducting the study. Included in this chapter are the research design, sources of data, data collection procedures, and data processing and analysis.

Research Design

The research design refers to the overall scheme that the researchers have chosen to integrate the different components of the study in a coherent and logical way, thereby, ensuring the researchers will effectively address the research problem. The study was descriptive and quantitative in nature. It was a study of what will be the forecasted volatility of Philippine Inflation using EGARCH model.

In a descriptive and quantitative research, quantifiable data involving numerical and statistical analysis are required. For the analysis of the data to be collected, descriptive statistic is used in order to describe the historical situation of the Philippine inflation. The presentation of data is shown through tables and graph.

The research was conceptualized by the researchers after making an exposition on a previous study entitled Forecasting the Volatility of Philippine Inflation using GARCH by Haydee Lopez. It was a master's thesis and first published in the University of the Philippines - College of Science and further issued by the BSP. By examination of the review of related literature, the researchers found out that EGARCH model was better than GARCH model in forecasting volatility of Philippine Inflation.

Sources of Data

The researchers used secondary data. Specifically, the study utilized the data of monthly inflation rate from Philippine Statistical Authority. The validity and reliability of data is good and accurate because the data is gathered from a national government institution.

Data Collection and Procedures

Data collection is the process of gathering and measuring data, information or any variables of interest in a standardized and established manner that enables the collector to answer or test hypothesis and evaluate outcomes of the particular collection. The researchers sent a formal letter for data request to Philippine Statistical Authority for the monthly inflation rate of Philippines to ask them for the availability of the data. According to PSA, the data is available online, on their webpage, and is ready to be downloaded.

Data Processing and Analysis

Data Analysis is the process of systematically applying statistical and/or logical techniques to describe and illustrate, condense and recap and evaluate data. The input of the research will be the data of Philippine inflation rates from the Philippine Statistical Authority. As stated in the scope of the research, the study will cover the Philippine Inflation rate from January 2000 to March 2019.

The process of this research have five stages. The five stages employed in the research process are as follows:

STAGE 1: Establishing the Preliminary Information. State the primary objective of the forecasting project and the three components of the forecasting system. Then specify the time line in forecasting. To provide an organized transition in building a forecast model, the researcher should first state the primary objective of the forecasting project and the three components of the forecasting system and then specify the time line in forecasting.

Forecasting system is constructed to provide order and structure in the study of forecasting. This system is an interaction of the three, namely; the data, the quantitative method and the software. The data or time series data is referred to observations gathered sequentially over time. The analysis of the data is usually on an equally spaced discrete time interval. In this study, the data are in monthly interval. Quantitative methods are statistical methodologies, to identify patterns and fit a mathematical or forecasting model to the given data. The researcher described the data using tables and graphs. Software is used to facilitate in the implementation of forecasting. Due to the repetition nature of many forecasting procedures, the use of software became beneficial and efficient to researchers. In this case, the study utilized the EViews software.

STAGE 2: Identification of a Stationary Series. Determine the features of the time series data by plotting a line graph. If the series is not stationary, remove the trend by taking first or second differences of the data. Use the correlogram and the until root test (URT) to verify if the stationarity condition of the series is satisfied.

The stationarity condition is needed before the researchers can build our time series models. Thus, the researchers attribute a specific stage to identify this condition. There are three phases used to identify a stationary series: (1) determine the features of the time series data; (2) changing the data, if necessary, into a stationary times series; and verifying if the stationarity condition is satisfied.

Phase 1: Determine the Features of the Data

There are seven features of a time series data commonly associated with general and financial time series data: stationarity, trend pattern and seasonality, presence of outliers, excess kurtosis, volatility, and conditional heteroskedasticity. These features had been identified by plotting a line graph of the data.

Phase 2: Changing into a Stationary Series

If the series is already stationary, then the researchers skip this step and proceed with the verification of the stationarity condition. However, most business and economic time series are not stationary with respect to its mean, variance and covariance (for instance, most series have trend). To induce a stationary series, the researchers introduce a data transformation known as differencing and difference of the logarithms.

Differencing is a simple operation that involves calculating successive changes in the values of data series. This method is simply to subtract the values of two consecutive observations in the series. To difference a series, define a variable W_t, which is the change in Y_t (the original series), that is;

$$W_t = Y_t - Y_{t-1}$$

Note that the researchers lost one observation because of differencing. The series W_t is called the first differences of Y_t.

If the first differences do not have a constant mean, the researchers define Z_t as the difference of the first difference, that is;

$$Z_t = W_t - W_{t-1}$$

The series Z_t is called the second difference of Y_t. Usually, differencing is sufficient to bring out a stationary mean for the most economic time series.

Phase 3: Verifying the Stationarity Condition

To pictorially decide whether the mean is stationary or not, bring to mind that the correlogram offers this purpose. The correlogram in EViews is computed using the Bartlett's test at the 5% significance level. Bartlett (1946) explained that if the time series Y_t is white noise (stationary series where $E\,(Y_t) = 0$ for all t, $Var\,(Y_t) = \sigma^2$ and $Cov\,(Y_t, Y_{t-k}) = 0$ for all $k \neq 0$), then the estimated autocorrelation coefficient ρ is approximately normal with mean zero and variance $1/T$, where T is the length of the series.

Figure 3.1 Test for Autocorrelation Coefficient using the Bartlett's Test

Bartlett's Test

1. H$_o$: $p_k = 0$
2. H$_1$: $p_k \neq 0$
3. Test Statistics : $\frac{p_k}{1/\sqrt{T}} \sim$ N (0,1)
4. Confidence Interval: ($-z_{\propto/2}\frac{1}{\sqrt{T}}, z_{\propto/2}\frac{1}{\sqrt{T}}$)
5. Decision: If the computed p_k lies outside the confidence interval then reject the hypothesis that $\rho = 0$; otherwise, do not reject the hypothesis.

These implies that if there is a spike in the p_k column of the correlogram (or the AC column in an EViews output) that extends past the solid lines enclosing the 95% confidence interval, reject the null hypothesis that $p_k = 0$ at the 5% level of significance.

However, visual inspection of the correlogram is not enough to check for the stationary condition of the series. To formally check for the stationary condition, the researchers make use of the unit root test (URT). To carry out the test, the researchers first consider this model

$$Y_t = \rho Y_{t-1} + \epsilon_t.$$

where ϵ_t is a white noise. The characteristic equation related with this model is

$$\Phi(z) = 1 - \rho z = 0.$$

when ρ = 1 the root of this equation is a unit root since z = 1. Substituting z = 1 in equation 3.40, the researchers now have this model

$$Y_t = Y_{t-1} + \epsilon_t.$$

This equation, also known as random walk, is non-stationary, since variance is not constant (i.e. $Var(Y_t) = Var(Y_{t-1}) + Var(\in_t)$ is not constant for different values of t). Therefore, the existence of a unit root implies non-stationary.

To formally check for the stationarity condition, the researchers used URT. The widely used test for unit root is the Augmented Dickey Fuller (ADF). The ADF test checks if there is a presence of unit root. If there is, it can be concluded that the data set is non-stationary. In EViews software, the null hypothesis is that there exists a unit root. Incorporating the decision that if $p > critical\ value\ which\ is\ 0.05$, then do not reject the null hypothesis and if $p < critical\ value\ which\ is\ 0.05$, then reject the null hypothesis.

STAGE 3: Estimation of SARIMA and EGARCH Model. After the stationary condition is met, generate parameter estimates for the tentative model. Construct SARIMA models to estimate the mean component by analyzing the correlogram plot. Remove models with non-significant terms and set aside models with significant terms for further evaluation.

Seasonal Autoregressive Integrated Moving Average (SARIMA)

The SARIMA model incorporates both non-seasonal and seasonal factors. SARIMA is formed by including additional seasonal terms in ARIMA models. One shorthand notation for the model is:

$$ARIMA\ (p, d, q) \times (P, D, Q)S$$

where,

$$p = non - seasonal\ AR\ order$$

$$d = non - seasonal\ differencing$$

$$q = non - seasonal\ MA\ order$$

$$P = seasonal\ AR\ order$$

$$D = seasonal\ differencing$$

$$Q = seasonal\ MA\ order$$

$$S = time\ span\ of\ repeating\ seasonal\ pattern$$

The seasonal part of the model consists of terms that are similar to the non-seasonal components of the model, but involve backshifts of the seasonal period wherein for the monthly data used, $S = 12$.

In considering the appropriate seasonal orders for SARIMA model, restrict attention to the seasonal lags. The modelling procedure is almost the same as for non-seasonal data, except for the need to select seasonal AR and MA terms.

The following are all rule of thumbs, not an exact science for picking the number of each parameters in $ARIMA\ (p, d, q) \times (P, D, Q)S$. It is an art picking good parameters from the ACF/PACF plots.

1. To identify the order of differencing:
   - $d = 0$ if the series has no visible trend or ACF at all lags is low
   - $d \geq 1$ if the series has visible trend or positive ACF values out to a high number of lags

2. To identify the number of AR and MA terms:
   - p is equal to the first lag where the PACF value is above the significance level.
   - q is equal to the first lag where the ACF value is above the significance level.
3. To identify the seasonal part of the model:
   - S is equal to the ACF lag with the highest value
   - $D = 1$ if the series has a stable seasonal pattern
   - $D = 0$ if the series has an unstable seasonal pattern over time
   - $P \geq 1$ if the ACF is positive at lag S, else $P = 0$
   - $Q \geq 1$ if the ACF is negative at lag S, else $Q = 0$

EGARCH (p, q) Model

Let,

$$y_t = f(w_t; \varphi) + \varepsilon_t, t = 1, \ldots, T \tag{1}$$

where f is at least twice continuously differentiable function of φ, with $w_t = (1, y_{t-1}, \ldots, y_{t-n}, x_{1t}, \ldots, x_{kt})'$. The error process is parametized as

$$\varepsilon_t = z_t h_t^{\frac{1}{2}}, t = 1, \ldots, T \tag{2}$$

where $\{z_t\}$ is a sequence of independent identically distributed random variables with zero mean and unit variance. A family of EGARCH (p, q) models may be defined as a combination of (1) and

$$\ln h_t = \alpha_0 + \sum_{j=1}^{q} g_j(z_{t-j}) + \sum_{j=1}^{p} \beta_j \ln h_{t-j} \tag{3}$$

EGARCH (p, q) where the $p - order$ is the last period's forecast variance and $q - order$ is the information about volatility from the previous period, measured as the lag of the squared residual from the mean equation.

The researchers evaluated the adequacy of models by performing the three tests on the residuals. (1) Correlogram Q-test, (2) Jarque-Bera test and (3) ARCH test.

1. The correlogram Q-test displays the autocorrelation and partial autocorrelation functions of the residuals. No serial correlation in the residuals exists when the

autocorrelation and partial correlations at all lags should be nearly zero, and all Q-statistics should be insignificant with large p-values. Q-statistics is computed with the degrees of freedom adjusted for the inclusion of ARMA terms in regression.

2. The Jarque-Bera is a statistic for testing normality. If the residuals are normally distributed, the histogram should be bell-shaped and the Jarque-Bera statistics should not be significant following the test of hypothesis in Figure 3.2.

Figure 3.2 Test of Hypothesis on the Normality of Residuals using the Jarque-Bera Test

Jarque-Bera Test

1. H_0: Residuals are normally distributed
2. H_1: Residuals are not normally distributed
3. Test Statistics: $JB = \frac{n}{6}\left[s^2 + \frac{(K-3)^2}{4}\right] \sim x^2(2)$
4. Decision: If JB is greater than the critical x^2 value at a given level of significance α, the researchers reject the null hypothesis of normality.

3. ARCH Test also known as ARCH LM Test is the Lagrange multiplier (LM) test for ARCH in the residuals. This particular specification of heteroskedasticity was motivated by the observation that in many financial time series, the magnitude of residuals appeared to be related to the magnitude of recent residuals. To test the null hypothesis that there is no ARCH up to order q in the residuals, the researchers run this test of hypothesis as given in Figure 3.3.

If SARIMA models are found adequate after to conduct the three previous tests of the residuals, the variance component is estimated using different orders of EGARCH (p, q). Each order combination shall include a specification for the distribution of the error terms which may be any of the following form using the EViews software: Normal, Student's t, the Generalized Error (GED), the Student's t with fixed d.f and the GED with fixed parameter.

ARCH Lagrange-Multiplier Test

1. H_0: There is no ARCH up to order q
2. H_1: There is ARCH up to order q
3. Test Regression: $\in_t^2 = \beta_0 + \left(\sum_{k=1}^{q} \beta_k \in_t^2\right) + v_t$
4. Test Statistic: Obs*R-squared= (No. Of observation)× R^2 from the test regression
5. Decision: If the p-value is less than the level of significance α, then the researchers reject the null hypothesis that there is no ARCH up to order q in the residuals.

Figure 3.3 Test of Hypothesis of no ARCH up to order q in the Residuals

At this stage, the researchers can answer the first question in the Statement of the Problem: *Is time-varying variance (conditional heteroskedasticity) exhibited in the data series?*

The model which are found significant and best-fitted for forecasting is the one exhibiting the conditional heteroskedasticity feature of the time series. This could be done after choosing which model have the lowest Akaike's Information Criterion (AIC) value. It is a fined technique based on in-sample fit to estimate the likelihood of a model to estimate the future values. AIC can be defined as:

$$AIC =- 2lnL + 2k$$

where

$$L = value\ of\ likelihood$$

$$k = number\ of\ estimated\ parameters$$

STAGE 4: Examination of Forecast Accuracy Measures. After the models with significant terms had been derived, the researchers perform static forecasting on these models to show measures of forecast accuracy. The researchers observe the model with the smallest measure of forecast error, that is, the one with the most accurate fit of the time series model. The researchers further evaluate predictive accuracy of the models using Diebold-Mariano (DM) test statistic. The model which is found significant under the DM test will be the most adequate choice for the error variance of Philippine inflation.

Figure 3.4 Test of Hypothesis using the DM test

The researchers can answer the second question of the Statement of the Problem which raised the question: *What EGARCH (p, q) model is reliable in forecasting a short-term volatility?* A reliable model is the one with the smallest forecasting error when the static forecasting method is used.

Diebold-Mariano Test

1. H_0: $E(d_t) = 0$
2. H_1: $E(d_t) \neq 0$
3. Test Statistics: $B = \frac{d}{\sqrt{\frac{f}{T}}} \sim N(0,1)$
4. Decision: If $|B|$ is greater than the critical normal value at a given level of significance α, we reject the null hypothesis of no difference in the accuracy of two competing forecasts.

STAGE 5: Dynamic Forecasting. Once a reliable model has been found, it can be integrated and future forecasts can be found using dynamic forecasting. The EGARCH terms, which represent volatility of the process, are computed for each of the point forecast.

By the end of this stage, the researchers can answer the third question of the Statement of the Problem*: What will be the predicted movement of Philippine Inflation in the coming months using the EGARCH model?*

After all stages are done, next is to estimate for GARCH model for comparing what model is better. Better model is the one with less forecast error compare to the other.

The paper is not mathematically precise. It takes advantage of the convenience of Econometric Views (EViews) software when estimating the parameters of the model. The researcher will impart more time on the implication of the software results which can be beneficial in modelling the volatility forecasts of the inflation rate.

CHAPTER IV

PRESENTATION, ANALYSIS AND INTERPRETATION OF DATA

This chapter provided the results generated from different statistical techniques that were introduce in the methodology. The answers to the different statement of the problem were presented and organized.

4.1 Establishing the Preliminary Information

The primary objective of the research is to forecast the volatility of Philippine inflation using EGARCH model. The existing study by Haydee Lopez have modelled the rates of inflation in the Philippines using the GARCH model. The idea of this study is to come up with a better model that will capture the ever-changing nature of inflation using the EGARCH model.

Recall that in forecasting, the researchers stated that there are three components; the data, the quantitative method, and the software to be used. The data of the research were the Inflation Rate (IR) of the Philippines. It was available at the PSA, a sole government agency responsible for the monthly computation of Philippine inflation. The inflation rate from the PSA are also the data used BSP. The values of IR used in this paper consisted of 231 monthly observations from January 2000 to March 2019. (Appendix A)

The second component of the forecasting system is to have a quantitative method. For this study, the researchers model the mean and error variance of the data to have a forecasted volatility. For the mean, the data were performed under Seasonal Autoregressive Integrated Moving Average Model (SARIMA). The error variance of the data forecasted was modelled in Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) Model. This proposed quantitative method was based on the January 2007 study published by BSP, Forecasting the Volatility of Philippine Inflation using GARCH model by Haydee Lopez. Instead of undergoing the data under the GARCH model in the error variance, the researchers performed EGARCH model as error variance.

Table 4.1 *Applicable Time Series Models for the Mean and Error Variance Components*

COMPONENT	MODEL
MEAN	Seasonal Autoregressive Integrated Moving Average (SARIMA) Model
ERROR VARIANCE	Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) Model

For the software component, the researchers utilized the benefits of EViews software. Eviews is an econometrics and statistical tool software. The command codes utilized in this paper are provided in appendix for reference. The researchers assigned a uniform 5% level of significance on the statistical tests conducted using the software.

To provide an organized transition in building a forecast model, the researcher specified the time line in forecasting. The historical data of inflation were from the period of January 1958 until March 2019. The sample period for analysis was from the period of January 2000 to March 2019. The data of February 2019 and March 2019 were the ex-post forecast period. It provided an opportunity to the researchers to determine the accuracy of the model to the given period where data is already available. On the other hand, the period in which there is no observation on the time series variable was the ex-ante forecast period. The volatility to be forecasted April 2019 and May 2019 was the ex-ante period.

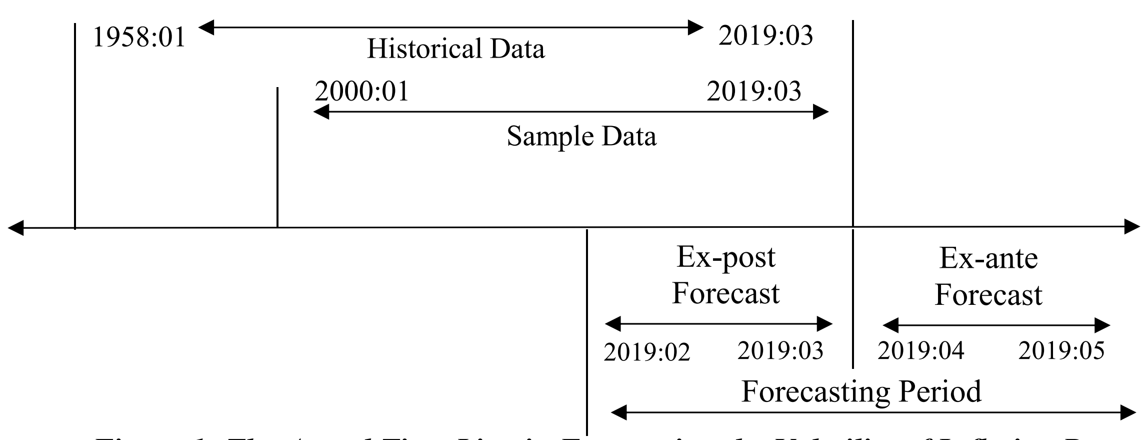


Figure 1: The Actual Time Line in Forecasting the Volatility of Inflation Rate

4.2 Identification of a Stationary Series

The stationarity condition is needed before the researchers can build our time series models. Thus, the researchers attribute a specific stage to identify this condition. There are three phases to identify a stationary series. First, to determine the features of the time series data. Second, changing the data into a stationary times series, if necessary. Lastly, verifying if the stationarity condition is satisfied.

Phase 1: Determine the Feature of the Data

There are seven features of a time series data commonly associated with general and financial time series data: stationarity, trend pattern and seasonality, presence of outliers, excess kurtosis, volatility, and conditional heteroskedasticity. These features had been identified by plotting a line graph of the data. The line graph of the original IR series in Figure 4.2 indicates the non-stationary feature of the series since volatile values are evident and said values does not fluctuate around a constant mean.

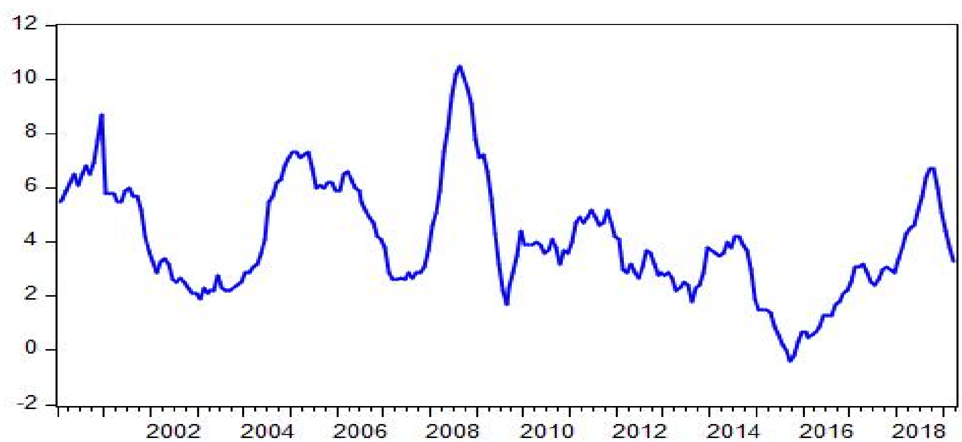
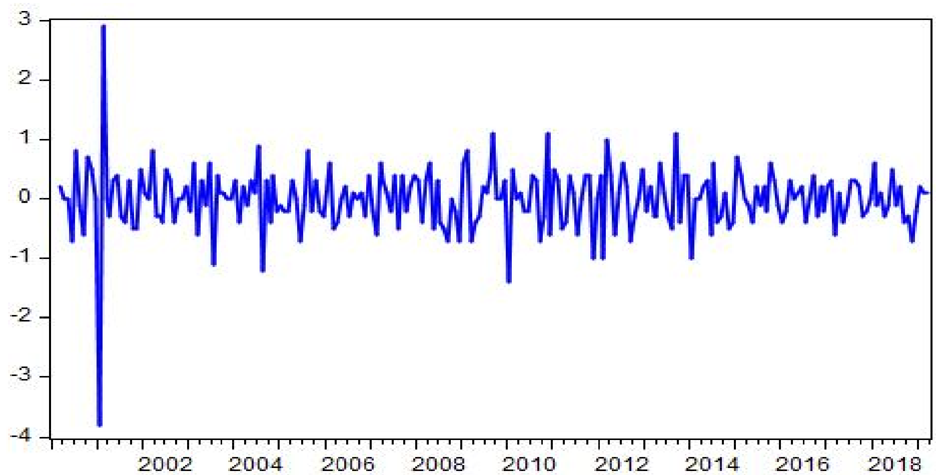


Figure 4.2 Line Graph of Inflation Rate

Phase 2: Changing into a Stationary Series

Stationary pattern exists when the mean, variance and covariance of a series are all constant. Most economic time series is usually not stationary. The data is frequently needed to be transformed to make it a stationary series. Thus, differencing is suggested for the sample data. This method is simply subtracting two adjacent observations in the series. As shown on Figure 4.3, the series seems to be stationary since it has no persistent trend. While in the graph of second difference, it is also stationary since the values fluctuate around a constant mean of zero.

Figure 4.3 Line Graph for the First Difference of Inflation Rate



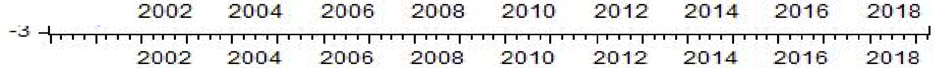


Figure 4.4 Line Graph for the Second Difference of Inflation Rate

Phase 3: Verifying the Stationarity Condition

For this phase, the data had undergone to correlogram and perform unit root test (URT). Correlogram is a view or a pictorial representation that displays the autocorrelation function (ACF) and partial autocorrelation functions (PACF) up to a specified order of k lags. Correlogram has two uses. First is to tentatively decide whether the mean is stationary or not. If the estimated ACF drops off rapidly to zero, then the mean of the series is stationary. On the other end, if the estimated ACF drops off slowly towards zero, then the mean is not stationary. Second is to provide a rough guide to model selection. The estimated PACF is used as a guide, along with the estimated ACF, in choosing one or more SARIMA models.

To study the correlogram, the researchers first designate the number of ideal lags T/4, where T is the number of observations. In this case, the researchers divided 231, the number of observations, by 4 to come up with the number of ideal lags, 57.75 and rounded off to 58. The correlogram of levelled inflation rates series in Figure 4.5, shows that it seems to have a stronger evidence of non-stationary since the ACF of the residuals does not drop-off to zero right away. On the other hand, the correlogram of the first differences in Figure 4.6, shows that it is mean stationary because most of the values cut off or drop to zero.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.970	0.970	220.28	0.000
		2	0.917	-0.407	418.11	0.000
		3	0.853	-0.102	589.70	0.000
		4	0.777	-0.149	732.71	0.000
		5	0.694	-0.062	847.33	0.000
		6	0.613	0.070	937.16	0.000
		7	0.531	-0.103	1004.8	0.000
		8	0.444	-0.125	1052.5	0.000
		9	0.363	0.081	1084.4	0.000
		10	0.285	-0.064	1104.1	0.000
		11	0.208	-0.040	1114.8	0.000
		12	0.142	0.109	1119.7	0.000
		13	0.100	0.304	1122.2	0.000
		14	0.068	-0.149	1123.3	0.000
		15	0.041	-0.060	1123.7	0.000
		16	0.020	-0.082	1123.8	0.000
		17	0.003	-0.008	1123.8	0.000
		18	-0.015	-0.047	1123.9	0.000
		19	-0.030	0.048	1124.1	0.000
		20	-0.039	-0.041	1124.5	0.000
		21	-0.049	-0.003	1125.1	0.000
		22	-0.055	0.001	1125.9	0.000
		23	-0.056	0.032	1126.7	0.000
		24	-0.055	0.040	1127.5	0.000
		25	-0.051	0.177	1128.2	0.000
		26	-0.043	-0.045	1128.7	0.000
		27	-0.032	-0.001	1129.0	0.000
		28	-0.018	-0.009	1129.1	0.000
		29	-0.005	-0.075	1129.1	0.000
		30	0.013	0.068	1129.1	0.000
		31	0.029	-0.043	1129.3	0.000
		32	0.042	-0.046	1129.8	0.000
		33	0.055	0.019	1130.6	0.000
		34	0.067	0.025	1131.8	0.000
		35	0.077	0.006	1133.5	0.000
		36	0.086	0.042	1135.5	0.000
		37	0.096	0.121	1138.1	0.000
		38	0.107	0.052	1141.3	0.000
		39	0.119	0.005	1145.2	0.000
		40	0.130	-0.027	1150.0	0.000
		41	0.140	-0.088	1155.5	0.000
		42	0.144	-0.004	1161.5	0.000
		43	0.148	0.004	1167.7	0.000
		44	0.149	-0.076	1174.1	0.000
		45	0.149	0.049	1180.5	0.000
		46	0.145	-0.043	1186.6	0.000
		47	0.139	-0.021	1192.2	0.000
		48	0.129	-0.008	1197.1	0.000
		49	0.114	0.026	1201.0	0.000
		50	0.093	-0.044	1203.6	0.000
		51	0.066	-0.021	1204.9	0.000
		52	0.039	0.068	1205.3	0.000
		53	0.015	0.048	1205.4	0.000
		54	-0.006	-0.054	1205.4	0.000
		55	-0.025	-0.024	1205.6	0.000
		56	-0.041	-0.016	1206.2	0.000
		57	-0.056	0.016	1207.1	0.000
		58	-0.067	0.005	1208.5	0.000

Figure 4.5 Correlogram of Inflation Rate

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.408	0.408	38.820	0.000
		2	0.214	0.056	49.499	0.000
		3	0.196	0.109	58.498	0.000
		4	0.127	0.006	62.281	0.000
		5	-0.014	-0.109	62.325	0.000
		6	0.010	0.030	62.347	0.000
		7	0.063	0.063	63.307	0.000
		8	-0.088	-0.147	65.149	0.000
		9	-0.079	-0.001	66.637	0.000
		10	-0.063	-0.038	67.603	0.000
		11	-0.198	-0.177	77.159	0.000
		12	-0.357	-0.237	108.27	0.000
		13	-0.179	0.072	116.12	0.000
		14	-0.111	0.016	119.16	0.000
		15	-0.098	0.045	121.57	0.000
		16	-0.065	-0.021	122.61	0.000
		17	0.020	0.025	122.71	0.000
		18	-0.084	-0.109	124.47	0.000
		19	-0.082	-0.006	126.18	0.000
		20	-0.002	-0.013	126.18	0.000
		21	-0.035	-0.039	126.50	0.000
		22	-0.071	-0.061	127.80	0.000
		23	-0.023	-0.064	127.94	0.000
		24	-0.032	-0.140	128.20	0.000
		25	-0.066	-0.008	129.33	0.000
		26	-0.076	-0.062	130.84	0.000
		27	-0.050	-0.011	131.49	0.000
		28	0.004	0.076	131.49	0.000
		29	-0.068	-0.092	132.72	0.000
		30	0.045	0.038	133.25	0.000
		31	0.038	-0.016	133.64	0.000
		32	0.012	-0.030	133.68	0.000
		33	0.009	-0.026	133.70	0.000
		34	0.044	-0.019	134.23	0.000
		35	0.011	-0.070	134.26	0.000
		36	-0.023	-0.080	134.41	0.000
		37	-0.025	-0.115	134.57	0.000
		38	0.001	-0.012	134.58	0.000
		39	-0.002	-0.003	134.58	0.000
		40	0.035	0.059	134.91	0.000
		41	0.060	0.004	135.92	0.000
		42	0.024	0.004	136.09	0.000
		43	0.056	0.037	136.98	0.000
		44	0.021	-0.052	137.11	0.000
		45	0.066	0.031	138.37	0.000
		46	0.037	0.011	138.76	0.000
		47	0.073	-0.006	140.31	0.000
		48	0.082	-0.020	142.28	0.000
		49	0.107	0.025	145.63	0.000
		50	0.099	-0.005	148.52	0.000
		51	0.016	-0.073	148.60	0.000
		52	-0.071	-0.087	150.12	0.000
		53	-0.048	0.020	150.81	0.000
		54	-0.054	-0.005	151.70	0.000
		55	-0.067	0.001	153.07	0.000
		56	-0.043	-0.012	153.64	0.000
		57	-0.061	-0.013	154.78	0.000
		58	-0.072	-0.041	156.40	0.000

Figure 4.6 Correlogram of First Differences of the Inflation Rate Series

However, visual inspection of the correlogram was not enough to check for the stationarity condition of the series. To formally check for the stationarity condition, the researchers used URT. The widely used test for unit root is the Augmented Dickey Fuller (ADF).

Table 4.2 *ADF Specifications*

INFLATION RATE SERIES	$p - value$
Levelled Inflation Rate	0.1149
First Differenced Inflation Rate	**0.0000**

The test carried out and revealed that p-value 0.1149, which is greater than the critical value 0.05. This resulted to do no reject the null hypothesis that a unit root exists and the data of levelled inflation rate suggests not stationary. On the other hand, first differenced inflation rate series is stationary because the p-value is less than the critical value that rejecting the null hypothesis that unit root exists.

4.3 Estimation of EGARCH Models

It was mentioned in the Phase 3 in 4.2 that correlogram provides a rough guide to model selection. In Figure 4.6, the correlogram of D(IR) exhibited lags. Considering the rules stated Stage 3 on picking appropriate SARIMA model, the researchers ended up having $p = 1$, $q = 1$, $D = 0$, $P = 0$ and $Q = 1$ and automatically, $d = 1$ because the first differenced inflation rate is the stationary series and $S = 12$ because of having monthly inflation rate as the data. $ARIMA\ (1,1,1) \times (0,0,1)12$ was the first model for the mean equation. D(IR), AR (1), MA (1) and SMA (12) terms are the other way around how the first model may display. If non-significant terms exist after the estimation under method of least square, non-significant terms are then removed.

Table 4.3 *Model 1 specifications for the Mean Equation using Method of Least Square with terms D(IR), AR (1), MA (1), and SMA (12)*

VARIABLES	$p - value$
AR (1)	0.0000
MA (1)	0.0489
SMA (12)	0.0000

Since all terms are significant, the researchers then perform the three tests on the residuals of this equation. To verify the adequacy of AR (1), MA (1), and SMA (12) terms of the mean equation, the researchers used the three tests on the residuals; the correlogram Q-test, the Jarque-Bera test, and ARCH test.

Indicated in the correlogram Q-test (Figure 4.7) that there seems to be no serial correlation on the residuals since the autocorrelations and partial autocorrelations at all lags are nearly zero wherein even the lag 12, where spike was evident, is significant at 5% level of significance. But, if we look at the first p-value of 0.441, which is testing the null hypothesis that correlations of residuals from lags 1 to 3 are zeroes, we can see that it is greater than 5% level of significance. Thus, the researchers do not reject null hypothesis and say that at least one of these correlations are zero. On the other hand, the Jarque-Bera test as shown in Figure 4.8, suggested normality because p-value was significant at 5% level of significance. Lastly, the output on the ARCH test in Figure 4.9, resulted that the researchers do not reject the null hypothesis that there is no ARCH up to order q in the residuals because of the p-value of 0.5075 is more than .05 level of significance.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.011	0.011	0.0296	
		2	-0.038	-0.038	0.3663	
		3	0.031	0.032	0.5871	
		4	0.005	0.003	0.5931	0.441
		5	-0.001	0.001	0.5936	0.743
		6	-0.083	-0.084	2.2223	0.528
		7	0.102	0.105	4.7234	0.317
		8	-0.068	-0.080	5.8504	0.321
		9	-0.001	0.017	5.8507	0.440
		10	0.012	-0.001	5.8881	0.553
		11	-0.097	-0.094	8.1738	0.417
		12	0.197	0.202	17.647	0.040
		13	-0.113	-0.129	20.793	0.023
		14	-0.059	-0.049	21.655	0.027
		15	-0.043	-0.044	22.104	0.036
		16	0.008	0.002	22.119	0.054
		17	0.065	0.061	23.170	0.058
		18	-0.115	-0.079	26.499	0.033
		19	0.003	-0.058	26.501	0.047
		20	0.004	0.045	26.506	0.066
		21	0.010	-0.004	26.532	0.088
		22	-0.022	-0.027	26.652	0.113
		23	-0.029	0.012	26.872	0.139
		24	0.117	0.030	30.416	0.084
		25	-0.124	-0.076	34.449	0.044
		26	-0.078	-0.073	36.035	0.041
		27	-0.055	-0.073	36.828	0.046
		28	0.052	0.064	37.548	0.051
		29	-0.049	-0.101	38.175	0.058
		30	-0.026	0.041	38.352	0.072
		31	0.047	0.007	38.950	0.082
		32	-0.021	-0.025	39.072	0.100
		33	0.018	0.012	39.164	0.122
		34	0.040	0.044	39.610	0.138
		35	-0.005	-0.008	39.616	0.167
		36	0.071	0.052	40.987	0.160

Figure 4.7 Correlogram Q-test of residuals

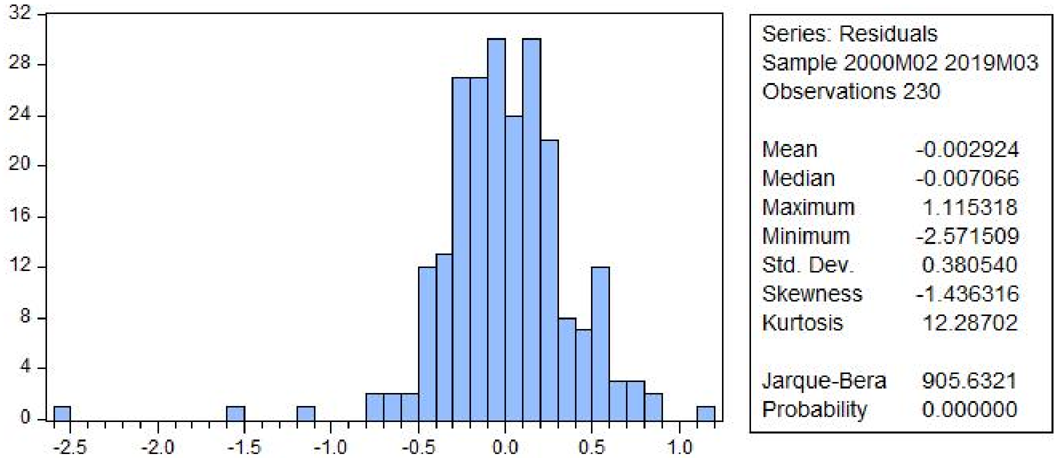


Figure 4.8 Histogram and Stats of residuals

F-statistic	0.440616	Prob. F(1,227)	0.5075
Obs*R-squared	0.443637	Prob. Chi-Square(1)	0.5054

Figure4.9 ARCH Test

The result of no serial correlation under the correlogram Q-test, using the AR (1), MA (1) and SMA (12) terms for the mean equation, indicates that the researchers can now proceed with the estimation of the conditional variance for the errors using EGARCH. The researchers limited the order of EGARCH (p, q) to 4, that is the researchers used different orders of p, q = 0,1,2,3 and 4 or four-month relationship of volatilities, since EGARCH is used for short-term forecasting. Incorporating the stationary series D(IR) and the mean equation with terms AR (1), MA (1) and SMA (12), the researchers estimated an EGARCH model by choosing the EGARCH (p, q) model with lowest AIC value that best fit for forecasting model.

Table 4.4 *EGARCH (p, q) Estimation*

EGARCH (p, q)	**AIC**	**EGARCH (p, q)**	**AIC**
EGARCH (0, 1)	0.4969	EGARCH (2, 3)	0.4574
EGARCH (0, 2)	0.4490	EGARCH (2, 4)	0.4130
EGARCH (0, 3)	0.4574	EGARCH (3, 0)	0.4994
EGARCH (0, 4)	0.4653	EGARCH (3, 1)	0.4787
EGARCH (1, 0)	0.5211	EGARCH (3, 2)	0.4532
EGARCH (1, 1)	0.5083	EGARCH (3, 3)	0.4068
EGARCH (1, 2)	0.4713	**EGARCH (3, 4)**	**0.4040**
EGARCH (1, 3)	0.4316	EGARCH (4, 0)	0.5218
EGARCH (1, 4)	0.4575	EGARCH (4, 1)	0.4869
EGARCH (2, 0)	0.5013	EGARCH (4, 2)	0.4937
EGARCH (2, 1)	0.4700	EGARCH (4, 3)	0.4612
EGARCH (2, 2)	0.4454	EGARCH (4, 4)	0.4605

After estimating an EGARCH model by finding a significant order combination under the normal error distribution, the researchers found out that all EGARCH (p, q) models were significant models after using different order of p and q. The researchers considered using AIC for finding the model best fit for the analysis. The researchers ended with EGARCH (3, 4) was adequate for the analysis.

4. 4 Examination of Forecast Accuracy Measures

To validate the goodness of fit of EGARCH (3, 4) model assuming Normal, Student's t with fixed degrees of freedom v = 10 and Generalized Error Distribution (GED) with fixed parameter r = 1.5 for the error terms, the researchers performed static forecasting on the models to show measures of forecast accuracy using Mean Absolute Error (MAE) over the estimation period. Table 4.5 shows the summary of results of forecast accuracy.

Table 4.5 *Forecast Errors for the Significant EGARCH (p, q) Models*

EGARCH (p, q)	ERROR DISTRIBUTION	MAE
EGARCH (3, 4)	Normal	0.2439
	Student's t with fixed degrees of freedom v = 10	0.2425
	GED with fixed parameter r = 1.5	**0.2424**

Also, Table 4.5 shows the summary of result after each models performed under static forecasting. EGARCH (3, 4) with GED with fixed parameter r = 1.5 have formulated the model with the smallest measure of forecast error under MAE.

The researchers further evaluate predictive accuracy of the models using the Diebold-Mariano (DM) test statistic. In DM test, if the |B| is greater than the critical normal value at a 5% level of significance. Therefore, the null hypothesis of no difference in the accuracy of two competing forecast is rejected.

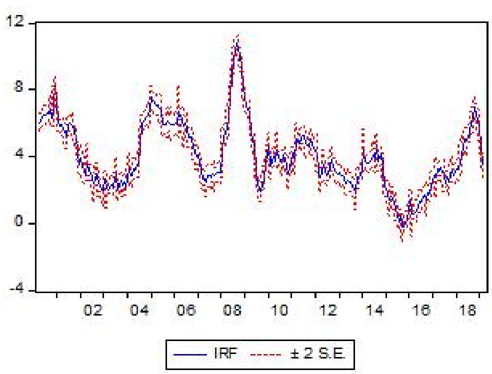
Table 4.6 *Diebold-Mariano Test*

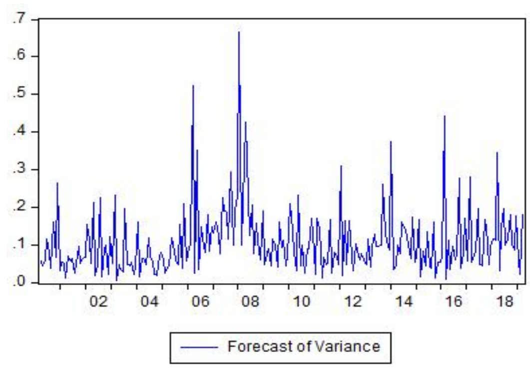
EGARCH (p, q)	ERROR DISTRIBUTIONS	DM Test Statistic B
EGARCH (3, 4)	Student's t with fixed degrees of freedom v = 10 vs. GED with fixed parameter r = 1.5	1.18
	Normal vs. GED with fixed parameter r = 1.5	0.61
	Student's t with fixed degrees of freedom v = 10 vs. Normal	**1.97**

After following the procedure of Diebold-Mariano test computation, the Table 4.6 indicated that at a 95% confidence interval. The positive value of B = 1.97, which is greater than the critical value of 1.96 in a normal table, indicates that the Student's t with fixed degrees of freedom v = 10 has higher square error than normal distribution. Therefore, the null hypothesis of no difference in the accuracy of two competing forecasts is rejected. Then, the EGARCH (3, 4) with normal error distribution is an adequate choice for forecasting the volatility of Philippine Inflation. Although, GED with fixed parameter r = 1.5 was found to have the smallest measure in its forecast errors based on MAE, the researchers laid much emphasis on the result of measuring predictive accuracy of the models through the DM test statistic.

Then, the researchers can present the forecast for the mean and error variance of the inflation rate as shown in Figure 4.10 using the in-sample observations under the static forecasting. Figure 4.10 simply implied that volatile values are evident all throughout the sample period.

Figure 4.10 EGARCH (3, 4) Forecast for the Mean and Error Variance of Inflation





Rate using the In-sample Observations under the Static Forecasting

4.5 Dynamic Forecasting

The stationary series D(IR), AR (1), MA (1) and SMA (12) terms for mean, and EGARCH (3, 4) with normal error distribution, formulated an adequate model of inflation rate. The researchers forecasted in duration of four months by extrapolating under dynamic forecasting (DF). Figure 4.11 show the forecasted for the mean and error variance of the inflation rate using the out-of-sample observations under dynamic forecasting. The forecasted values for the inflation rate, denoted by IRDF and its variance, denoted by EGARCHDF, were shown in Table 4.7. The table also included the lower and upper bounds of the inflation rate considering the forecast horizon from February 2019 to May 2019.

Ex-ante forecasts from February 2019 to March 2019 are 3.6% and 3.1%, respectively. As can be noticed, forecasted and the actual inflation rates during the ex-ante period lie in lower and upper bound of the forecast. The forecast for the variance of the errors or EGARCHDF indicated an irregular trend, that is, as the period lapses through time, the variance of the errors will fluctuate.

Table 4.7 *EGARCH (3, 4) Forecast of the Inflation Rate including the Lower and Upper Bounds from February 2019 to May 2019*

PERIOD	IR	IRDF	LOW	HIGH	EGARCHDF
2019:02	3.8	3.5698	3.2	3.9	0.03
2019:03	3.3	3.0482	2.3	3.8	0.09
2019:04	-	2.7659	1.1	4.5	0.47
2019:05	-	3.0217	0.3	5.7	0.55

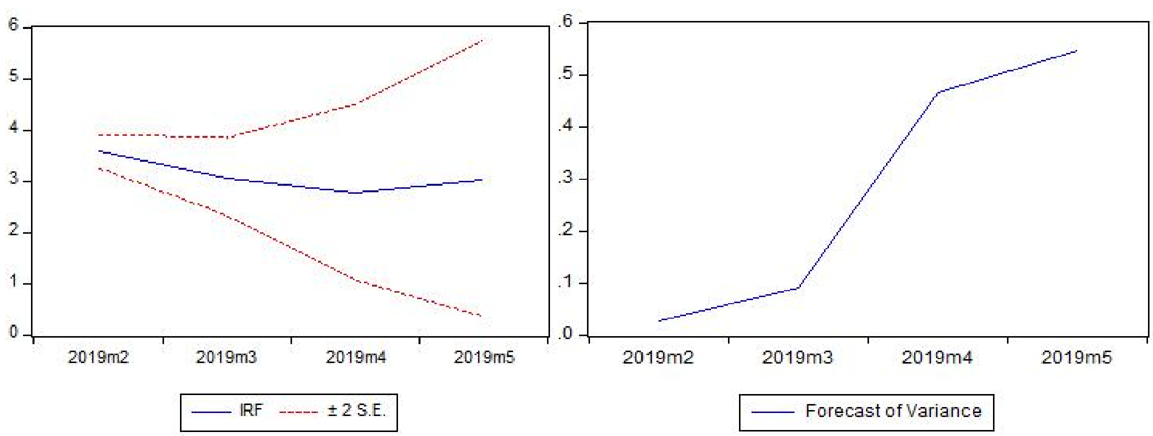


Figure 4.11 EGARCH (3, 4) Forecast for the Mean and Error Variance of the Inflation Rate using the Out-of-Sample Observations under the Dynamic Forecasting

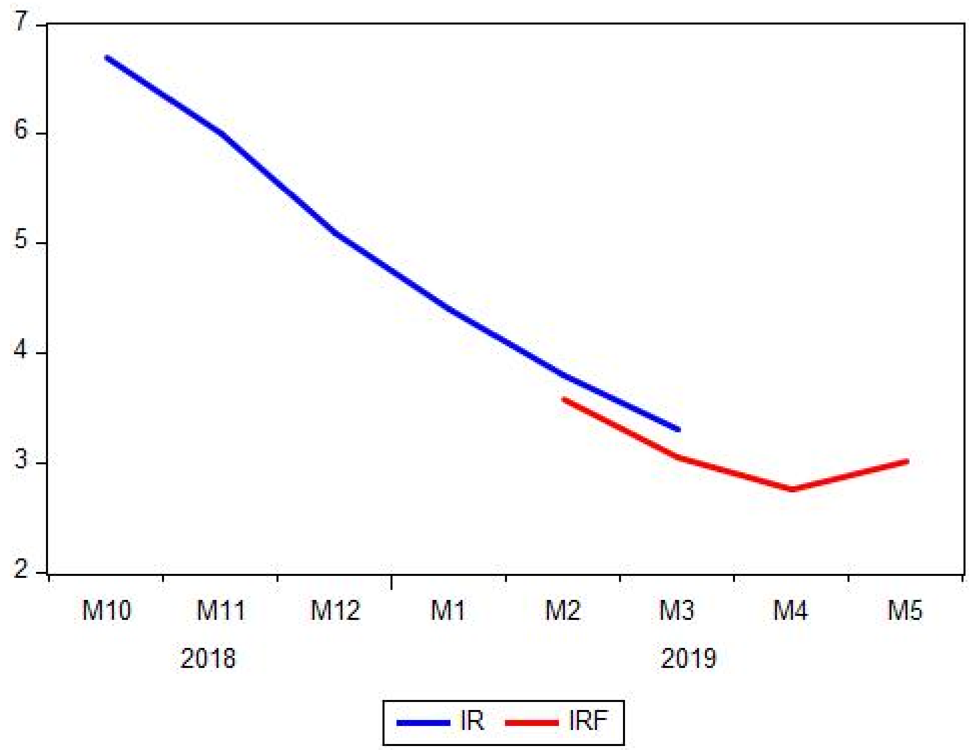


Figure 4.12 Actual Inflation Rate and the Forecasted Inflation Rate Values

4.6 Comparison of EGARCH and GARCH

For further evaluation of the results, the researchers have worked on comparing the forecasting using GARCH and EGARCH. The mean component is still the formulated component of the sample data; D(IR), AR (1), MA (1), and SMA (12). The researchers estimated GARCH model by finding a significant order combination under a specific error distribution where p and q = 0,1,2,3 and 4. The p-values should all be less than .5 level of significance and coefficients of the variance equation are all positive.

After estimating a GARCH model by finding a significant order combination under the normal error distribution, the researchers found out that GARCH (0, 1) and GARCH (1, 0) were significant after using different order of p and q. The researchers considered using AIC for finding the model best fit for the analysis. The researchers ended with GARCH (0, 1) was adequate for the analysis.

Table 4.8 *Estimation of GARCH (p, q)*

GARCH (p, q)	AIC
GARCH (0, 1)	**0.5154**
GARCH (1, 0)	0.5409

To validate the goodness of fit of GARCH (0, 1) model assuming Normal, Student's t with fixed degrees of freedom v = 10 and Generalized Error Distribution (GED) with fixed parameter r = 1.5 for the error terms, the researchers performed static forecasting on the models to show measures of forecast accuracy over the estimation period. Table 4.9 shows the summary results of forecast error.

Table 4.9 *Forecast Errors for the Significant GARCH (p, q) Models*

GARCH (p, q)	ERROR DISTRIBUTIION	MAE
GARCH (0, 1)	Normal	0.2447
	Student's t with fixed degrees of freedom v = 1	0.2443
	GED with fixed parameter r = 1.5	**0.2438**

Table 4.9 shows the summary of result after each models performed under static forecasting. GARCH (0, 1) with GED with fixed parameter r = 1.5 have formulated the model with the smallest measure of forecast error using Mean Absolute Error (MAE).

Now, the researchers can present the forecast for the mean and error variance of the inflation rate as shown in Figure 4.13 using the in-sample observations under the static forecasting. The figure imply that volatile values are evident all throughout the sample period.

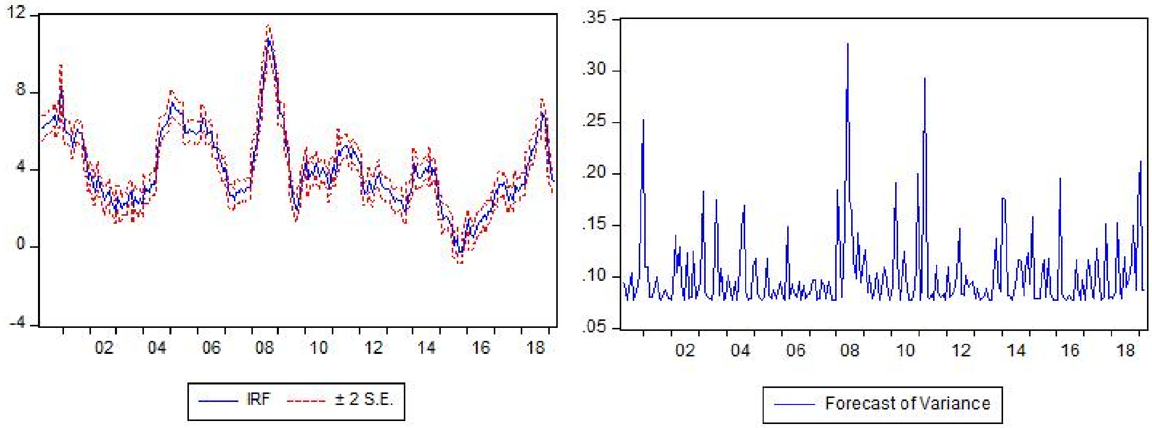


Figure 4.13 GARCH (0, 1) Forecast for the Mean and Error Variance of Inflation Rate using the In-sample Observations under the Static Forecasting

The researchers can now forecast in duration of four months by extrapolating under dynamic forecasting (DF). The stationary series D(IR), AR (1), MA (1) and SMA (12) terms for mean, and GARCH (0, 1) with GED with fixed parameter r = 1.5 estimated in dynamic forecasting. Figure 4.14 show the forecasts for the mean and error variance of the inflation rate using the out-of-sample observations under dynamic forecasting.

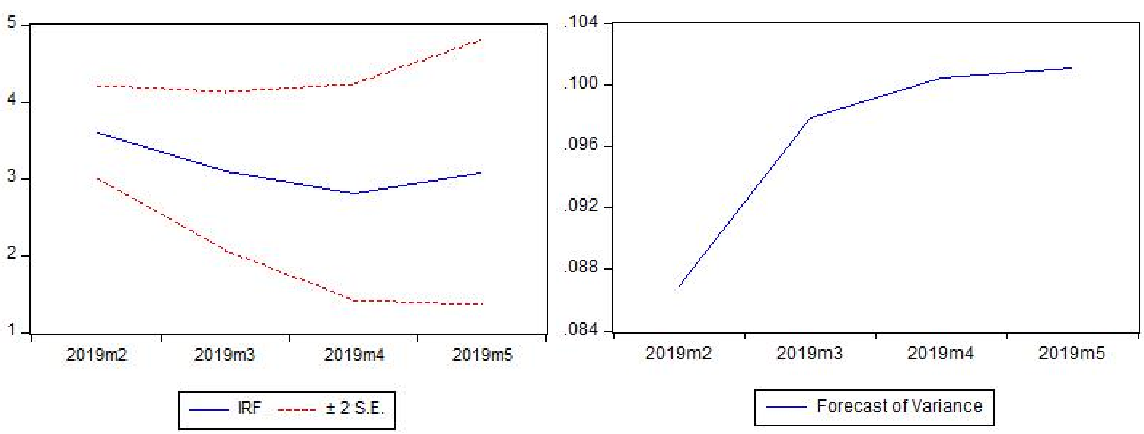


Figure 4.14 GARCH (0, 1) Forecast for the Mean and Error Variance of the Inflation Rate using the Out-of-Sample Observations under the Dynamic Forecasting

As can be noticed, forecasted inflation rates during the ex-ante period lie in lower and upper bound of the forecast with 95% level of significance. The forecast for the variance of the errors or GARCHDF indicates an increasing trend, that is, as the period lapses through time.

The forecasted values for the inflation rate, denoted by IRDF and its variance, denoted by GARCHDF, are shown in Table 4.10. The table also included the lower and upper bounds of the inflation rate considering the forecast horizon from February 2019 to May 2019.

Table 4.10 *GARCH (0, 1) Forecast for the Inflation Rate including the Lower and Upper Bounds from February 2019 to May 2019*

PERIOD	IR	IRDF	LOW	HIGH	GARCHDF
2019:02	3.8	3.5930	3.0	4.2	0.0870
2019:03	3.3	3.0841	2.1	4.2	0.0978
2019:04	-	2.8079	1.5	4.3	0.1004
2019:05	-	3.0700	1.5	4.9	0.1010

The researchers can now show which model was better fit by comparing each model's AIC. The researchers compared the EGARCH (3, 4) with normal error distribution and GARCH (0, 1) with GED with fixed parameter r = 1.5.

Table 4.11 *AIC Comparison of models*

MODEL	AIC
EGARCH (3, 4) with normal error distribution	**0.4130**
GARCH (0, 1) with GED with fixed parameter r = 1.5	0.5154

Hence, estimated and the best model selected based on the minimum values of Akaike's Information Criteria (AIC). From Table 11, the EGARCH (2, 4) with GED with fixed parameter r = 1.5 model was better model based on the selection criteria used.

CHAPTER V

SUMMARY, CONCLUSION AND RECOMMENDATIONS

The research's main objective was to formulate for the mean and variance error to forecast Philippine inflation. The specifications were based on the monthly inflation rate data from January 2000 to March 2019. The researcher used different statistical procedures such that SARIMA and EGARCH

The parameter estimation procedure started with transforming the Inflation Rate (IR) data into a stationary series. After investigating the autocorrelation function (ACF) and partial autocorrelation functions (PACF) plots, and conducting a formal Augmented Dickey Fuller (ADF) test on stationarity, it was shown that the first differences, D(IR), was the stationary series.

To estimate the mean component, the correlogram of D(IR) was performed and exhibited lags were observed. Considering the rules stated Stage 3 on picking appropriate SARIMA model, the researchers ended up having $p = 1$, $q = 1$, $D = 0$, $P = 0$ and $Q = 1$ and automatically, $d = 1$ because the first differenced inflation rate is the stationary series and $S = 12$ because of having monthly inflation rate as the data. $ARIMA\ (1,1,1) \times (0,0,1)12$ was the first model for the mean equation. To verify the adequacy of AR (1), MA (1), and SMA (12) terms of the mean equation, the researchers used the three tests on the residuals; the correlogram Q-test, the Jarque-Bera test, and ARCH test. The correlogram Q-test indicated no serial correlation on the residuals, thus the researchers proceeded to the next stage of estimation of an EGARCH model.

After estimating an EGARCH model by finding a significant order combination under the normal error distribution, the researchers found out that EGARCH (3, 4) was significant model after using different order of p and q. To validate the goodness of fit of EGARCH (3, 4) model assuming Normal, Student's t with fixed degrees of freedom v = 10 and Generalized Error Distribution (GED) with fixed parameter r = 1.5 for the error terms, the researchers performed static forecasting on the models to show measures of forecast accuracy over the estimation period. EGARCH (3, 4) with GED with fixed parameter r = 1.5 formulated the model with the smallest measure of forecast error using

Mean Absolute Error (MAE). However, when the Diebold-Mariano test was conducted to compare predictive accuracy of the models, the EGARCH (3, 4) with normal error distribution is an adequate choice for forecasting the volatility of Philippine Inflation. Although, GED with f.p. r = 1.5 was found to have the smallest measure in its forecast errors based on MAE, the researchers laid much emphasis on the result of measuring predictive accuracy of the models through the DM test statistic.

The researchers also made comparison between the EGARCH model formulated and GARCH model to see which model forecasts Philippine Inflation better. A GARCH model was estimated with same procedures how EGARCH model was formulated. GARCH (0, 1) with GED with fixed parameter r = 1.5 drawn as adequate GARCH model. After the comparison was made, the EGARCH (3, 4) with normal error distribution model was a better model based on the selection criteria used.

For the conclusion, there has a time-varying variance exhibited in the inflation rate after the researchers formulated EGARCH (3, 4) as the error variance of the forecasting system. Then, EGARCH (3, 4) with normal error distribution model was a reliable in forecasting a short-term volatility after testing its accuracy under DM test. A four-month forecast of the monthly rates of inflation from the EGARCH (3, 4) with normal error distribution model produced close values to the actual values for the forecasting months implying that the model was able to mimic the underlying stochastic behavior of the monthly inflations rates of the Philippines. Lastly, EGARCH model was a better fit model to the Philippine Inflation compare to GARCH model formulated after holding a lower AIC value.

The empirical results and findings from this study will be significant to the policy makers, industry practitioners, to the investors, and to the public. The model formulated will help for quantifying the possibility of the future occurrence of inflation. The researchers hope that this study will serve as reference for future studies about forecasting Philippine Inflation. The researchers can recommend to consider other variance models for forecasting volatility such as TARCH, PARCH, and other model in GARCH model for variance.

APPENDIX A

The Inflation Rate from January 2000 to March 2019

INFLATION RATE	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
2000	5.5	5.6	5.9	6.2	6.5	6.1	6.5	6.8	6.5	6.9	7.8	8.7
2001	5.8	5.8	5.8	5.5	5.5	5.9	6.0	5.7	5.7	5.2	4.2	3.7
2002	3.3	2.9	3.3	3.4	3.2	2.6	2.5	2.7	2.5	2.3	2.1	2.1
2003	1.9	2.3	2.1	2.2	2.2	2.8	2.3	2.2	2.2	2.3	2.4	2.5
2004	2.9	2.9	3.1	3.2	3.6	4.1	5.5	5.7	6.2	6.3	6.8	7.1
2005	7.3	7.3	7.1	7.2	7.3	6.7	6.0	6.1	6.0	6.2	6.2	5.9
2006	5.9	6.5	6.6	6.3	6.0	5.9	5.5	5.2	4.9	4.7	4.2	4.1
2007	3.8	2.9	2.6	2.6	2.7	2.6	2.9	2.7	2.9	2.9	3.1	3.7
2008	4.6	5.1	5.9	7.3	8.2	9.4	10.2	10.5	10.1	9.7	9.1	7.8
2009	7.1	7.2	6.6	5.6	4.3	3.2	2.2	1.7	2.3	2.9	3.5	4.4
2010	3.9	3.9	3.9	4.0	3.9	3.6	3.7	4.1	3.8	3.2	3.7	3.6
2011	4.0	4.7	4.9	4.7	4.9	5.2	4.9	4.6	4.7	5.2	4.7	4.2
2012	4.1	3.0	2.9	3.2	2.9	2.7	3.1	3.7	3.6	3.2	2.8	2.9
2013	2.8	2.9	2.7	2.2	2.3	2.5	2.4	1.8	2.3	2.4	2.9	3.8
2014	3.7	3.6	3.5	3.6	4.0	3.8	4.2	4.2	3.9	3.7	3.0	1.9
2015	1.5	1.5	1.5	1.4	0.9	0.6	0.2	0.0	-0.4	-0.2	0.3	0.7
2016	0.7	0.5	0.6	0.7	0.9	1.3	1.3	1.3	1.7	1.8	2.1	2.2
2017	2.5	3.1	3.1	3.2	2.9	2.5	2.4	2.6	3.0	3.1	3.0	2.9
2018	3.4	3.8	4.3	4.5	4.6	5.2	5.7	6.4	6.7	6.7	6.0	5.1
2019	4.4	3.8	3.3	-	-	-	-	-	-	-	-	-

APPENDIX B

EViews Command

The EViews software was utilized by creating a work file and object, plotting a line graph, making the ACF and PACF plots, performing the Unit Root Tests, checking the correlograms and Q-statistics, displaying the Histogram and Stats, conducting the ARCH-LM residual test, estimating EGARCH models, and performing a forecast.

A. New Workfile and Object

To create a new workfile:

1. Click on File/New/Workfile.
2. Specify the frequency, and the starting and ending dates of the data.
3. Choose one of the following options to specify the frequency of the workfile, then click OK.
4. On the workfile window, click Object/New Object.
5. Indicate the name of the object, then click OK.
6. Click Edit, then type data series.

B. Line Graph

To examine a line graph of the series

1. Double click on the series name in the work file.
2. Select View/Line Graph

C. ACF and PACF Plots

To generate the sample ACF and PACF:

1. Click Quick/Series Statistics/Correlogram.
2. Type the time series data in question.
3. Choose the series type: level, first difference or second difference series.
4. Indicate the number of lags.
5. Click OK to view the plot

D. Unit Root Tests

To perform the unit root test (URT):

1. Double click on the series name to open the series window.
2. Choose View/Unit Root Test.
3. Specify the following:

   (a) Type of test: Augmented Dickey-Fuller (ADF) test or the Phillips-Perron (PP) test

   (b) Number of unit roots in the series: level, first difference, or second difference

   (c) Test equation option: include a constant, a constant and linear trend, or nothing

   (d) Order of serial correlation
4. Click OK to carry out the test.

E. Correlograms and Q-statistics

To display the ACF and PACF of the residuals, together with the Ljung-Box Q-statistics for high-order serial correlation:

1. Double click on the equation name in the workfile.

2. Select View/Residual Test/Correlogram-Q-statistics on the equation toolbar.

F. Histogram and Stats

To display the frequency distribution in a histogram and the descriptive statistics (i.e. mean, median, maximum, and minimum, standard deviation, skewness, kurtosis and JarqueBera statistic) of the series:

1. Double click on the series name in the wokfile.

2. Select View/Descriptive Statistics/Histogram and Stats or Quick/Series Statistics/Histogram and Stat

G. ARCH-LM Residual Test

To carry out the Lagrange multipliers (LM) test for ARCH in the residuals:

1. Push View/Residual Tests/ARCH LM Test on the equation toolbar.
2. Specify the order of ARCH.

H. Estimating GARCH models

To estimate a GARCH model:

1. Open the Equation Specification dialog by selecting Quick/Estimate Equation or by selecting Object/New Object/Equation.
2. Select ARCH from the method combo box.
3. Indicate the following, then click OK:

   (a) Mean equation

   To specify the mean equation, least any or combination of the following:

   Dependent variable followed by regressors

   Constant or C

   Explicit expression

   (b) Variance equation

   To specify the variance equation:

   i. Select any of the following entries:

   GARCH/TARCH

   EGARCH

   PARCH

   Component ARCH

   ii. Under the Options label, choose the number of ARCH and GARCH terms.

   (c) Error distribution

   To specify the form of the conditional distribution for your errors:

   i. Select an entry from the combo box labelled Error Distribution.

   ii. Choose one among the following error distributions:

   Normal (default)

Student’s t

Generalize Error (GED)

Student’s t with fixed d.f.

GED with fixed parameter

iii. Enter a value for the fixed parameter in the latter two cases.

(d) Equation toolbar appears and on the work file window, the *resid* series which stands for residuals are created.

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