Forecasting Backyard Farm Gate Hog Prices:

Evidence from the ARIMA Model

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Submitted by:
Roca, Jayvee G.

Submitted to:
Dr. Cesar Rufino

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Roca, J.

Abstract

The forecasting of the price of agricultural as well as livestock and poultry products is important to the decision making of farmers in what to produce in order to maximize their time and profit. Comprising around 70% of the overall pig production in a market where pork is highly regarded as valuable meat, backyard farmers play an important role in the Philippine society. The study makes use of the state of the art TRAMO software in order to accurately forecast future backyard farm gate prices for pigs bred for slaughtering.

I. Introduction

1.1 What is Pork to Filipinos?

Pork is one of the major sources of protein for many Filipinos due to its relatively cheap price and easy accessibility in "*Palengkes*" or wet markets and very recently, in supermarkets across the country. All throughout history, the importance of pork in the culture of Filipinos are readily seen from routinary ritual sacrifices for traditional marriage ceremonies, or prayers for good harvest, up to the iconic modern day *Lechon* in different festivals spread across the different regions in the country. Even before the colonization of the Spaniards, the Filipinos have always made use of pork as staples in their daily lives; in fact, they valued pork enough to use it as offerings to their gods in order to gain their favor (Veneracion, 2001, as cited in Velasco, 2014). Today, the popularity of pork in different Filipino homesteads is noticeably present, a Filipino breakfast is not complete without *tocino* nor is their christmas complete without the traditional ham, pork is much more than food to the Filipinos, it is a way of life, a preservation of their culture and this is evident in their numerous dishes all created with pork. In terms of actual amounts, pork really is the main staple meat for majority of the Filipinos. Keynes (n.d.) records the consumption and production of pork at 1.9 million metric tons is significantly the highest among all meat products in the country even compared to beef which is only produced at around 0.3 million metric tons in a year. Equivalently, Stanton, Emms & Sia (2010) record these amounts to be around 59% of overall meat as well as poultry production in the country [See Figure 1].

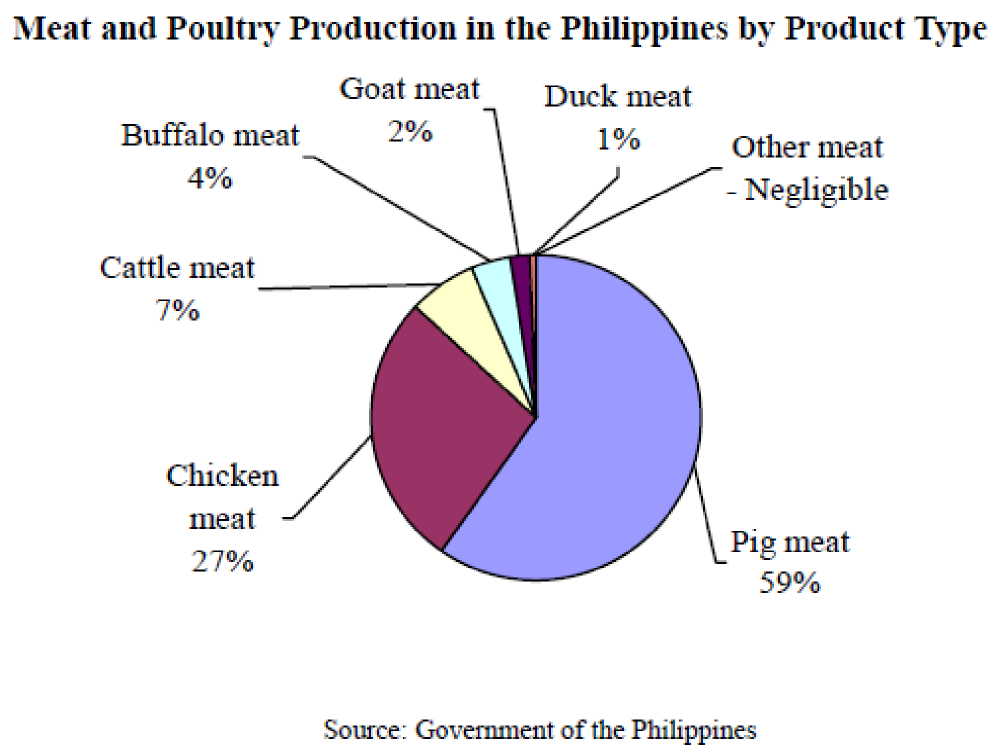

Figure 1. Meat and Poultry Production in The Philippines by Product Type. Adopted from *The Philippine's Pig Farming Sector: A Briefing for Canadian Livestock Genetics Suppliers*, by Stanton, Emms & Sia (2010)

Pork is one of the most common and most valued meat for majority of the population in the Philippines which is also why Filipinos are generally very picky in the freshness of their pork. Keynes (n.d.) also observes this phenomenon, wherein, Filipinos generally tend to view imported or frozen products to be inferior substitutes to freshly slaughtered pork found in the wet markets, which equivalently, enhances the local hog raising industry across different regions in the country. Indeed, even the market for hog raisers is quite unique in the Philippines where majority of the producers, around 70%, are actually small scale backyard farmers scattered around the different regions in the country (Keynes, n.d.; Stanton, Emms & Sia, 2010).

1.2 The Hog Raiser's Dilemma

Similar to many goods in the market today, a typical consumer can easily observe a gradual increase of prices of pork available to consumers over the years; however, the opposite is true for the prices that the producers or hog raisers actually earn when they sell off the pigs to slaughter [see Figure 2]. There is a steadily growing concern among different hog raisers about the low prices of live meat per kilo sold; the words *"matumal"* which is a Filipino term that connotes extremely low points or prices always comes to mind. One would also hear the constant complaints of many hog raisers concerning the low prices which they attribute mainly to the large influx of cheaper frozen pork imports in the country. In fact, it turns out that the large amount of imports is a legitimate concern among hog raisers in the world, important enough to threaten a *pork holiday* early this year (Lim, 2016; Domingo, 2016). This phenomenon has always been seen as a problem especially for backyard farmers, where, the country is recorded to have people moving out of the pork industry mainly due to the high production costs of the business and partnered with the large influx of minimally tariffed as well as cheap imported frozen meat (Cabarles, 2007)

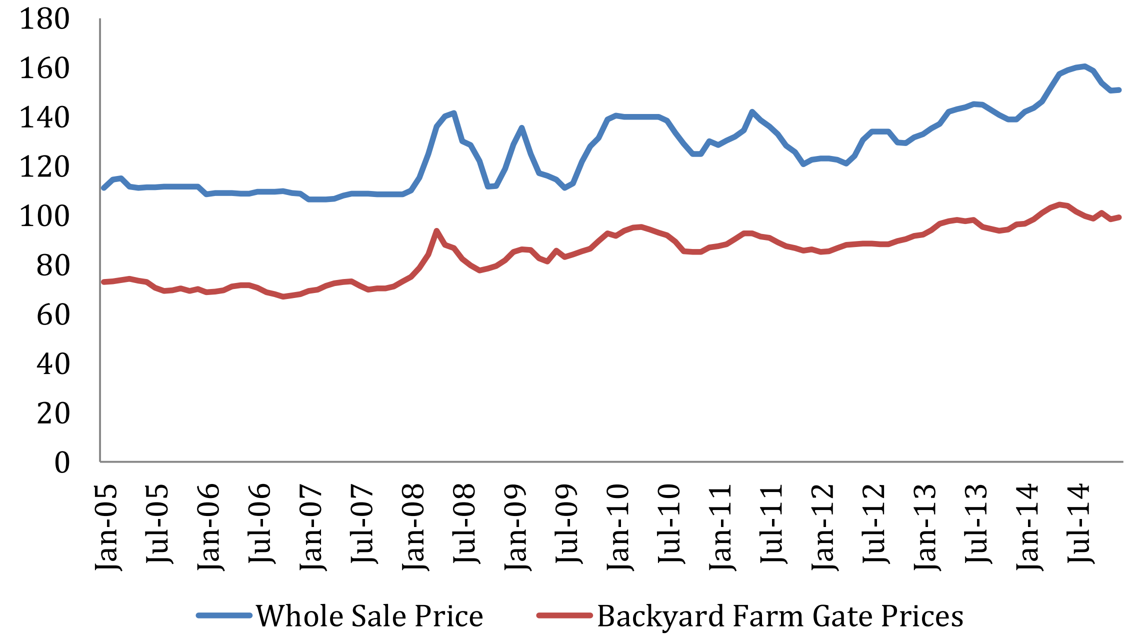

Figure 2. Wholesale Vs Backyard Farm Gate Prices. Source: CountrySTAT Philippines database

The Hog Raiser's Dilemma represents the situation described in the previous paragraph, where, there exist large increases in the market retail prices of pork while there is a persisting downward trend in farm gate prices especially for backyard farms. In or der to accurately grasp the phenomenon, it is important to understand the different supply chain processes that pork goes through from farm gate to the dinner table. For local hog raisers, the supply chain process may be summarized into three main categories: the farmers, the processors and the retailers (Varley, 2012) [See Figure 3].

Figure 3. Supply Chain Process. Variables adopted from *The Development of Pig Production& Pork Markets in Asia* by Varley, 2012.

. The backyard farmers either outsource their piglets from commercial farms or have breeder pigs for themselves; the piglets are then selected and bred for slaughtering for around 3 to 5 months depending on the growth rate of the pig. Once it reaches its maturity, the hog raisers usually contact *byaheros* or caravan traders that go around the area looking for live pigs for slaughtering; these *byaheros* are usually composed of a group of people: an expert or the owner/trader itself and accompanied with *kargadors* or lifters. In usual practice, hog raisers and *byaheros* alike follow the market prescribed prices for live hogs which is somewhere between Php 90 to Php 130 per kilogram depending on the area, as to the accuracy the selling prices both of them seem to follow a quasi-trust based system of determining said prices where the actual prices are inexplicably determined by word of mouth and consensus through neighboring hog raisers as well as other caravan traders in the area. The live pigs are then transported to slaughter houses where they are primly chopped up at a fixed rate of around Php 50 per head, after which they are then loaded up to be distributed to retailers and wet markets in their respective coverage area. The retailers whether institutional or individuals will then sell the parts to the different consumers available in their area which then follows retail prices on the different cuts of the meat.

1.3 General Overview of the Study

Based on the facts presented in the previous section of this paper, the researcher observe that hog raisers most especially backyard hog raisers or even pork in general play a very important role on not just the household level but the general agricultural sector as well. Pork itself is a multibillion dollar industry being the second most produced agricultural product at 18.28% of total value of production, second only to the production of rice in the country (Livestock Research Division, 2016) and as previously mentioned, 70% of the production is attributed to local backyard farms (Stanton, Emms & Sia, 2010). While this may be the case, in recent years the country has recorded a drop in the farm gate prices for live pigs especially for backyard farmers which are highly associated with large increases in the supply of cheaper imported pork. Especially considering the currently implemented ASEAN integration, the supply of low tariffed and lower priced pork may further drive down the already low prices for local pork supply thereby bankrupting our local farmers in different regions all throughout the county. Given this phenomenon, it is therefore important to look into the outlook of backyard farm prices for pigs bred for slaughtering; which is why this study seeks to answer the questions "How much can econometric time series modeling accurately and consistently predict the farm gate (backyard) prices of pigs bred for slaughtering specifically for the medium term?"

In order to answer this question, the researcher has set the following as the main objectives of the study:

(1) To determine and describe the variation found in as well as forecast the farm gate backyard prices of pigs bred for slaughtering using the ARIMA model.

(2) To identify the presence of time series trend and seasonality in the said prices for the time range 1990-2016

(3) To accurately predict and forecast next period backyard farm prices for pigs bred for slaughtering

As mentioned in the previous sections of this study, the dataset to be used in this study is comprised of backyard farm gate prices of pigs bred for slaughtering which was retrieved from the Philippine Statistical Authority through the Bureau of Agricultural Statistics' CountrySTAT Philippines database covering the time range of January1990 – June 2016 on a monthly frequency which then amounts to a total of 318 observations. Using both E-views and TSW software, a forecast period of 24 months is expected from the results which will then be used to achieve the objective of the study.

II. Review of Related Literature

2.1 The Pork Industry in a Glance

The world has had an unprecedented rate of population growth especially in the end of the 20^{th} century, while this growth rate has been seen to gradually decrease in recent years the fact still remains that the world population is somewhere between 8 Billion people and counting (Ortiz-Ospina & Roser, 2016). Food security and sustainability is a major concern in the fast changing world today, especially in countries found in Asia where we see the largest growth rate in terms of population, even accounting for 56% of the total world population (Asian Development Bank, 2013), as well as having large areas where hunger is an endemic problem for majority of the population (Food and Agriculture Organization of the United Nations, 2015). Many researchers have taken a look into the different characteristics of consumption patterns across different regions. Asian Development Bank (2013) records that majority of the Asian countries are effectively switching from the basic cereals for sustenance to more complex meals such as meat, dairy, processed foods, etc. In fact, the global consumption as well as the production of meat products is expected to double by the year 2050 especially in developing countries (Humane Society International, 2011). Pork is one of the main meat groups that dominate markets across different countries in the world, it comprises the largest share of meat consumed/produced in the world at 42% of all meats consumed globally (Varley, 2012); the world production of pork is highly attributed, around 50%, to the productions from developing countries especially in the

Asian continent (Food and Agriculture, 2007, as cited in Humane Society International, 2011).

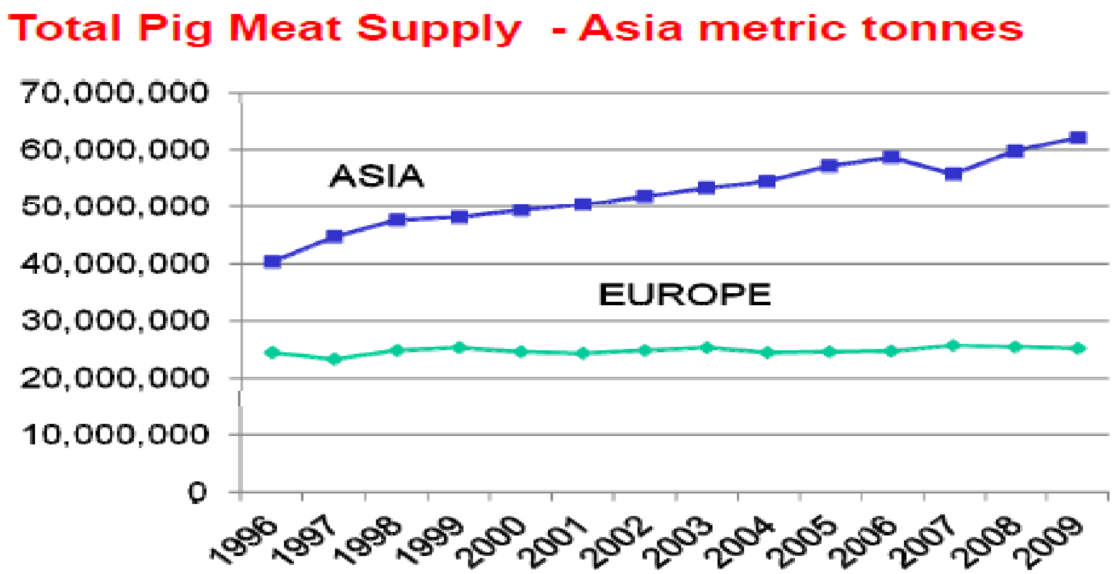

Figure 3. Total Pig Meat Supply. Adopted from *The Development of Pig Production and Pork Markets in Asia* by Varley (2012)

In Figure 3, the researcher observe a vast differences in the supply of pork between Europe and Asia where the pork supply in the latter is evidently far greater than that of the former. The large supply of pork in Asia as seen in the figure is largely attributed to the production of pork in China, although majority of the countries, specifically in the ASEAN region also significantly produce a large volume of pork as compared to the European countries. One of the defining traits for the production in the region is the domination of small scale backyard farms spread out across different regions complimenting as well as competing with large scale commercial farms in different areas especially in China and the Philippines (Varley, 2012; Huynh, Aamik, Drucker & Verstegen, 2006).

2.2 Forecasting Pork Prices

There is vast literature when it comes to forecasting the prices of agricultural products as well as the prices of livestock and poultry. The works of Zhang, Chen and Wang (2010), Allen (1994), Shonkwiler (1986) and Helmers and Held (1977) will be discussed in this section of the paper. Zhang, Chen and Wang (2010) makes use of multivariate simple regression model through the use of the SPSS software; the authors argue that the price of pork is determined by several factors, mainly: historical, internal and external factors. Furthermore, the authors also managed to infer that the fluctuation of pork prices will eventually increase the prices of pork significantly thereby affecting the CPI index itself. On the other, Allen (1994) discusses the different developments and available approaches in the forecasting of different aspects of agricultural as well as poultry and livestock products. The author acknowledges the importance of the forecasting of prices to the general welfare of farmers everywhere, where, the author points out that at the moment of commitment farmers will then be price bargainers. Furthermore, the researchers also acknowledges how majority of the current research made are from economists that make use of econometric models in order to forecast said prices. Shonkwiler (1986) in a different perspective approaches the futures prices of swine and cattle in tackling rational expectation among investors. The author concludes that rational forecasts for said prices are rather suboptimal due to the irrationality of the market itself. Lastly, this research looks into the work of

Helmers and Held (1977) where in the authors compares different forecasting approaches and concluded that no one method in forecasting the prices of agricultural product is dominant than any of the other.

This research will look into the forecasting of backyard farm gate prices for hogs bred for slaughtering in the Philippines. To the extent of knowledge of the researcher, this will be the first time that said variable is forecasted using the ARIMA methodology.

III. Framework and Methodology

3.1 Data Collection and Treatment

The monthly data observed in this study ranges from the periods of January 1990 up to the latest available data of June 2016 which was obtained from the Philippine Statistical Authority's Bureau of Agricultural Statistics' CountryStat Philippines Database. The chosen data was selected by the researcher based on the availability as well as consistency of the dataset. The given dataset contains the backyard farm gate prices for pigs bred for slaughtering in Philippine Pesos as the base currency. Backyard farm gate price is simply defined as the price per kilogram in which small scale hog raisers sell their pigs bred for the purpose of slaughtering; 'small scale farm' in the context of hog raising is defined by the National Statistical Coordination Board as farms who have fewer than 21 heads adult hogs, fewer than 41 heads young hogs or in the presence of having both adult and young hogs, it should have fewer than 10 and 22 heads respectively.

Statistically, the data used in this study is classified as a time series data (denoted as Y_t). The analysis of time series data considers four major components, mainly: (1) Secular Trend (2) Cyclical Variation (3) Seasonal Variation (4) Irregular Variation. An important consideration in using this form of data is the stationarity of the time series dataset. Gujarati and Porter (2009) defines stationarity as the condition in time series data where the mean, variance as well as covariance are not affected by time, in other words, are time invariant. Boğaziçi University (n.d.) discusses the problems arising from a non-stationary time series dataset, specifically the problems of spurious regressions as well as problems in the normality of t distribution thereby decreasing the accuracy of analysis for forecasting purposes. Statistics provide us with a wide array of identifying the stationarity of a given time series dataset, the most popular of which are the Augmented Dickey-Fuller Test and the Philipps-Perron Tests. If the tests determine non stationarity in a given data set, the next step is to proceed to the first differencing of the data until stationarity is achieved (Rufino, Lecture on Economic Forecasting, 2016).

The dataset will then be subject to treatment as well as analysis using the TSW+ software through a program known as the TRAMO program. TRAMO is strictly defined as "*Time Series Regression with ARIMA Noise, Missing Observations, and Outliers*" (Gomez & Maravall, PROGRAMS TRAMO AND SEATS: INSTRUCTIONS FOR THE USER, 1996). Both the software and program are top of the line statistical tools from the Bank of Spain that are used for any number of purposes especially in identifying optimal and non-structural model for the given data set specifically applying the Univariate Box-Jenkins (UBJ) approach.

3.2 Box Jenkins Methodology (ARIMA Modelling)

The Box-Jenkins (BJ) methodology is powerful tool used for forecasting time series analysis. The BJ methodology is unique and contrasted from a basic regression model such that the approach makes use of a-theoretic modelling or modelling without respect to economic theory which is often the case for regression based methodologies in forecasting, furthermore, the time series model Y_t for the BJ methodology are explained by the past values of the series itself and the stochastic error terms which is evidently different from that of the regressors based forecasting done by a common regression methods (Gujarati & Porter, 2009). Since the study will only observe one variable for the *Autorgressive Integrated Moving Average (ARIMA)* model the study will be employing a Univariate Box Jenkins (UBJ) methodology.

3.2.1 UBJ Modelling Requirements

In using a UBJ model, as well as assuring the stationarity of the given data, it is important to identify the optimal model processes which are categorized in to four different processes: Autoregressive (AR), Moving Average (MA), Autogressive Moving Average (ARMA) and Autoregressive Integrated Moving Average (ARIMA) process (Baltagi, 2011). The most important consideration in identifying the process that the forecasting model follows will be due to three factors *p, d, q* which is explained in the succeeding paragraphs of this section.

AR(p) is an autoregressive process of the pth-order where the values are obtained with respect to the previous time period t-*p* and also considers a random error term (Lutkepohl & Kratzig, 2004). Furthermore, the forecasts computed for using AR is simply computed as deviations from the mean with the inclusion of a random shock value (Gujarati & Porter, 2009).

MA(q) is a moving average of the qth-order, the process makes use of random shocks or white noise errors in order to forecast values of a given dataset; alternatively, it also makes use of a constant value partnered with the current as well as past values of these random shocks in order to accurately forecast a given time series dataset (Baltagi, 2011).

ARMA(p,q) is basically the presence of the characteristics for both AR(p) and MA(q) in forecasting. The process therefore follows the same assumptions for both AR and MA processes especially in the treatment of random shock values as well as past values for any given dataset. It is notable that ARMA requires stationarity at level for any given data, if the process requires differencing of any form in order to make it stationary the model will then follow an *ARIMA(p,d,q,)* process where AR(p), MA(q) and d is the number of times that the given data series was differenced in order to achieve stationarity. The general equation for an ARIMA forecasting model is as follows:

$$\hat{Y}_t = \mu + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} - \theta_1 e_{t-1} - \cdots - \theta_q e_{t-q} \qquad \text{(Eq. 1)}$$

$\hat{Y}_t$ is the forecasted variable (dependent variable) where it is a function of its own lagged (p) values, Y_{t-p}. μ in this case is a constant term usually denoting the average period to period changes. While ϕ_p is one of the most important variable in the equation it is used to represent the slope of the coefficient where the analysis is largely dependent upon the value of said equation variable; the value for the variable should always be less than 1 if the given dataset is stationary. If ϕ_p is positive then the predicted value for the given set is $\phi_p \times (Y_{t-p})$ greater than the mean while the opposite is true for a negative valued ϕ_p (Duke University, n.d.). θ_q in this case is defined to be the moving average parameters of the equation while e_{t-q} is the error term for said equation. It is worth noting that the first half of Eq. 1 is considered to be the AR process while the latter is shown to be the MA model.

Gujarati and Porter (2009) identify four steps in order to properly execute a UBJ Methodology which is enumerated as follows: (1) Identification (2) Estimation (3) Diagnostic Checking (4) Forecasting.

(1) Identification

This step of the in the UBJ methodology seeks to identify the dominant process enumerated in the previous section of this chapter. In essence, identification here pertains to the values of p,d,q by using the different statistical tools available to researchers in order to identify candidate models. These tools pertain to the Autocorrelation Function (ACF), Partial Autocorrelation Function (PACF) and their respective Correlograms. ACF denoted by ρ_k , where k is the lagged value for the given series, is one of the basic tests for stationarity and has a value that is between +1 and -1; since the nature of a time series dataset is ordered it is very useful to identify the correlation between the different time lags in a given series and this is what ACF seeks to address. PACF on the other hand is denoted by ρ_{kk} where the only difference is the control used in transitional lag values. Finally, correlograms are used in plotting the PACF and ACF against the *k* lagged values of the given dataset (Gujarati & Porter, 2009).

There are certain indicators on the pattern of a correlogram that help identify the process that the model makes use of (University of Arizona, 2015). For an AR process, the ACF coefficient is characterized as having a gradual decline towards zero, while for the PACF coefficient for this process reveal a straight decline to zero after a certain lag *p.* MA process on the other hand sees a straight decline to zero after lag order q for its ACF coefficient while the PACF coefficient records a gradual decrease towards zero.

Finally, for the ARMA process, since it contains both AR and MA processes, both the ACF and PACF values are seen to decline gradually towards zero.

(2) Estimation

The estimation pertained to in this case requires that the results of the model fall in the acceptable standard of 0.05 or at 5% level of significance. The software that the researcher uses computes for these p-values as well as the coefficients of forecasts automatically. Since the researcher makes use of the TSW+ software, the estimation procedure fits the model to the data then reveals the different parameter estimates as well as the different diagnostic statistics that pertain to the model-data fit.

(3) Diagnostic Checking

In order to accurately gauge the performance of the selected best fitting model, the research shall compute and compare the results using the following criteria (Rufino, Lecture on Economic Forecasting, 2016): (1) Root Mean Square Error (RMSE) (2) Mean Absolute Error (MAE) (3) Mean Absolute Percentage Error (MAPE) (4) Theil Inequality Coefficient (Theil's U). The following diagnostic tests have the following equations respectively.

$$RMSE = \frac{\sqrt{\sum_{T=1}^{T} \widehat{u_t^2}}}{T} \qquad (Eq.2)$$

$$MAE = \frac{\sum_{T=1}^{T} |\widehat{u_t}|}{T} \qquad (Eq.3)$$

$$MAPE = \frac{\sum_{T=1}^{T} \left|\frac{Y_t - \widehat{Y}_t}{T}\right|}{T} \qquad (Eq.4)$$

$$Theil's\ U = \frac{\frac{\sqrt{\sum_{T=1}^{T} \widehat{u_t}}}{T}}{\sqrt{\frac{\sum_{T=1}^{T} Y_t^2}{T}} + \sqrt{\frac{\sum_{T=1}^{T} \hat{Y}_t^2}{T}}} \qquad (Eq\ 5)$$

The following criteria mentioned in this section make use of the past observed value of the given data's residuals; which means that the lower the value for these criteria the better the given forecasts (Rufino, Lecture on Economic Forecasting, 2016).

(4) Forecasting

The forecasted values are estimated using the best model available using the different tests and statistics discussed in the previous section of this chapter. It is worth noting that in the best fitted model, a leveled data series makes use of an Exact Maximum Livelihood Estimation while at logged series the Kahlman Filter Estimation (Rufino, 2016).

IV. Results and Discussion

This section shall be discussing the results through the output of the TSW software of the best fitted model selected based on the UBJ Criteria discussed in the previous chapter of this paper.

4.1 Pre Test

The initial pre-test results are gathered from the TRAMO output of the TSW software. The results show a significant Easter effect since the Easter correction was observed; interestingly, this result coincides with the rational expectation that Filipinos in general tend to have different meat eating patterns during the holy week, where, the general population holds off the consumption of meat up until Easter Sunday hence the observed Easter effect in this case (Stanton, Emms & Sia, 2010). The test whether log values or level values are used in this model was also conducted on the same pre-test output, where, the results show that the given data is transformed to logged values specifically at the selection of around 1.05 logs.

4.2 Fitness of the Model

Figure 4 reveals the different criteria to determine the fitness of the model. *Mq* in this instance simply describes the number of observations per year; since the data is monthly in nature the value in this study is 12, while *Nz* in this study describes the total number of observations which is at 318. The results reveal a value of Lam to be equal to 0 which basically means that the data used in this case is logged and similarly, the mean is also 0 suggesting that no mean correction was made in this case (Gomez & Maravall, PROGRAMS TRAMO AND SEATS: INSTRUCTIONS FOR THE USER, 1996). The standard errors *SE(res)* of the residuals are measure to be at 0.0162812 and the Bayesian Information Criterion (BIC) is at -7.91297 which then automatically identifies and corrects outliers on the said model.

Model Fit

Mq	Nz	StartObs	Mo	Lam	Mean	P	D	Q	BP	BD	BQ	SE(res)	BIC	#OUT	TD	EE
12	318	0	0	0	0	3	1	1	0	1	1	0.0162812	-7.91297	16	0	0

Figure 4. Fitness of the Model.

The results further show the presence of certain outliers through the *#OUT* component of the model fitness test, 16 are identified to be outliers and the effects are already controlled for by the TSW software through the methodologies proposed by Tsay (1989) and Chen and Liu (1993) (as cited in, Gomez and Maravall, 1997). Furthermore, the model explicitly identifies various effects as well including the Trading Day Effect (TD) and Easter Effect (EE) (Rufino, 2016). The model fitness test records no TD and EE for this data set. Finally, the optimal model chosen in this case is as observed as follows ARIMA(3,1,1)(0,1,1) suggesting the use of data with a first differenced series [see Figure 5].

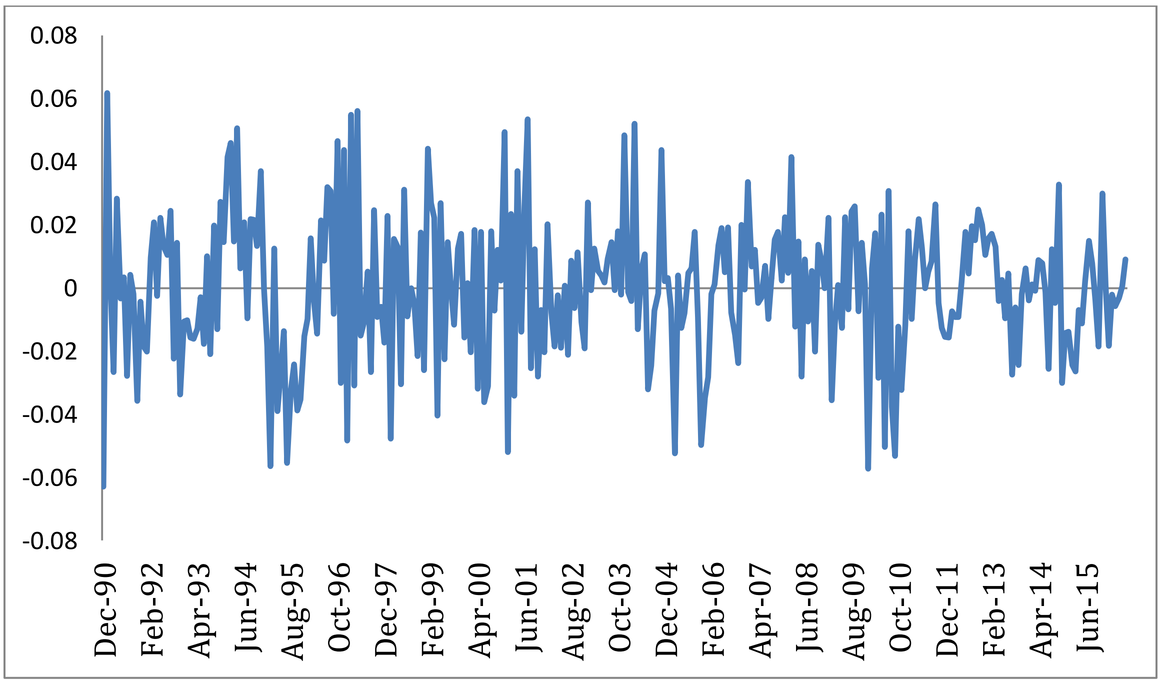

Figure 5: First Differenced Data Series. Data Source: TSW+Output

4.3 MODEL SELECTION: ARIMA

The optimal ARIMA model identified using the dataset follows ARIMA(3,1,1)(0,1,1) which the program identified to be the best fitted model. This means that the given model has 3 autoregressive order, 1 unit root, and 1 moving average order while the seasonal component contains 0 seasonal autoregressive order, 1 seasonal unit root and 1 seasonal moving average order.

The identification of the model in the Tramo output includes the identification of different types of outliers as identified by Gomez and Maravall (1997) as follows: (1) Transitory Change represents a spike that eventually fades over time (2) Level Shifts represents steps (3) Additive Outliers represents a spike in the given period. In the given data set, the results managed to identify 6 Period of Transitory Change outliers, 6 periods of Level Shifts and 4 periods of additive outliers.

Table 1. LIST OF OUTLIERS

169 LS (1 2004)	232 TC (4 2009)
220 TC (4 2008)	170 LS (2 2004)
121 TC (1 2000)	219 TC (3 2008)
114 AO (6 1999)	20 LS (8 1991)
75 LS (3 1996)	72 LS (12 1995)
19 LS (7 1991)	106 TC (10 1998)
16 TC (4 1991)	129 AO (9 2000)
81 AO (9 1996)	11 AO (11 1990)

The TRAMO output also identifies the different ARMA parameters in the model. Results for the model identification reveal that there are 3 autoregressive roots, 1 regular as well as 1 seasonal moving average roots that are also reflected in the given ARIMA model.

Table 2. ARMA PARAMETERS

PARAMETER	ESTIMATE	STD ERROR	T RATIO	LAG
PHI1	0.62651	0.11085	5.65	1
PHI2	-0.33513	0.63509E-01	-5.28	2
PHI3	-0.26711	0.56121E-01	-4.76	3
TH1	0.53989	0.13638	3.96	1
BTH	-0.87223	0.28798E-01	-30.29	12

The overall test for identifiable seasonality is seen to record seasonality in the series. [See Table 3]

Table 3. OVERALL TEST FOR IDENTIFIABLE SEASONALITY

AUTOCORRELATION FUNCTION EVIDENCE	YES
NON-PARAMETRIC EVIDENCE	YES
F-TEST	YES
SPECTRAL EVIDENCE	YES

On the other hand, the overall test for identifiable seasonality in the residuals reveal the opposite, where, no identifiable seasonality was found in the residuals of the given dataset [See Table 4].

Table 4. OVERALL TEST FOR SEASONALITY IN RESIDUALS

AUTOCORRELATION FUNCTION EVIDENCE	NO
NON-PARAMETRIC EVIDENCE	NO
F-TEST	NO
SPECTRAL EVIDENCE	NO

Furthermore, in the process of the TRAMO Ouput the results reveal that the chosen ARIMA model is “ACCEPTABLE”, however due to the number of outliers (or variability especially in the residuals), the program cautions on some of the inferences from the results [See Table 5].

Table 5. QUALITY ARIMA MODEL TESTS

Mean in residuals	GOOD
Autocorrelation in residuals	GOOD
Normality of residuals	GOOD
Skewness of residuals	GOOD
Kurtosis of residuals	GOOD
Randomness of residual sign	GOOD
Instability of residual mean	GOOD
Instability of residual variance	ACCEPTABLE
Seasonality in residuals	GOOD
Trading day in residuals	GOOD
Out-of-sample forecast errors	GOOD
Number of outliers	ACCEPTABLE

4.4 ACF and PACF

The model provides the autocorrelation function (ACF) and partial autocorrelation function (PACF) in this study which is summarized in Figure 7 and Figure 8 below.

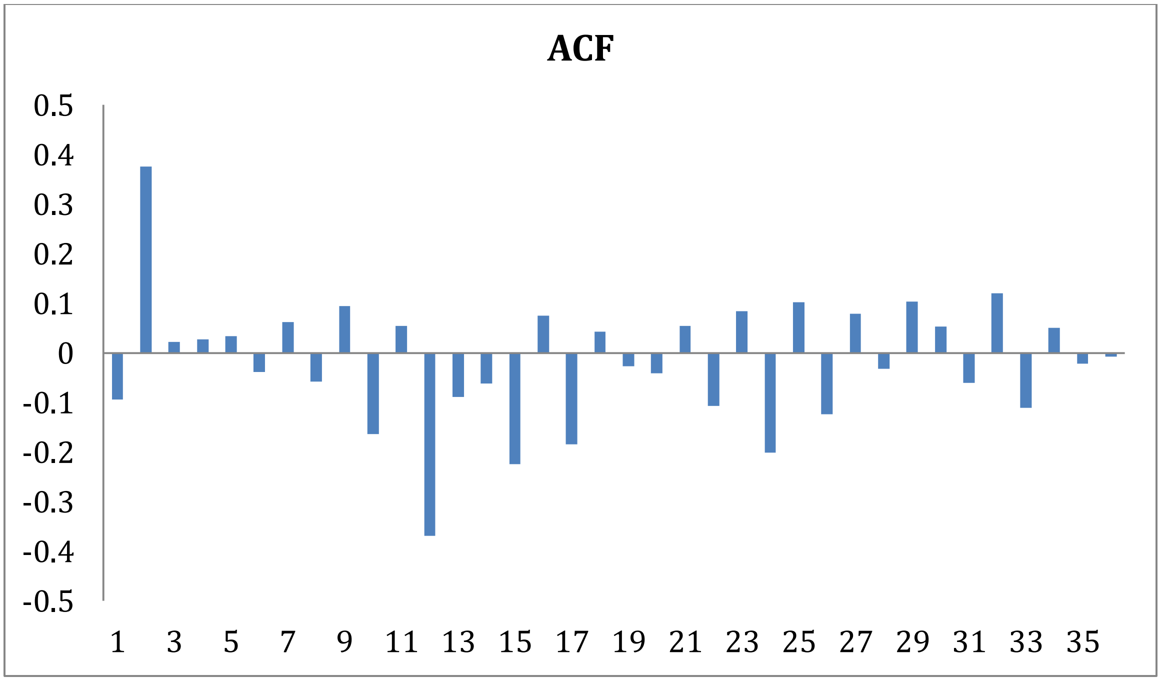

Figure 7. Autocorrelation Function of First Differenced Series

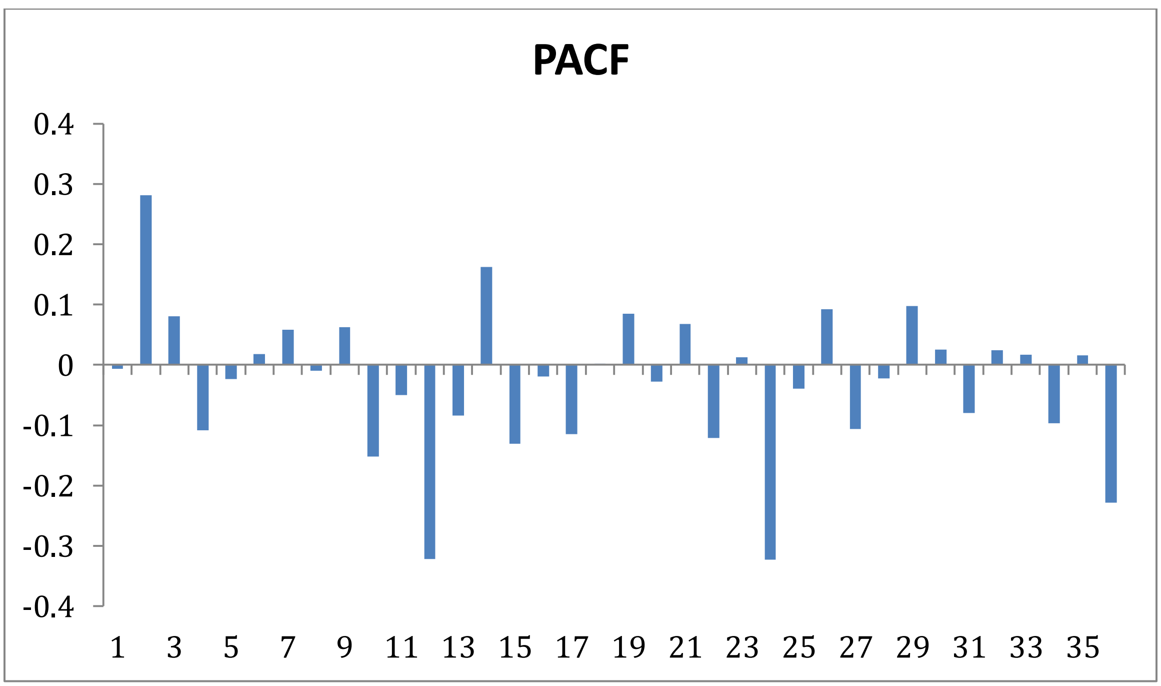

Figure 8. Partial Autocorrelation Function of First Differenced Series

4.5 Diagnostic Checking

The first step in identifying the diagnostic checking of the forecasted value is to look into the graphical output versus the actual values found in the data which is represented is in Figure 9. The researchers observe that initially the forecasted and actual values are to some degree significantly different from each other specifically from the early periods of 1990 up until the first half of 2004 but this eventually narrows down and become an accurate forecast from the second half 2004 onwards with the exception of early 2008 where an obvious spike in the actual value is seen to occur in the graph. Now, there are many possible reasons in explaining the results of the graph, one of the standing reason mentioned in the results of the TRAMO output relate the problems in the variability of residuals as well as the presence of multiple outliers in the leveled series. Although it is also rightly observed that the forecasted values from the period 2009 onwards eventually match the original series thereby ensuring that the ex post forecast of this study is accurate enough to make further inferences.

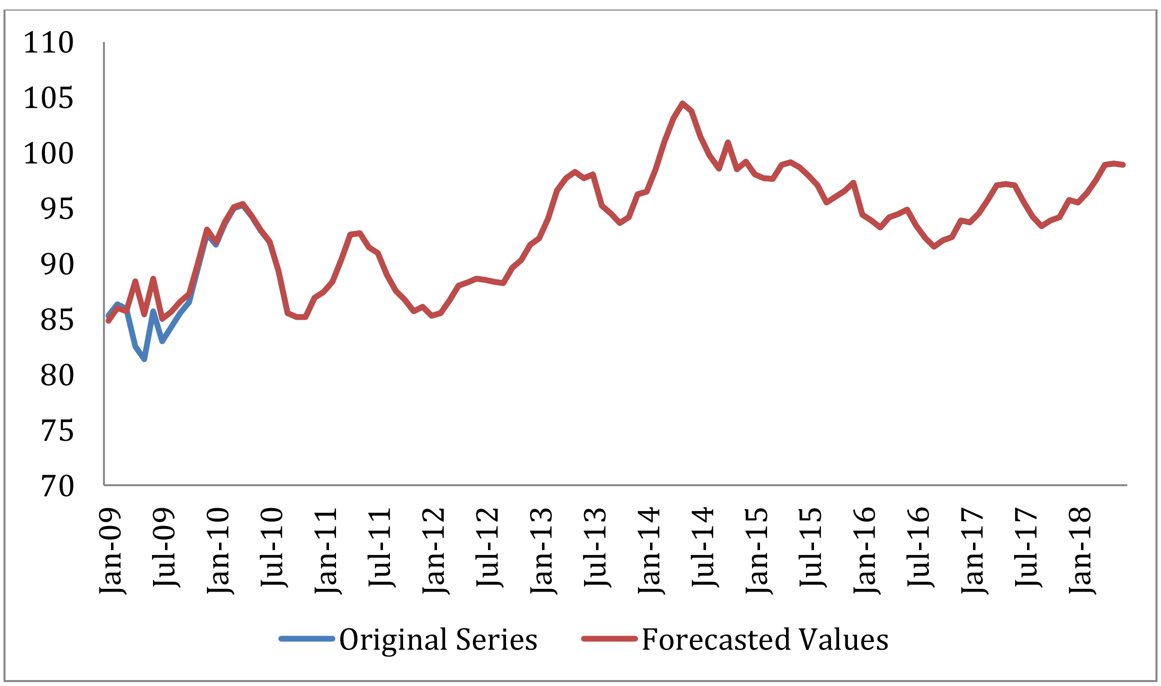

Figure 9. Original Series vs Forecasted Values

In this section of the paper, the researcher will also be discussing the different results of the statistics computed for the purpose of diagnostic checking. The results reveal the following statistics:

RMSE = 0.773101

MAE =0.182035

MAPE= 0.000652367

Theil's U = 0.09367

RMSE and MAE are measures of variation in the errors of the forecast statistics, the lesser the value for the statistics the better the result (Rufino, Lecture on Economic Forecasting, 2016). Furthermore, it is worth noting that the greater the difference for the RMSE and the MAE values, the greater the variability or variance in the individual errors of the given sample. The MAPE on the other hand is a percentage value to reveal the accuracy of the forecasted error; according to the results, the given forecast, on average, is off by around 0.07% which is a very promising result given the forecasted results and further supplemented by Figure 8 in the graph. Finally, the Theil's U identifies the accuracy of the forecasted value itself; the results of the statistics for the given model reveal that the forecasting technique is actually better than guessing since the values is evidently less than 1 specifically at around 0.09367 (Rufino, Lecture on Economic Forecasting, 2016).

4.6 Ex Ante Forecast of Backyard Farm Prices for Hogs Bred for Slaughtering

The TSW+ program provides the researcher with an acceptable forecast of prices two years (24 months) into the future as shown in Table 6 below. The ex-ante forecast is revealed to range from July of 2016 up until June of 2018; while there still exists variability in the forecasted values, the researchers expect the backyard price of live pigs for slaughtering on a national scale will generally remain around the same range of 90 and above unless relevant legislation and policies are implemented to drive prices upward in the near future.

Table 6. Forecast for Backyard Farm Gate Prices for Pigs (24 Months)

OBS	DATE	FORECAST (SERIES IN LOGS)	STD ERROR (SERIES IN LOGS)	FORECAST (SERIES IN LEVELS)	STD ERROR (SERIES IN LEVELS)
319	Jul-16	4.53726	1.63E-02	93.4345	1.52162
320	Aug-16	4.5252	2.21E-02	92.3144	2.03619
321	Sep-16	4.51651	3.06E-02	91.5155	2.80117
322	Oct-16	4.52284	3.72E-02	92.097	3.42537
323	Nov-16	4.52595	4.37E-02	92.3832	4.03722
324	Dec-16	4.54236	4.96E-02	93.9124	4.6589
325	Jan-17	4.54021	5.50E-02	93.7106	5.15376
326	Feb-17	4.54902	6.01E-02	94.5398	5.68232
327	Mar-17	4.56135	6.47E-02	95.7122	6.20044
328	Apr-17	4.57549	6.92E-02	97.0756	6.72233
329	May-17	4.57657	7.33E-02	97.1807	7.13461
330	Jun-17	4.5753	7.73E-02	97.0571	7.51238
331	Jul-17	4.55973	8.17E-02	95.5581	7.82077
332	Aug-17	4.54561	8.59E-02	94.2175	8.10401
333	Sep-17	4.53654	9.01E-02	93.3674	8.42527
334	Oct-17	4.5423	9.41E-02	93.9069	8.85286
335	Nov-17	4.54509	9.80E-02	94.1688	9.2485
336	Dec-17	4.56141	0.101756	95.7188	9.7652
337	Jan-18	4.55906	0.105411	95.4938	10.0942
338	Feb-18	4.56788	0.108959	96.3398	10.5283
339	Mar-18	4.58011	0.112393	97.5249	10.9958
340	Apr-18	4.59426	0.115733	98.9152	11.4861
341	May-18	4.59531	0.118974	99.0185	11.8225
342	Jun-18	4.59404	0.122134	98.8927	12.1234

V. Conclusion and Recommendation

The study forecasted the backyard farm gate prices for hogs raised for slaughtering using the UBJ methodology. Through the use of the program TSW+ the researchers also managed to show the identifiable trend as well as the presence of identifiable seasonality in the series.

The ARIMA model was used to forecast the values based on the historical prices of said data ranging from January 1990 up to June 2016, the given data set was differenced at first level in order to achieve stationarity. The identified optimal model for the given data series as selected by the TRAMO program is ARIMA(3,1,1). In order to confirm that this is indeed the best model, the researchers computed for the MAPE and Theil's U on the actual and forecasted values for the series which yielded highly assuring results on the accuracy of the forecasts.

There is in fact a positive trend for the given series as well as identifiable seasonality; however, no identifiable seasonality was recorded in the residuals. While this may be the case, the statistics shows that the given forecast model is actually adequate and parsimonious as required by the ARIMA framework (Rufino, Lecture on Economic Forecasting, 2016).

The researcher recommends future researchers to look into the retail prices of pork and compare the forecasted values in the values predicted in this series as well as taking a look into the individual backyard farm gate prices across different regions in the country since the prices differ from area to area.

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