MODELLING ELECTRICITY PRICE SPIKES IN THE PHILIPPINES: A MARKOV REGIME SWITCHING AND TOBIT REGRESSION APPROACH

by

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Abstract

The main objective of this study is to model the electricity price spikes of the Philippines using a two-state Markov Regime Switching method. It utilizes the Expectation-Maximization algorithm, a more efficient method to compute the parameters compared to the Maximum Likelihood method. Results showed that the Markov Regime Switching of order 3 or MRS(3) model is capable of capturing the spikes of electricity price. The transition probabilities indicated that the normal state is more dominant than the spikes state. It also indicates that the average duration that a spike occurs is 1.9 months. Meanwhile, the average duration for the normal state is 5.9 months.The tobit regression analysis revealed that the natural gas price and the Indonesian coal price have no significant effect to the electricity price spikes. This finding showed that their effects do not extend to the occurrence of such phenomenon and that there are other factors affecting it, but not included in the study.

INTRODUCTION

Electricity Market in the Philippines

The Philippine government has long been making efforts to make electricity available for all. The commodity was first used in the country in 1890 and since then it has asserted its significance. The country's economy is undeniably dependent on the availability of the said commodity. In 1970, the country's Gross Domestic Product declined due to the oil crisis that affected energy production in the country (Patalinghug, 2003). Since then, a lot of laws and mandates were made to guarantee the availability

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of electricity. Since market liberalization was successful in other countries, the country aimed to replicate the success. The aim was not only to distribute the commodity swiftly with lower price due to competition but to have an efficient, transparent and reliable market for electricity (www.wesm.ph).

The electric spot market of the Philippines was materialized due to the electric industry reforms mandated by the Electric Power Industry Reform Act of 2001 (EPIRA) in June 2001. The law mandated the Department of Energy to establish the Wholesale Electricity Spot Market (WESM) and come up with the rules for the operation of WESM. Together with the participation of the electric industry institutions, the WESM Rules were established and promulgated in June 2002. Following this, the Philippine Electricity Market Corporation (PEMC), a non-profit and non-stock corporation, was incorporated in November 2003. It was established to serve as the Autonomous Group Market Operator (AGMO) assigned to prepare for the initial operations of WESM. A number of trial operations were conducted and soon after WESM started operating in the Luzon grid on June 26, 2006. The Visayas grid was added into WESM four years later,commencing its operation on December 26, 2010.

Electricity Price on the Spot Markets

Since the liberalization of electric markets, there has been better monitoring on the prices. The modernization of the markets together with the technological advances of the operation has provided a better view of its nature. Common to markets worldwide are the observed high volatility and mean reversion. This means that prices tend to exhibit large jumps but always pull back to its long term mean. Much like other common goods, electricity is widely driven by the cost of production. Furthermore, it is observed to be stable in the long run but is usually disturbed by factors driving the demand and supply (Blochlinger, 2008). This supply disturbance for instance is caused by the weather conditions in the short run or the amount of rainfall in the medium run.

Philippine electric price, much like in the other countries, also possesses the same common characteristic. It hasshown seasonality as price usually goes up during peak hours on a daily scale or during summer time on a monthly scale.The country regularly experiences a wet and a dry season for the whole year. These seasons usually affect the market price drivers. The availability of supply during wet season for example is caused by the higher output of the hydroelectric plants (PEMC, 2014). Extreme weather conditions also greatly affect the price in the market. Since the country is prone to typhoons, it is usually common to observe a destroyed electric facility during such season. The inability of the companies to deliver electricity due to a destroyed transmission line affects the market price (www.wesm.ph). A concrete example is the impact of typhoon Glenda in July 2014 when around 86% of the Meralco customers had no power due to destroyed facilities. The event caused the price to rise in August 2014 to recuperate the damage (www.inquirer.net).

Rationale of the Study

Electricity prices have been largely watched not only by the government but also by the electric industry participants. These include the private companies involved in the generation and distribution of the said commodity. With the occurrence of spikes, the participants are more exposed to risks. Power plant operators are keen on price spikes as their values are more dependent on it, as spikes facilitate the recovery of high marginal costs (Higgs and Worthington, 2010). Profitability analysis and power planning is also dependent to vast knowledge in the electric prices while forecasting it in the short run is important for pricing the derivative contract (Serati, *et al*., 2009). The government on the other hand is concerned on the public interest. It is the one which determines when subsidies and other consumer policies are required. The importance of knowing the dynamics of electricity prices then is vital. Due to this, a number of studies have been conducted worldwide to rationalize the problem underlying it. In the Philippines, the level of importance of understanding the price dynamics is the same as those abroad. Consumers are very concerned about the price as evidenced by the formation of advocate groups and all sorts of information drive given by these non-government organizations. With so few literatures which are available to refer to, there is a need to expose the subject to broaden the information. The lack of enough literature is evident in this research. There have been few authors who studied the electricity rates but did not have enough exposure to the concern of the public sector.

The Philippine electricity rates have been ranked among the highest in the survey of 44 countries in 2012 (www.interaksyon.com). With this problem and with the supply shortage, it is necessary to study the implications of the dynamics of the electricity prices to help both the regulators and the participants on the mitigation process. Furthermore, input prices or fuel costs have long been determined to be factorsin the movement of electricity prices (www.eia.gov). The need to provide this information is important as more than 70% of the power generatedin the country uses coal and natural gas as fuel. Unfortunately, the literature lacks this information.

Objectives of the Study

The main objective of this study is to investigate the occurrence of electricity price spikes in the Wholesale Electricity Spot Market (WESM) in the Philippines using the Luzon grid data. Specifically, the study attempted to:

1. model the electricity price spikes using the Markov Regime Switching method;
2. determine the periods or months when spikes on electricity price occur in the Philippines;
3. determine whether or not prices of Indonesian coal and natural gas affect the spikes of electricity in the Philippines.

Scope and Limitations of the Study

The study focuses on the electricity spot price of the Philippines particularly in the Luzon grid. Data weretaken from the database of WESMon a monthlybasis, from January 2009 to December2015. The author used the Luzon data since it was the first market launched by WESM in 2006 and the Visayas market was only added in 2010. Furthermore, Luzon has the greatest consumption with more than 4000GWh per month compared to the Visayas region which only consumes 400GWh in the current market (www.wesm.ph). Mindanao meanwhile does not have a permanent electricity market as of the moment since it is only using the Interim Mindanao Electricity Market implemented by DOE on 2013.

METHODOLOGY

Theoretical Framework

Spikes in electricity price are common to spot markets. Its liquidity is sometimes attributed to the frequency and volume of the trades happening on the modern and complex world of trading. Electricity prices are determined by the equilibrium of supply and demand like any other commodity. However, it is much different from the common goods because storing it is very uneconomical. This characteristic limits the market players' strategies in trading (Noren, 2013).

Figure 3 shows the dynamics of the electricity price based on the movement of supply and demand. It represents two different scenarios of having a higher market price due to the shifts. Demand curve is usually steeper in an electricity market as consumption is considered inelastic.The first figure shows the positive shift of demand from D to D'. This change pushes the market price upward from P_1 to P_2, resulting to a higher quantity of production from Q_1 to Q_2. The second figure on the other hand shows the negative shift of supply from S to S' and a steeper demand curve D. This happens when there is a lower quantity of production noted by the change of Q_1 to Q_2. This negative change pushes the market price upward from P_1 to P_2even when supply changes slightly. This depicts the scenario of having sudden decrease of power generation due to weather conditions or transmission failures.

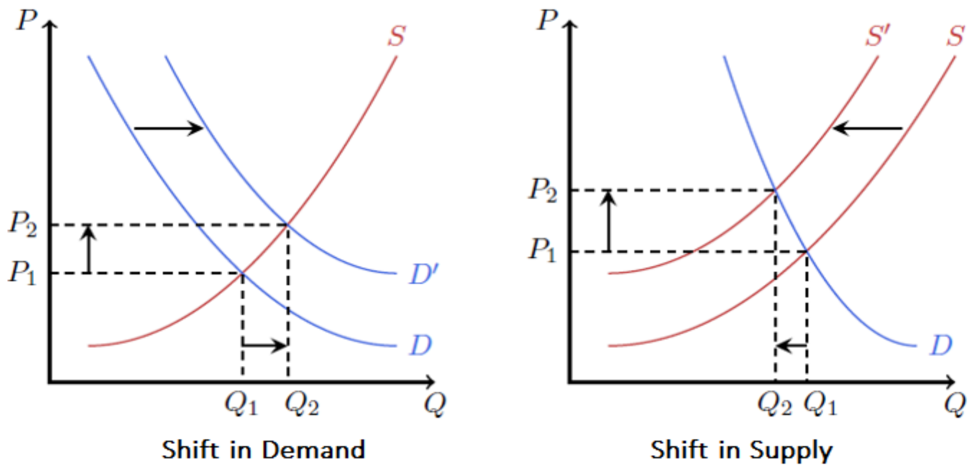

Figure 3. Electricity price based on the movement of supply and demand.

Source: Noren, 2013.

Conceptual Framework

This study implements the Markov Regime Switch – Tobit Regression approach inspired by the Markov Regime Switch – Logistic Regression approach of Cruz and Mapa (2010). The estimation process for the MRS is much different from that of Cruz and Mapa as this study utilizes the EM Algorithm, perceived to be a more efficient process compared to the traditional Maximum Likelihood. In addition, using Tobit regression is also justified given the nature of the dependent variable given by the result in the MRS analysis. The spikes are identified through the decision rule imposed by Hamilton (1989). This decision rule is used as the threshold for the method. The dependent variable therefore is left censored at 0.5 and the influence of the natural gas and Indonesian coal price to the price spike are investigated through this process.

Using the natural gas and Indonesian coal price is based on previous assumptions. The price was identified to be driven by a number of contributing factors. According to the Energy Information Agency (EIA), input prices of power production were found to be factors of the movement of the electricity prices (www.eia.gov). Its effect to the price spikes however are yet to be determined. Natural gas and coal comprises around 70% of the total power produced throughout the country. This study attempts to determine their effects on the Philippine setting and investigate using the Tobit regression.

Econometric Model

The econometric model in this study explainsthe dynamics of electricity price spike. The study used the Markov Regime Switch Model to model and determines the period of spikes. Tobit Regression meanwhile was used to determine the influence of the input prices to the existence of the spikes.

Markov Regime Switching Model

One of the most popular approaches in modeling nonlinearity in a time series is taking an assumption of multiple behavior or structural breaks. That is, modeling separately the different periods of a time series as normal and spike periods (Mahieu and Huisman, 2001). Such method is also widely known as Markov Regime Switching and was popularized by Hamilton (1989). The advantage of using Markov Switch Model in an economic variable is its ability to capture different patterns over time.

To better understand the Markov Regime Switch model, it is preferable to start presenting it through a simple form. It is important to remember that this is only for the simplification of the presentation and the model could be any type of a time series model for this study. Thus, consider a stationary AR(1) model. Assuming it has two structural breaks or regimes, a twostate Markov Switching Model should be represented as (Kuan, 2002):

$$Y_t = \begin{cases} \alpha_0 + \beta Y_{t-1} + \varepsilon_t, & S_t = 0 \\ \alpha_1 + \beta Y_{t-1} + \varepsilon_t, & S_t = 1 \end{cases}$$

whereS_t is the state or period of the variable at time *t* and assumes the values 1 or 0, it is governed by a Markov process and changes based on its underlying transition probabilities. The parameter $|\beta| < 1$ and the error term ε_t is normally distributed with mean 0 and variance of σ_ε^2,while the coefficient α_1 is the parameter of the time series with switching effect. The equation can also be viewed as $Y_t = \alpha_0 + \alpha_1 S_t + \beta Y_{t-1} + \varepsilon_t$for $S_t = 0, 1$. The same idea also applies to more complex model of AR or ARCH to which more parameters define the states. To generalize, take for example an AR(*k*) model (Chen, 2013):

$$Y_t = \alpha + \sum_{i=1}^{k} \beta_i Y_{t-i} + \varepsilon_t.$$

A generalized two-state model for Markov Regime Switch should look like:

$$Y_t = \begin{cases} \alpha_0 + \sum_{i=1}^{k} \beta_{0i} Y_{t-i} + \varepsilon_{0t} , & S_t = 0 \\ \alpha_1 + \sum_{i=1}^{k} \beta_{1i} Y_{t-i} + \varepsilon_{1t} , & S_t = 1 \end{cases}, \tag{1}$$

where we let the vectors $\emptyset_0 = \{ \alpha_0, \beta_{01}, \ldots, \beta_{0k}, \sigma_0^2, \varepsilon_{0t}\}$ and $\emptyset_{\mathbf{1}} = \{ \alpha_1, \beta_{11}, \ldots, \beta_{1k}, \sigma_1^2, \varepsilon_{1t}\}$are the parameters for the models at $S_t = 0$ and $S_t = 1$ respectively. It should also be noted that the models are stationary at any given state.

The EM Algorithm

The use of EM Algorithm in Markov Switch models was introduced by Hamilton (1990) and the idea was generally taken from Dempster, *et al* (1977). Later on, it was widely used by researchers using Switching models. It is composed of the Expectation and Maximization stages, thus the name EM Algorithm. Hamilton (1990), utilizes the smoothed probabilities of S_t to provide the maximum likelihood estimates of the parameters. Taking the smoothed probability is accepting the assumption that the unobserved state is s_t on time *t* based on the entire sample **T**.

Chen (2013) has summarized the E and M steps for Markov Switch model to the following details:

1. Pick an initial value for $\boldsymbol{\Omega} = \boldsymbol{\Omega_0}$
2. The Expectation stage:

   Calculate the values of the following probabilities:

   a. $P(s_t = 1|F_{\boldsymbol{T}}; \boldsymbol{\Omega_0})$for all values of *t*.
   b. $P(s_t = 0|F_{\boldsymbol{T}}; \boldsymbol{\Omega_0})$for all values of *t*.
   c. $P(s_t = 1, s_{t-1} = 1|F_{\boldsymbol{T}}; \boldsymbol{\Omega_0})$for all values of *t*.
   d. $P(s_t = 0, s_{t-1} = 1|F_{\boldsymbol{T}}; \boldsymbol{\Omega_0})$for all values of *t*.
   e. $P(s_t = 1, s_{t-1} = 0|F_{\boldsymbol{T}}; \boldsymbol{\Omega_0})$for all values of *t*.
   f. $P(s_t = 0, s_{t-1} = 0|F_{\boldsymbol{T}}; \boldsymbol{\Omega_0})$for all values of *t*.
3. The Maximization stage:

   Set the next value of $\boldsymbol{\Omega_1} = \arg\max_{\boldsymbol{\Omega}} \; E[\log f(F_T|S_T, \boldsymbol{\Omega_0})]$
4. Repeat steps 2 and 3 until convergence of $\boldsymbol{\Omega}$.

Randomly selecting the starting values for $\boldsymbol{\Omega_0}$is easy. For as long as the values picked are feasible or positive and probability values are from 0 to 1. However it should be noted that the distribution parameters for the 2 regimes is significantly different from each other (Kole, 2010). As remarked by Kole (2010), variances should be set such that regime 1 is three to four times larger than regime 0.

Data and Variables

This study is based on a time series data taken from the Wholesale Electricity Spot Market (WESM). It is a monthly Load Weighted Average Price (LWAP) for the Luzon grid and covers the period of January2009 – December 2015. The explanatory variables on the other hand were taken from the data provider *www.Indexmundi.com* and*www.minerba.esdm.go.id*where the primary sources are the World Bank and the International Monetary Fund.

Dependent Variable

LWAP

This refers to the monthly Load Weighted Average Price of electricity generated in the Luzon grid. The variable's unit is in peso as it is the medium used by the participants of the market. This is the exogenous variable studied in the first phase of this study. As its name suggests, the variable is a weighted monthly average of the spot price.

Inputs

These input variables are used as the explanatory variable on the second part of the modelling which is the Tobit regression. These are the variables that are hypothesized to affect the occurrence of high price periods of the *LWAP:*

1. ***Natural Gas Price***

   This variable refers to the spot price of the natural gas being traded at the Henry Hub Terminal sourced from the International Monetary Fund. Its unit is in US Dollars per Million Metric British Thermal Unit.

2. ***Indonesian Coal Price***

   This refers to the price of reference for the Indonesian coal index. It is one of the most common coal which is being traded worldwide and composes around 90% of the Philippine's total coal imports (www.manilatimes.net).Its unit is in US dollar per metric tons.

RESULTS AND DISCUSSION

This chapter presents the trend of electricity price in the Philippines. The stationarity test, AR specification, Markov Regime Switching analysis and Tobit regression was also discussed in this chapter. The results were obtained using the R statistical software and Shazam.

Price Trend

Figure 6 shows the monthly Load Weighted Average Price (LWAP) of the electricity from January 2009 to December 2015. It is visually observable that the price exhibited spikes at times. The price started low from February 2009 up to December 2009 but started to indicate high variation after that period up to December 2015. As recorded by WESM, the demand for energy throughout the year 2010 increased by 13.77% from 2009. The supply meanwhile was insufficient through the first quarter of 2010 due to the El Nino phenomenon. This results to an upward trend during that period. The following year, 2011, the highest price was observed in October which immediately declined until the 1st quarter of 2012. The year 2012 on the other hand saw the highest price during the 2nd through the 3rd quarter. In 2013 meanwhile, the extreme values were observed and the highest price of the period was recorded during the last quarter of the year. During the same period, the Malampaya power plant was shut down and a series of outages from major coal plants occurred. In addition, Yolanda, the strongest typhoon ever recorded, hit the country in November 2013 causing the outages on various locations (PEMC, 2014).

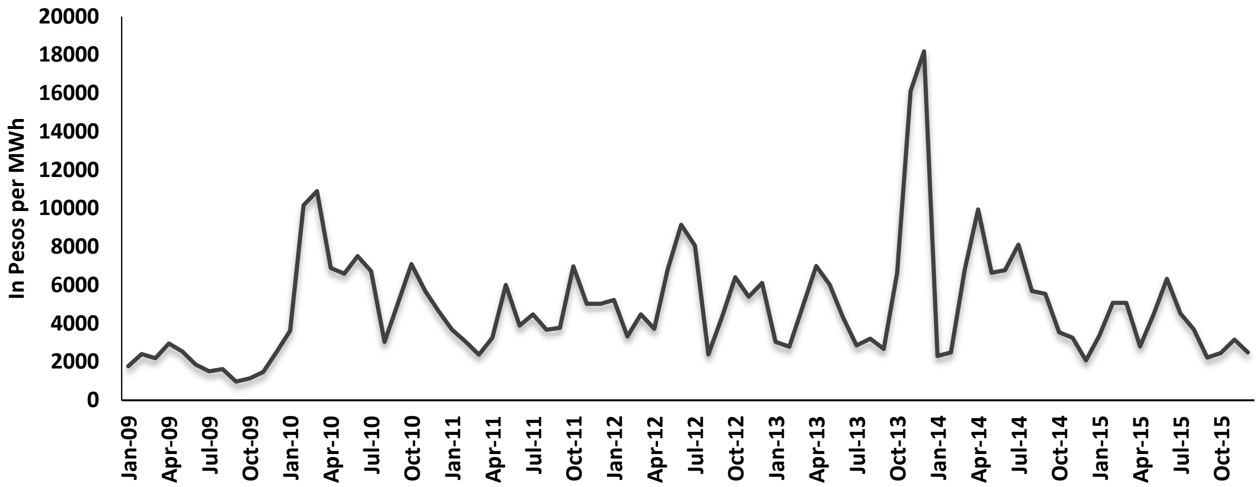

Figure 6. Monthly LWAP: January 2009 – December 2015.

Source: WESM.

Stationarity Test

The LWAP was first tested indicates that for the Augmented Dickey-Fuller test, the statistic is determined to be -3.23 with the p-value of 0.089. This implies that the null hypothesis is rejected and therefore LWAP is stationary at 90% confidence.On the other hand, the statistic for the Phillips-Perron test is determined to be -4.75 with p-value of 0.01. This indicates that the null hypothesis is rejected and therefore LWAP is stationary with 99% confidence. This also implies that the raw data do not need to be differenced as they are already stationary in level form. Furthermore, this is a fair indication that the model to be calibrated will be dependable and allows the study to proceed to the calibration of the MRS model.

As for the natural gas and the Indonesian coal, both were found to be non-stationary at the raw level. Both of the tests show large p-values and are incapable of rejecting the hypothesis that a unit root exists. The variables are then differenced to investigate further. The results show that the variables are stationary at the first difference. All p-values given by the ADF and Phillips-Perron tests are significant with 99% confidence.

Lag Order Specification

The author chose to compare up to 6 lags of the AR to be able to capture the structure of the desired model. First, a correlogram of the partial autocorrelation function was investigated. As shown on Figure 9, the PACF suggests that the lag order of the series is 3.

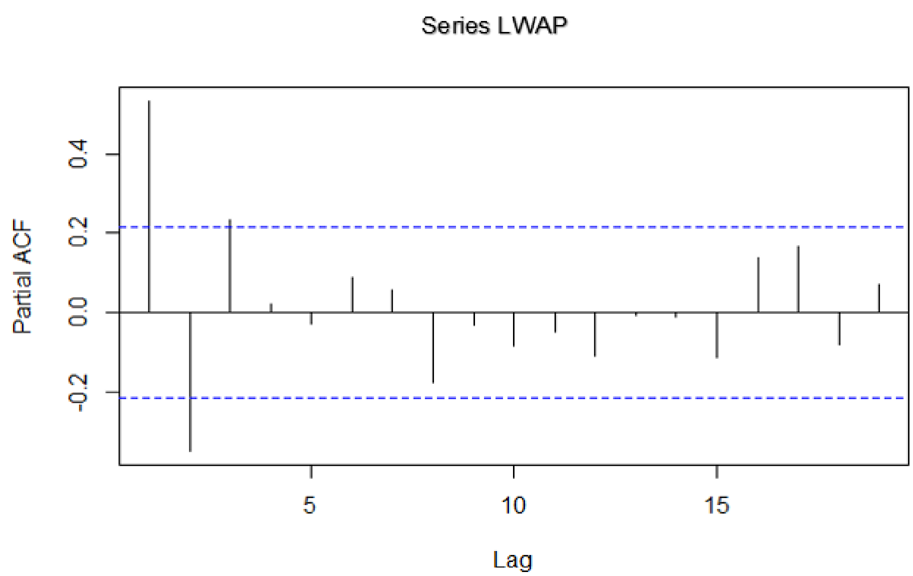

Figure 9. Partial Autocorrelation Correlogram.

The correlogram alone would not guarantee the true lag order of the series. The Akaike Information Criterion (AIC) is the best criterion to estimate an autoregressive lag length (Liew, 2004). The lesser the value of AIC, the better is the fit of the model. Table 4 gives the comparison of all 6 lags and consistent with the information given by the PACF, the model with the least AIC is the AR(3).

Table 4.Akaike Information Criterion Comparison.

Order	df	AIC	LogLikelihood
1	3	1537.4	765.68
2	4	1529.1	760.53
3	5	1526.4*	758.19
4	6	1528.3	758.16

5	7	1530.3	758.13
6	8	1531.5	757.74

Regime Identification

The estimated parameters for MRS with order 3 were shown in Table 5. Regime 1 represents the model for the normal state while Regime 2 is considered the spike state or the period when the spikes were observed. All the parameters for both models were found to be highly significant. The R^2 for Regime 1 is at 0.65 which indicates that 65% of the variations on the normal state were explained by the model. Meanwhile, the R^2 for Regime 2 indicates that it explains 80% of the variations on the spike state. The intercepts (α) were both observed to be significantly different between both models with 782.73 for Regime 1 and 9794.70 for Regime 2. Regime 2's intercept then is more than 10 times larger than the intercept of Regime 1. This alone indicates that Regime 2 is indeed the spike state between the 2 models.

The coefficients for $LWAP_{t-1}$ were all positive for both regimes. This indicates a positive effect to the current observed price. To be specific, when all factors are to be held constant, Regime 1 has β_1 =0.70 which implies that every peso increase of $LWAP_{t-1}$ increased the current price by 0.70 pesos given that it is in normal state. As for Regime 2, β_1 =-1.03 which also indicates that the price has been increased by 1.03 pesos for every peso increase of $LWAP_{t-1}$ when it is in a spike state. In addition, both models have shown that the coefficient of the $LWAP_{t-2}$, $\beta_2$has a negative effect to the current price. For Regime 1, β_2 =-0.19 implies that if the given month is at normal state, every peso increase of its $LWAP_{t-2}$ has reduced the current price by 0.19 pesos. It follows that for Regime 2, β_2 =-1.26 implies that every peso increase of $LWAP_{t-2}$ reduces the price by 1.26 pesos if the month is at the spike state.

Lastly, $LWAP_{t-3}$ was also found to have a positive effect to the current price. At β_3 = 0.26, when the regime is on normal state, this means that every peso of $LWAP_{t-3}$ has increased the current price by 0.26 peso. On the other hand, at β_3 = 0.67, when the regime is on the spike state, the coefficient implies that every peso of $LWAP_{t-3}$ has decreased the current LWAP by 0.67 pesos.

Table 5. Markov Regime Switching Model Coefficients.

	Intercept (α)	β1	β2	β3	Standard Error
Regime 1	805.65**	0.70**	-0.19**	0.26**	1063.98
Regime 2	9807.66**	-1.03**	-1.26**	0.67**	1909.71
Significance Level: 0.001 '***' 0.01 '**' 0.05 '*'					
Multiple Rsquared:					
Regime 1	0.65				
Regime 2	0.80				

This result can be summarized into an equation in the form of equation (1) from Chapter 3. If S_t =0 represent the regime 1 and S_t = 1 represent regime 2, then theMRS(3) model for LWAP is presented as follows,

$$LWAP_t = \begin{cases} 805.65 + 0.70LWAP_{t-1} - 0.19LWAP_{t-2} + 0.26LWAP_{t-3} + \varepsilon_{0t}\,, & S_t = 0 \\ 9807.66 - 1.03LWAP_{t-1} - 1.26LWAP_{t-2} + 0.67LWAP_{t-3} + \varepsilon_{1t}\,, & S_t = 1 \end{cases}$$

Another important result of the estimation is the transition probabilities of the regimes. The results indicate that the probability that a price spike may occur from the normal state or as the table configures, from regime 1 to regime 2 is p_{12} = 0.17. Meanwhile, the probability that the price will shift from spiked state to normal or regime 2 to regime 1 is p_{21} = 0.53. Additionally, the probabilities that the regimes will not change were p_{11} = 0.83 and p_{22} = 0.47 for regimes 1 and 2 respectively.

The expected duration or months that the regimes will occur were also calculated given the probabilities. It was found that the average month that the price spike occurs is 1.9 months. This implies that whenever the price will shift to the spike state, it will stay there for about 1.9 months. On the other hand, the average duration that the normal state occurs is 5.9 months. Accordingly, this also implies that whenever the price will shift to the normal state, it will stay there for about 5.9 months. The periods indicate that the normal state occurs around 3 times as long as the spiked state.

The smoothed probabilities were used to classify the months into the normal state and the spike state. Table 7 shows the classification. The classification indicates that there are about 5 times that the spike occurred for just a month. The longest happened twice for about 4 months. First was during May 2012 – Aug 2012 and again in Oct 2013 – Jan 2013.

Table 7. Date Classification of the Regimes.

Regime 1	Regime 2
Jan 2009 Jan 2010	Feb 2010 March 2010
Apr 2010 Jul 2010	10Aug
Sep 2010 Sep 2011	11Oct
Nov 2011 Apr 2012	May 2012 Aug 2012
Sep 2012 Dec 2012	13Jan
Feb 2013 Mar 2013	13Apr
May 2013 Sep 2013	Oct 2013 Jan 2014
Feb 2014 Mar 2014	14Apr
May 2014 Dec 2015	

Effect of Natural Gas and Indonesian Coal Prices toElectricity Price Spikes

The second stage is the investigation of the effect of the natural gas and Indonesian coal prices to the electricity price spikes. Tobit regression was used to quantify this effect. This method requires that the dependent variable has been censored either from the left or right. For this study, the censoring was based on the value imposed by the decision rule in the MRS analysis. The author used the decision rule implemented by Hamilton (1989) which is also followed by some authors in the study of electricity prices, e.g. Weron and Janzcura (2010). The notion was to categorize any probabilities higher than 0.5 as spikes.Hence, this value was used to censor the dependent variable from the left.

Table 8 shows the result of the tobit regression for the raw form of the input prices. It is noticeable that the relationship is statistically non-existent at all of the independent variables.Neither of the prices of natural gas and Indonesian coal exhibited a significant coefficient as all t-ratios are too small.

Table 8. Summary of Results for Tobit Regression – Data in Level

Variable	Normalized Coefficient	Standard Error	t-ratio	Regression Coefficient
natural gas	0.01	0.18	0.54	0.13
Indo coal	0.001	0.01	0.81	9.37
Intercept	-1.84	0.98	-1.86*	-2.47

The investigation however should not stop at this stage. As the independent variables were found to be non-stationary, it is therefore necessary to examine the effect further through the stationary form of the data. The data is stationary at its first difference as also shown on section 4.2. With this form, the study proceeded using the tobit regression again. Table 9 shows the result for this investigationbut it propagates the same outcome to the first tobit regression. The coefficients were all found to be insignificant for both the natural gas and the Indonesian coal prices. The relationship therefore is non-existent and the movement of the input prices does not affect the spikes in the electricity price.

Table 9. Summary of Results for Tobit Regression – Differenced Data

Variable	Normalized Coefficient	Standard Error	t-ratio	Regression Coefficient
natural gas(1)	0.13	0.35	0.38	0.18
Indo coal(1)	0.005	0.03	0.13	0.007
Intercept	-0.86	0.16	-5.30*	-1.17

SUMMARY AND CONCLUSION

This paper investigated the electricity price spikes and the relationship of the input prices such as the natural gas and the Indonesian coal to the occurrence of the spikes. By implementing two different stages of estimation, it has yielded two different results regarding the subject. First, the spikes were identified by using a 2-state process of the popular method Markov Regime Switching model, popularized by Hamilton (1989). Second, a Tobit Regression was applied to quantify the effects to the electricity price spikes of two of the largest contributing resources to Philippine power generation namely Natural Gas and the Indonesian Coal. The study used the monthly price these popular resources for the tobitregression.

The MRS was estimated using the EM Algorithm. Such method was used by numerous authors and was said to be more efficient than the traditional maximum likelihood estimation. The results show that the electricity price is very well explained by an MRS(3) model. The coefficients were highly significant up to the 3rd lag of the series. Furthermore, much of the pre-identified spikes was captured by the model. The transition probabilities also indicated that the normal state is more dominant which was found to have occurred more than 3 times longer than the spike state.

The tobit regression found that the input prices has no significant effect to the price spikes. This is despite much of the power produced in the Philippines comes from this two resources. The findings proved that, in the Philippine setting,natural gas and Indonesian coal prices' effect to the electricity price does not extend to the occurrence of the spikes. There may have been other factor affecting the spikes and input prices are not one of them, at least on the scope of this study.

AREAS FOR FURTHER RESEARCH

The following are the suggested areas for further research:

- The study was conducted using a constrained amount of data points. It was implemented using the monthly average of the electricity price for a seven year period. Meanwhile, the trading transaction in WESM is conducted on hourly basis. Thus, having an hourly data may provide an interesting extension to this study. Furthermore, hourly data is known to have a negative value. This will be an interesting subject to extend the MRS modeling to 3-states, a model with a negative, normal, and the spike state.
- When conducting the tobit regression, there were other factors not considered for this study due to the unavailability of the data as far as the author is concerned. Typhoons and temperature were identified to be factors by some research. If availing the data is possible, then incorporating them may provide more information regarding the factors affecting the price spikes.
- Another way of modeling the MRS is by using the MRS-Vector Autoregression method. This method incorporates the input variables directly to the system. This type of modeling will give a different view in interpreting the price spike by the direct effects of the factors.

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