MODELING PHILIPPINE INFLATION USING NONLINEAR MODELS: THRESHOLD AUTOREGRESSIVE AND MARKOV REGIME-SWITCHING APPROACHES

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ABSTRACT

Given the high impact of inflation on the poor households, inflation studies deserve more attention especially now that the Philippines is at the onset of TRAIN Law. This paper aims to study inflation rate in the Philippines using nonlinear models: (1) Threshold Autoregressive Model (TAR) and (2) Markov Regime-Switching Model (MSW). Using the Diesel price as the threshold variable, the TAR model for the change in Headline Inflation identified a threshold value of PHP 30.05, which is slightly lower than the estimated threshold of PHP 30.25 in the change in Bottom 30% Inflation model. Findings suggest that growth in Diesel price has indeed threshold effects on inflation, with its coefficient being significant only when price is above the threshold. Results of the MSW affirm that growth in price of Diesel has significant positive effect within the high inflationary regime. In both models, the growth in price of Rice remains to have positive and significant effect on inflation rate. The highest expectation is for a high inflation rate regime to succeed itself - 97% for change in Headline Inflation and 91% for change in Bottom 30% Inflation. The corresponding expected durations indicate that Headline Inflation and Bottom 30% Inflation are expected to stay in the high inflationary period for 35 months and 11 months, respectively. As the current price of diesel is above the identified thresholds, the imposed excise tax on Diesel price due to the TRAIN Law will have a 0.29 and a 0.27 percentage points impact on the change in Headline Inflation and on the change in Bottom 30% Inflation, respectively, based on the results of the TAR models. Furthermore, with the current state of inflation, the excise tax on Diesel price is expected to have a 0.14 and 0.15 percentage point impact on change in Headline Inflation and on change in Bottom 30% Inflation, respectively. Policymakers should monitor inflation and direct government policies toward stabilizing prices.

Keywords: Inflation Rate, Threshold Autoregression, Markov Regime-Switching

1 INTRODUCTION

Prices of goods and services do not remain the same over time. A kilo of rice costs more today than it used to be ten years ago. As such, one cannot buy the same thing for the same price as one could a few years back. This is referred to as inflation. Inflation, as defined by the Bangko Sentral ng Pilipinas (2017), is rate of change in the average prices of goods and services typically purchased by consumers. Like many developing countries, one of the fundamental objectives of macroeconomic policies in the Philippines is to sustain high economic growth while maintaining low and stable levels of inflation.

According to the Philippine Statistics Authority (PSA), inflation in the Philippines has hit 4.8% in March of this year which is recorded as the highest in over 3 years, as cost rose faster for both food and transport which hugely impacted the jump. This was beyond the government's target of between 2% and 4% for full year 2018. In fact, analysts expect inflation to continue an upward trend this year in view of the new or higher taxes imposed on a number of goods, as this year marks the full implementation of the first tax reform package of the government, also known as the TRAIN Law, and the continued increase in the global prices of oil.

The Republic Act No. 10963, otherwise known as the Tax Reform for Acceleration and Inclusion (TRAIN) Act, was signed into law December 19, 2017. TRAIN will provide income tax cuts for majority of Filipino taxpayers while raising additional funds to help support the government’s accelerated spending on its “Build, Build, Build” and social services programs. Revenues from the law is needed to support the government’s priority social and infrastructure programs. In line with the Philippines’ commitment to the Sustainable Development Goals, the TRAIN Law aims to eradicate extreme poverty by reducing the poverty rate from 21.6% down to 14%, which translates to an uplift of about 10 million Filipinos from poverty into middle-income status by 2020. Under the TRAIN, majority of Filipino taxpayers will receive hefty income tax cuts with the restructured personal income tax rates, while slapping higher taxes on fuel, cigarettes, sugar-sweetened beverages and vehicles.

While much has been said about the benefits of TRAIN to drive overall growth and acceleration of the Philippine economy, the tax reform may further propel the already rising inflation rate upon implementation. The National Economic and Development Authority (NEDA), explained that momentary impact of TRAIN and the continued depreciation of the Philippine peso will "mainly influence" price movements in the coming months. Similarly, the Bangko Sentral ng Pilipinas (BSP) highlighted in its "Inflation Rate Report for 4th Quarter 2017" that the transitory impact of the government's fiscal reform program is one of the main upside risks to inflation. In terms of inflationary impact, higher consumption taxes, together with the demand stimulus from the fiscal reform program, are expected to initially generate higher inflation.

In 2015, PSA estimated about 21.6% of the Philippine population living below the national poverty line. Moreover, about 8% Filipinos are living below the food threshold, or the minimum amount needed to meet a person's basic food needs and satisfy the nutritional requirements. Based on the Family Income and Expenditure Survey (FIES), an additional monthly income of PHP2,649 is needed by a family with five members to rise above poverty.

Consequently, when the prices of essential goods and services rise, it becomes harder for the poor, with a limited budget, to be able to afford these goods and services. The limited purchasing power of the poor shrinks when prices of essential commodities increase but the income does not increase at the same pace (Wilson, 2011). A study by Hyun Son (2008) found that inflation hits poorer families much harder than the rich in the Philippines. Specifically, the results of his study showed that:

> *"The poor are highly sensitive to price changes in food, particularly staple food items such as rice. Estimates on the price elasticity of poverty by commodity suggest that a 10% increase in food prices will create an additional 2.3 million poor people, while a 10% increase in non-food prices will drive an additional 1.7 million people into poverty. Notably, a 10% increase in the price of rice will force an additional 0.66 million people into poverty, while a 10% increase in fuel prices will cause an additional 0.16 million poor people."*

Therefore, with the diesel products becoming less affordable due to TRAIN's adjusted excise tax and the current food system in the country being highly fuel and transport-dependent, poor consumers are expected to face higher commodity prices for the rest of the year 2018.

Nevertheless, the Department of Finance (DOF; 2018) argued that the effect of TRAIN on inflation will only be “very minimal” and “manageable” as the DOF’s estimate of the percentage point increase in inflation during the first year of implementation is just around 0.73 with the impact tapering off over time. Specifically, food prices may increase by up to 0.73 percentage point, transportation up to 2.8 percentage points, and electricity up to 0.70 percentage point. Citing historical data, DOF further argued that despite a PHP14 increase in diesel oil prices from PHP18.25 to PHP32.10 in 2016, inflation still remained low and stable with prices of food, transportation and other goods and services increasing only by 2% to 3%. Basic commodities did not increase in prices despite the 75% increase in diesel price. The DOF stressed that with a smaller increase in fuel cost in the recent excise reform under TRAIN, the economy can manage growth and inflation well.

However, the said relationship between diesel price and inflation might not be linear, instead a nonlinear behavior might have existed. In this case, the usual linear framework may fell short of properly describing the data which instead exhibit important nonlinear features. As such, the significant effect of increase in diesel prices on inflation is evident only when the price hits a certain threshold. Nonlinear models aim to characterize such features observed in the data (Rajbhandari, 2015). This possible nonlinearity in inflation and the threshold effects of diesel price on inflation are the main impetus for this paper.

The concern over inflation has drawn popular interest over the years. In fact, a number of studies have been carried out to study inflation. However, there has been some debate in the literature about the correct characterization of inflation dynamics (Simon, 1996). Various empirical evidences suggest that the time series behaviors of economic and financial variables may exhibit different patterns over time (Kuan, 2002). Although linear time series models are quite successful in numerous applications and they remain at the forefront of academic and applied research, it has often been found that these models usually leave certain aspects of economic and financial data unexplained and they are unable to represent many nonlinear dynamic patterns especially in the analysis of macroeconomic relationships that are subject to regime change (Zivot & Wang, 2010).

In some cases, researchers may wish to allow the model variables to depend nonlinearly on past observations of the model variables rather than just linearly (Kilian & Lütkepohl, 2017). Such models are collectively referred to as nonlinear models. Examples of nonlinear dynamics include models with smoothly evolving time-varying coefficients and models with coefficients that change with the state of the economy. Nonlinear models allow economists to model target zones, stochastically switching regimes in the economy, gradual transitions to new economic regimes, thresholds induced by transaction costs, asymmetries in the responses of model variables to positive and negative shocks, and many other economically relevant phenomena (Kilian & Lütkepohl, 2017).

A study by John Simon (1996) showed that inflation process is usually modeled as a function of macroeconomic and policy-related variables including wages, commodity prices and business cycle conditions, which often involves complicated dynamic structures. These models can be highly successful in tracking actual inflation, given the behavior of the explanatory variables. However, an issue not addressed in this kind of modelling is that structural changes may have occurred in the underlying processes generating inflation, with possible implications for inflation expectations. To address these issues, this study will apply an alternative modelling approach based on some recent studies that use non-linear models to describe inflation.

To model nonlinear behavior in economic and financial time series, it seems natural to allow for the existence of different states of the world or regimes and to allow the dynamics to be different in different regimes (Zivot & Wang, 2010). Nonlinear models are state-dependent and its parameters may change according to the states (Rajbhandari, 2015). There is a host of nonlinear models used in modelling and forecasting inflation, but this paper will focus on two statistical models, namely, (1) Threshold Autoregressive Model (TAR) and (2) Markov Regime-Switching Model (MSW).

The Threshold Autoregressive Model (TAR) allows the model coefficients to evolve from one regime to another when some model variable exceeds an estimated or pre-specified threshold value (Kilian & Lütkepohl, 2017). TAR model was first proposed by Howell Tong (1978) and discussed in detail by Tong and Lim (1980) and Tong (1983). A common theme in the application of TAR models to economic price data has been transaction costs. Economic arbitrage requires that the prices of related goods move together, but the presence of transaction costs can produce a band-threshold effect, where only deviations above a threshold will have an effect on price movements (Hansen, 2011). The general idea is that a process may behave differently when the values of a variable exceed a certain threshold. That is, a different model may apply when values are greater than a threshold than when values are below the threshold. In this case, significant movement in prices occur only if the diesel price exceeds a certain level. The movement from low to high inflation is allowed to depend on the price of Diesel. Diesel price can thus act as a 'warning signal' of the risk of the departure of inflation from the price stability regime.

The changes in regimes may also be modeled by making them dependent on a discrete Markov process. The Markov Regime-Switching (MSW) model of Hamilton (1989) is one of the most popular nonlinear time series models in the literature. This model involves multiple structures that can characterize the time series behaviors in different regimes. By permitting switching between these structures, this model is able to capture more complex dynamic patterns (Kuan, 2002). The distinctive feature of this approach is the use of very simple equations for inflation, within a framework that allows for discrete regime shifts that can govern the inflation process at different points in time (Simon, 1996). In each period, the state of the process is determined endogenously and the specific state can change from period to period (Kilian & Lütkepohl, 2017). A novel feature of the Markov switching model is that the switching mechanism is controlled by an unobservable state variable that follows a Markov chain where the probability of being in a particular state is only dependent upon the previous state. This technique has several advantages, including endogenous structural breaks and encompassing ARCH models. Initial work was done by Hamilton (1989, 1990) with applications to business cycles, while various recent studies have applied the technique to inflation. Similar analysis in the literature has commonly been univariate with only a limited number of studies have included independent variables in modelling inflation.

Given the current scale of poverty in the Philippines and the high impact of inflation on the poor households, inflation studies deserve more attention. It is thus highly relevant for policymakers to monitor inflation and direct government policies toward stabilizing prices, especially now that the Philippines is at the onset of TRAIN Law. Therefore, this paper attempts to contribute to the literature by making use of an alternative time-series characterization for inflation that allows for distinct and differing periods of inflationary behavior, each characterized by its own time-series properties. Specifically, this study will model inflation as a regime-switching process, in which inflation is characterized by two regimes – low and high inflation. It describes the inflation process as being governed by two different regimes where switches between them (1) are triggered by a threshold or (2) evolve according to a Markov chain. This approach is intuitively appealing, as the behavior of economic time series often seems to go through distinct phases (Simon, 1996).

1.1 Objectives of the Study

In general, this paper aims to study inflation rate in the Philippines using nonlinear models. Specifically, the study intends:

1. To model the inflation rate using Threshold Autoregression (TAR) with diesel price as the threshold variable
2. To model inflation rate using Markov Regime-Switching (MSW) and estimate transition probabilities and expected duration of a state.
3. To determine the impact of imposed diesel excise tax on the inflation rate using the results of the Threshold Autoregression (TAR) and Markov Regime-Switching (MSW).

1.2 Significance of the Study

To great extent, econometric models are much needed analytical tools to assist policy decisions particularly at this time when poverty remains to be a serious problem and significant cases of inflation persist. Findings of this study will highlight the importance of inflation as key statistic in policy and program design, and in the targeting and monitoring of national goals. In addition, this study will add to the many benefits of nonlinear models as one of the primary tools for econometric and statistical analysis.

The remaining sections of the paper are organized as follows. Chapter 2 presents detailed review of existing literature and necessary topics. Chapter 3 describes all the data to be used and their respective sources, as well as the research methodology. It also introduces the empirical models and explores methods of estimating the model parameters and their properties. Chapter 4 discusses the results which is followed by the conclusion and important extensions and interesting areas for future work in Chapter 5. This is followed by the Appendices and the References.

2 REVIEW OF RELATED LITERATURE

The following sections are topics deemed necessary in understanding the conceptual framework of the study:

2.1 TRAIN Law

The Republic Act No. 10963, otherwise known as the Tax Reform for Acceleration and Inclusion (TRAIN) Act, was signed into law December 19, 2017. TRAIN will provide income tax cuts for majority of Filipino taxpayers while raising additional funds to help support the government's accelerated spending on its "Build, Build, Build" and social services programs.

TRAIN aims to make the current tax system simpler, fairer, and more efficient. This tax reform package "corrects a longstanding inequity of the tax system" by reducing personal income taxes for 99% of taxpayers. Under TRAIN, Income taxpayers with an annual salary of P250,000, or those earning approximately PHP22,000 monthly and below, are now exempt from income tax payment.

Diesel, which is not taxed at present, will be imposed P2.50-per-liter tax in 2018, PHP4.50 in 2019, and PHP6 in 2020. LPG will be taxed PHP1 per liter in 2018, PHP2 in 2019, and PHP3 in 2020. For gasoline, from the current tax of PHP4.35 per liter, it would be imposed a levy of PHP7 per liter in 2018, PHP9 in 2019, and PHP10 in 2020. The law also applies a 4-tier tax scheme for automobiles. It also imposed a tax of PHP6 per liter for drinks using sugar and artificial sweeteners and PHP12 per liter for using high fructose corn syrup. Milk and instant coffee, drinks consumed by a majority of Filipinos, are exempted. Tobacco products will also be more expensive as under the Train law, the sin tax on such products will be increased.

To cushion the impact of these higher taxes on the poorest Filipinos, the law provides a cash transfer mechanism. About 10 million households will be given targeted cash transfers of PHP200 per month in 2018 and PHP300 per month in 2019 and 2020, sourced from higher consumption taxes that the rich will contribute, as well as better social services, healthcare, and education.

Based on the 2017 4th Quarter report of the BSP, the expected net increase in revenue from these reforms, together with some tax administration measures, are intended largely for funding the government's key infrastructure and social spending programs, which could boost domestic economic activity and raise the country's future productive capacity. This will help realize the administration's goal of reducing the poverty rate from 21.6% to 14% by 2022.

2.2 Inflation Rate

The United Nations (UN) defined inflation as an indicator that measures the change in prices of consumer goods and services acquired, used or paid for by households. The rate of inflation is one of the indicators monitored by the authorities to set monetary policy.

Although it may vary around the world, most countries use the Consumer Price Index (CPI), including the Philippines, as the main indicator of inflation levels. Consumer price indices are based on a representative basket of goods and services purchased by consumers in an economy, which are weighted according to their importance to the metropolitan household. Composition and relative weights of the basket are reviewed periodically (UN, 2007). In the Philippines, the CPI basket is composed of various consumer items as determined by the PSA through the nationwide Family Income and Expenditure Survey (FIES), which is conducted every three years by the National Statistics Office (NSO), now the PSA. The Philippine Statistics Authority (PSA) calculates and announces the monthly CPI and the rate of inflation based on a nationwide monthly survey of prices for a given basket of commodities.

2.3 Inflation Rate in the Philippines

The inflation rate in Philippines was posted at 3.90% in February of 2018 using to the new rebased series with 2012=100. Under the old series, inflation was recorded at 4.5 percent. From 1958 until 2018, inflation rate in the country averaged 8.43%, with an all-time high of 62.80% in September 1984 and a record low of -2.10% in January of 1959

(TradingEconomics.com, 2018). In 2017, the inflation was posted at 3.20% which is within the National Government's announced target range of 2.0% and 4.0% for the year.

2.4 Headline Inflation vs. Inflation of the Poor

Headline inflation refers to the rate of change in CPI, a measure of the average price of a standard "basket" of goods and services consumed by a typical family. Aside from the headline inflation, PSA also reports quarterly the inflation of the bottom 30% households which is based on the movements of prices of items in the basket of commodities and services consumed by the bottom 30% Filipino household.

2.5 Consumer Price Index and the Food Basket

Like most countries, the Philippines uses the Consumer Price Index (CPI) as the main indicator of inflation levels and are calculated based on an average consumption basket. This consumption basket consists of different commodities with different prices.

Guinigundo (2005) suggested to develop a CPI based on income class as consumption patterns differ across various income classes. When prices of necessities such as food rise much faster than luxuries, the poor who tend to spend more of their budget on necessities suffer more than the non-poor households. Hyun Son (2008) showed that the impact of changes in prices on the poor is different from that of the rich. If food prices go up at a faster rate than non-food prices, this will hit the poor harder than the rich. This is because a higher proportion of the poor's consumption basket is devoted to necessary goods and services such as food items. Hyun Son (2008) highlighted that the increase in food prices has been the major factor causing high inflation in the Philippines in recent periods. The nonfood items of consumption have played a relatively minor role.

In the 2006-based CPI computation, the highest weight was given to Food and Non-alcoholic Beverages at 38.98% while Non-Food items contribute 58.99%. Of the Non-Food items, Housing, Water, Electricity, Gas and Other Fuels has the highest contribution at 22.47% with Electricity, Gas and Other Fuels having 7.1% weight.

The PSA (PSA, 2016), reporting the results of the Family Income and Expenditure Survey for the year 2015, showed that average annual family income in all deciles increased, the average ranged from PHP 86,000 for the lowest 10% families to PHP 786,000 thousand pesos for the highest 10% families. In 2015, about 41.9 percent of the total annual family expenditures was spent on food, but for families in the bottom 30 percent income group, the percentage was much higher at 59.7 percent. Furthermore, in the Household Final Consumption Expenditure (HFCE) report of PSA, Food and Non-alcoholic Beverages shared 41% of the total household expenditure in 2017. Miscellaneous Goods and Services is the next top contributor of HFCE at 13.7% followed by Housing, water, electricity, gas and other fuels at 10.9%.

2.6 Price of Rice

There are a number of earlier studies which have analyzed the impact of increase in the price of rice. Results of a study by Reyes et al. (2009) confirmed that the impact of increasing prices of rice would vary across different groups of households based on the level of urbanity, income group and geographical location. Some important findings of the study include:

- Most of the households in the Philippines are net consumers rather than net producers of rice.
- Urban households would be the more adversely affected as compared to those living in the rural areas. About 94.1% of households in the urban areas would lose, primarily because a majority of urban households are net consumers of rice.
- Households which belong to lowest income deciles, particularly 1st to 5th income decile, tend to be the most adversely affected group. The decline in their net benefit ratio (NBR), or the value of net sales of a commodity as a proportion of income, after rice price increase is higher as compared to the richer households. It is also important to note that the poorer households are the most vulnerable to price changes.
- Poorest farmers tend to be the most adversely affected by rice price increase.

2.7 Price of Fuel

Based on the Department of Energy weekly report (2018), most of the oil companies increased their price of gasoline by P1.15/liter, diesel by P1.10/liter and kerosene P1.00/liter effective 27 March 2018. Year-to-date adjustment now stands net increase of P2.20/liter in gasoline P2.65/liter in diesel, and P2.35/liter in kerosene.

Reyes et al. (2009) also stressed that the impact of higher fuel prices can either be a direct effect of higher prices of petroleum products consumed by the household or an indirect effect on the prices of other goods and services consumed by the households that use fuel as an intermediate input. Their findings showed Filipino households generally allot a relatively small proportion of their total expenditure on fuel as petroleum and LPG account only about 1.5% of their budget. However, fuel expenditures increase as household move from a lower decile to a higher decile. Notably, the poorest of households has higher budget share for fuel compared to those belonging to the richest households. It is also worth noting that the increase in fuel prices would affect other sectors that are highly dependent on fuel as a major input to production - not only the transportation sector, but the agriculture-related industries as well. This means that farmers, particularly those who are poor, would also be affected eventually by fuel price increases.

2.8 Inflation Models

It is hard to forecast inflation (Stock & Watson, 1999). Simon (1996) argued that models of the inflation process typically specify inflation as a function of a wide set of macroeconomic and policy-related variables often involving complicated dynamic structures, which can give high predictive power in tracking actual inflation. An issue not addressed by this kind of modelling, however, is that structural changes may have occurred in the underlying processes generating inflation.

In the Philippines, the BSP uses a set of quantitative macroeconomic models to forecast inflation over a policy horizon of two years. These models are also used in conducting policy simulations and analysis. Statistical tests show that these models predict the actual inflation outcomes reasonably well. In 2009, Cruz reported that the BSP uses its single-equation model (SEM) that for short-term inflation forecasting to generate a two-year ahead monthly track for inflation. The forecasts from the SEM are combined with the monthly forecasts from the BSP's multi-equation model (MEM) to provide a more comprehensive assessment of the inflation outlook. In 2014, Mariano et. al enumerated the new features of Long-Term Inflation Forecasting Model (LTMM) of the BSP. These include (1) detailed treatment of the monetary sector and the channels, (2) careful treatment of demand and supply side influences on inflation, (3) the model provides likely directions of both core and headline inflation. (4) the model is flexible to handle different scenarios.

2.9 Non-Linear Models in Empirical Economics

Many economic time series occasionally exhibit dramatic breaks in their behavior, associated with events such as financial crises or abrupt changes in government policy (Hamilton, 2005). Grynkiv and Stentoft (2016) emphasized that theoretical and empirical modelling of financial time series remains challenging because of the following:

> *"First, the usual linear framework often falls short of properly describing the data which instead exhibit important nonlinear features. Second, economic theory regularly results in models with multiple equilibria and asymmetries which the time series model should be able to accommodate. Finally, data is often interconnected and hence simple univariate models generally fall short of describing the complex nature of the data."*

Grynkiv and Stentoft (2016) reinforced the need to use a multivariate non-linear framework in economic models, in general, and in empirical finance, in particular.

Gonzalo et al. (2012) recognized that that linear time series models are sometimes too restrictive in capturing economically interesting asymmetries and empirically observed nonlinear dynamics. Gonzalo et al. (2012) further mentioned that this has generated wide-eyed curiosity over the past years on designing models which could capture such features while "remaining parsimonious and analytically tractable". Models that can account for nonlinear dynamics were also the objectives of earlier and extensive research. One specific behavior of interest to economists is that of "regime change or regime switching whereby the parameters of a model are made to change depending on the occurrence of a particular event, episode or policy but are otherwise constant within regimes". This was also mentioned by Zivot and Wang in 2010, citing that economic systems go through both structural and behavioral changes. Zivot and Wang (2010) said that it is reasonable to assume that different time series models may be required to explain the empirical data at different times.

While nonlinear time series has a lot of advantages, these models are not perfect and have their own limitations. First, implementing nonlinear models is typically complicated. Moreover, most nonlinear models are designed to describe certain nonlinear patterns of data and hence may not be so flexible as one would like. Thus, the success of a nonlinear model largely depends on the data set to which it applies (Kuan, 2002).

2.10 Threshold Autoregressive (TAR) Models

The discrete Threshold Regression model describes a simple form of nonlinear regression featuring piecewise linear specifications and regime switching that occurs when an observed variable crosses unknown thresholds. TR specifications are quite popular as they are easy to estimate and interpret, and able to produce interesting nonlinearities and rich dynamics. Among the applications of TR are models for sample splitting, multiple equilibria, and the very popular Threshold Autoregressive Model (TAR) and Self-Exciting Threshold Autoregressive Model (SETAR) specifications (Hansen 1999, 2011; Potter 2003).

A standard multiple linear regression model with T observations and m potential thresholds (producing $m+1$ regimes) has linear regression specification below for the observations in regime $j = (0, 1, \ldots, m)$:

$$y_t = X_t'\beta + Z_t'\delta_j + \epsilon_t \qquad (2.10.1)$$

Note that the regressors are divided into two groups. The X variables are those whose parameters do not vary across regimes, while the Z variables have coefficients that are regime-specific. Suppose that there is an observable threshold variable q_t and strictly increasing threshold values $(\gamma_1 < \gamma_2 < \cdots < \gamma_m)$ such that the state is in regime j if and only if $\gamma_j \leq q_t < \gamma_{j+1}$where we set $\gamma_0 = -\infty$ and $\gamma_{m+1} = \infty$. Thus, regime j is active if the value of the threshold variable is at least as large as the j^{th} threshold value, but not as large as the $(j+1)^{th}$ threshold.

A single threshold, two-regime model, is written as:

$$y_t = \begin{cases} X_t'\beta + Z_t'\delta_1 + \epsilon_t, & -\infty < q_t < \gamma_1 \\ X_t'\beta + Z_t'\delta_2 + \epsilon_t, & \gamma_1 \leq q_t < +\infty \end{cases} \tag{2.10.2}$$

Using an indicator function $1(\cdot)$ which takes the value 1 if the expression is true and 0 otherwise and defining $1_j(q_t, \gamma) = 1(\gamma_j \leq q_t < \gamma_{j+1})$, the $m + 1$ individual regime specifications may combine into a single equation:

$$y_t = X_t'\beta + \sum_{j=0}^{m} 1_j(q_t, \gamma) \cdot Z_y'\delta_j + \epsilon_t \tag{2.10.3}$$

The identity of the threshold variable q_t and the regressors X_t and Z_t will determine the type of TR specification. If q_t is the dth lagged value of y, Equation (2.10.3) is a self-exciting (SE) model with delay d; if it is not a lagged dependent, it is a conventional TR model. If the regressors X_t and Z_t contain only a constant and lags of the dependent variable, we have an autoregressive (AR) model. Thus, a SETAR model is a threshold regression that combines an autoregressive specification with a lagged dependent threshold variable.

The Threshold Autoregressive (TAR) models was first proposed by Tong (1978) and discussed in detail by Tong and Lim (1980) and Tong (1983). The TAR models are simple and easy to understand, but rich enough to generate complex nonlinear dynamics. TAR models can have limit cycles and thus be used to model periodic time series, or produce asymmetries and jump phenomena that cannot be captured by a linear time series model. In spite of the simplicity of the TAR model form, there are many free parameters to estimate and variables to choose when building a TAR model, and this has hindered its early use. Recently, however, much progress has been made with regard to specification and estimation of TAR models (Zivot & Wang, 2010).

Grynkiv and Stentoft (2016) claimed that, among the many non-linear models, Threshold Autoregressive (TAR) models are particularly interesting and have been extensively used in existing empirical literatures. TAR models are “straightforward generalizations of linear models”. A simple two-regime TAR model specifies a different autoregressive structure for each of the regimes where a threshold variable determines which regime is active. Grynkiv and Stentoft (2016) highlighted that TAR models are relatively simple to estimate versus other nonlinear models since the regime state is known at time ‘t’, thus TAR models are more suitable for forecasting. TAR models also allow for reasonably simple tests of the nonlinear structure against linear alternatives and to test the number of regimes. The multivariate generalization of the TAR model uses vector autoregressive (VAR) structures in the regimes and is known as the TVAR model.

Oduro-Afriyie et al. (unpublished) tested for the presence of threshold effects in food inflation in Ghana using a regime switching TAR Model to identify thresholds and the effect of food inflation on agricultural output growth. Findings suggested that threshold effects exist within Ghana’s food inflation, with the estimated threshold of 11.5%-15.2% lying outside the targeted inflation band for the entire economy. In addition, the study identified a threshold of 6.1% for the rainy season as general food prices in Ghana drop during periods of sustained rainfall, while no threshold was identified for the dry season. Aleem and Lahiani (2014) used TVAR model to examine the exchange rate pass-through in the presence of nonlinearities, noting that linear modelling techniques may give imprecise coefficients. The paper estimated the nonlinear responses of domestic prices to an exchange rate shock by taking into account the threshold levels of the rate of inflation where the threshold level of inflation is determined endogenously. Furthermore, they allowed for a simultaneous regime switching in model and tested for the presence of more than two regimes. Results of the study showed that the nonlinearity test suggested two regimes with one threshold value of inflation estimated at 0.79% between regimes.

Allen and Robinson (2015) also employed TVAR model in the impact assessment of nonlinear monetary policy shocks in Jamaica on key macroeconomic variables under regime switching behavior associated with three monetary policy stances: tight, neutral or loose. Statistical tests confirmed the presence of threshold effects and the results revealed that the effects of monetary transmission to inflation and exchange rate differed depending on whether the central bank is in in a neutral or intervention policy stance.

Avdjiev and Zeng (2014) examined the nonlinear relationship among credit market conditions, monetary policy, and real economic activity changes using structural TVAR model with five variables: real GDP growth, inflation, the federal funds rate, real credit growth, and the spread between Baa-rated corporate bonds and 10-year Treasury bonds. The TVAR model allowed for the presence of a second threshold in the system. Results provided strong evidence that the interactions among credit market conditions, monetary policy, and economic activity change significantly as the economy moves from one stage of the business cycle to another. Results also revealed that the three-regime TVAR model captures important contributions of the non-idiosyncratic shocks to output growth fluctuations.

Furthermore, structural changes and threshold effects motivated Yélou et al. (2007) to use TAR in panel data stochastic frontier models and to propose three different estimators allowing for multiple thresholds to address the heterogeneity issue. TAR models can also include unit root variables for the purpose of capturing economically interesting phenomena such as asymmetric adjustment to equilibrium. Nonetheless, Gonzalo et al. (2012) claimed that despite the enormous methodological developments over the past years, this line of research is still at its infancy.

2.11 Markov Regime-Switching Models

Another class of models that can be categorized within the Nonlinear Models are the well-known Markov Regime-Switching (MRS) models popularized by Hamilton's early work and which model parameter change via the use of an unobservable discrete time Markov process. Gonzalo et al. (2012) discussed that class of models in which parameter changes are triggered by an unobservable binary variable has been used extensively as an intuitive way of capturing policy shifts in macroeconomic models as well as numerous other contexts such as forecasting economic growth and dating business cycles.

Discrete state Markov processes are popular choices for modeling state-dependent behavior in natural phenomena, and are natural candidates for modeling the hidden state variables in Markov switching models. A discrete state Markov process classifies the state of the world S_t at any time t into a few discrete regimes (Zivot & Wang, 2010). The state switches between different regimes according to its previous value and transition probabilities given by:

$$P(S_t = j|S_{t-1} = i) = P_{ij} \geq 0 \tag{2.11.1}$$

where $i, j = 1,2, \dots, k$ with k different possible states or regimes, and:

$$\sum_{j=1}^{k} P(S_t = j|S_{t-1} = i) = 1 \tag{2.11.2}$$

It is usually convenient to collect the transition probabilities into a transition matrix given by:

$$\mathcal{P} = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1k} \\ P_{21} & P_{22} & \cdots & P_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ P_{k1} & P_{k2} & \cdots & P_{kk} \end{bmatrix} \tag{2.11.3}$$

where each row sums up to one.

Yu (2007), studying the Philippine inflation rate, showed that the Markov-switching model outperforms a naive random walk model in terms of forecasting accuracy. Sotocinal (2015) used a Markovian Regime Switching Vector AutoRegressive model based on an extended inflation targeting system under the presence of a fiscal gap and public debt using Philippine data. Results revealed that the fiscal gap significantly impacts on the target variables in the inflation targeting system and directly affects the short-term interest rate contrary to the standard assumption of zero fiscal dominance. There was evidence of the existence of interest rate regimes, such that activist fiscal policies in the low output regimes are only effective in the short term, as their impact on interest rates are larger and tend to lead to interest rate increases beyond those intended by the monetary authorities.

Simon (1996) study focused on simple equations framework by allowing regimes to change. As such, Markov-switching models appear to provide a useful supplement to conventional modelling strategies for inflation. The results suggested that inflation in

Australia since the early 1960s is reasonably well modelled by a two-regime specification, with regime changes occurring in the early 1970s and early 1990s. In each regime, inflation in the preferred model is characterized by a simple autoregressive process supplemented by information about the output gap. Specifically, the 1970s and 1980s can be characterized by a high-inflation process with relatively persistent deviations from the mean, while the 1960s and 1990s can be characterized as a process with a low mean and less persistent deviation from that mean. The study chose this model in preference to one where the high inflation 1970s and 1980s are characterized by a random walk.

Amisano and Fagan (2010), followed the extensive literature in which inflation is modelled as a Markov-Switching process, in which inflation shifts from regimes of low to high inflation and vice versa. Under the Bayesian Markov Switching framework, this paper developed a money-based early warning indicator for shifts in inflation regimes. The paper then modelled inflation as a process characterized by two regimes - low and high inflation - in which the probability of shifting from one regime to the other depends on a measure of lagged money growth which can be computed in real time. The model was applied the model to data from Canada, the euro area, Germany, the US and the UK using quarterly data from the early 1960s to the present. The results obtained supported the view that money growth provides timely warning signals of transitions between inflation regimes.

Other studies include that of Kaihatsu and Nakajima (2015) where the researchers proposed a new econometric framework for estimating trend inflation and the slope of the Phillips curve with the regime-switching model. As a unique approach, the regimes for the trend inflation were assumed at one-percent intervals, and the probability of the trend inflation being in each regime were estimated. The empirical result indicated that Japan’s trend inflation stayed at zero percent for about 15 years after the late 1990s, and then shifted away from zero percent after the introduction of the price stability target and the quantitative and qualitative monetary easing in 2013. Kaihatsu and Nakajima (2015) concluded that this modeling framework is simple enough that it can be applied to a wide range of models and can be extended to a multivariate inflation model.

3 METHODOLOGY

3.1 Data

This study focused on three variables, namely: (1) Inflation Rate, (2) price of Diesel, and (3) price of Rice. Monthly Philippine inflation rate data, which includes the (1) Headline Inflation and the (2) Inflation of the Bottom 30% Households, released by the Philippine Statistics Authority (PSA) were used. The PSA calculates and announces the monthly rate of inflation and the CPI based on a nationwide monthly survey of prices for a given basket of commodities. The PSA also determines the composition of the CPI basket through the nationwide Family Income and Expenditure Survey (FIES), which is conducted every three years. Prices of Rice was also obtained from the PSA. Specifically, the price of rice is based on the retail price of Regular Milled Rice (RMR) obtained from the weekly Cereals and Fertilizer Price Monitoring (CFPM) report. Meanwhile, the common domestic price of diesel was obtained from the Price Watch - Oil Monitor report published weekly by the Department of Energy. First differences of logged values of variables were generated to reduce asymmetry, induce stationarity, and obtain growth rates as this allows for better implications during analysis and discussion of results. Furthermore, the study used monthly data from January 2008 to April 2018.

3.2 Statistical Analyses

Descriptive statistics were generated to describe the trend of inflation and prices of commodities. Unit Root Test using Dickey-Fuller GLS was utilized to test for the stationarity of the data and for the presence of unit roots. Granger Causality test was used to determine the relationship among the variables. Threshold Autoregressive model was fitted on inflation using diesel price as the threshold variable. Finally, Markov Regime-Switching was fitted on inflation and the transition probabilities and expected duration of the states were estimated. All necessary statistical analyses were done with the aid of *Eviews*. Each statistical method used is discussed in detail in the following subsections.

3.2.1 Unit Root Tests

A series is said to be stationary if the mean and autocovariances of the series do not depend on time (Zivot & Wang, 2010). Any series that is not stationary is said to be nonstationary. Standard inference procedures do not apply to regressions which contain an integrated dependent variable or integrated regressors. Therefore, it is important to check whether a series is stationary or not before using it in a regression. The formal method to test the stationarity of a series is the unit root test. This study utilized the GLS-detrended Dickey-Fuller (Elliot, Rothenberg, and Stock, 1996) in testing the variables for the presence of a unit root. Consider a simple AR(1) process:

$$y_t = \rho y_{t-1} + x_t'\delta + \epsilon_t \tag{3.2.1.1}$$

where x_t are optional exogenous regressors which may consist of constant, or a constant and trend, ρ and δ are parameters to be estimated, and the ϵ_t are assumed to be white noise.

If $|\rho| \geq 1$, y_t is a nonstationary series and the variance of y_t increases with time and approaches infinity. If $|\rho| < 1$, y_t is a stationary series. Thus, the hypothesis of stationarity can be evaluated by testing whether the absolute value of ρ is strictly less than one. The DF-GLS tests the null hypothesis $H_0\colon \rho = 1$ against the one-sided alternative $H_1\colon \rho < 1$. For the constant or constant and linear time trend cases, Elliot, Rothenberg, and Stock (1996) proposed a simple modification of the ADF tests in which the data are de-trended so that explanatory variables are “taken out” of the data prior to running the test regression.

Elliot, Rothenberg, and Stock (1996) defined a quasi-difference of y_t that depends on the value a representing the specific point alternative against to test the null:

$$d(y_t|a) = \begin{cases} y_t & if\ t = 1 \\ y_t - ay_{t-1} & if\ t > 1 \end{cases} \tag{3.2.1.2}$$

Next, consider an OLS regression of the quasi-differenced data $d(y_t|a)$ on the quasi-differenced $d(x_t|a)$:

$$d(y_t|a) = d(x_t|a)'\delta(a) + \eta_t \tag{3.2.1.3}$$

where x_t contains either a constant, or a constant and trend, and let $\delta(a)$ be the OLS estimates from this regression.

Elliot, Rothenberg, and Stock (1996) recommended the use of $= \bar{a}$, where:

$$\bar{a} = \begin{cases} 1 - 7/T & if\ x_t = \{1\} \\ 1 - 13.5/T & if\ x_t = \{1, t\} \end{cases} \tag{3.2.1.4}$$

Therefore, using the estimates associated with the $\bar{a}$, the GLS de-trended data, y_t^d, is defined as:

$$y_t^d = y_t - x_t'\delta(\bar{a}) \tag{3.2.1.5}$$

Then, the DF-GLS test involves estimating the standard ADF test equation after substituting the GLS de-trended y_t^d for the original y_t:

$$\Delta y_t^d = \alpha y_{t-1}^d + \beta_1 \Delta y_{t-1}^d + \cdots + \beta_p \Delta y_{t-p}^d + \upsilon_t \tag{3.2.1.6}$$

Note that since the y_t^d are de-trended, the x_t is not included in the DF-GLS test equation. As with the ADF test, consider the t-ratio for $\hat{\alpha}$ from this test equation. While the DF-GLS t-ratio follows a Dickey-Fuller distribution in the constant only case, the asymptotic distribution differs when both a constant and trend are included. The null hypothesis is rejected for values that fall below the critical values (Zivot & Wang, 2010).

3.2.2 Granger Causality Test

The Granger Test was used to check for causal relationships among the variables. This test aims to check whether x causes y and to see how much of the current y can be explained by past values of y and then to see whether adding lagged values of x can improve the explanation (EViews User Guide, 2017). y is said to be Granger-caused by x if x helps in the prediction of y, or equivalently if the coefficients on the lagged x's are statistically significant. Note that two-way causation is frequently the case; x Granger causes y and y Granger causes x.

It is important to note that the statement "x Granger causes y" does not imply that y is the effect or the result of x. Granger causality measures precedence and information content but does not by itself indicate causality in the more common use of the term (EViews User Guide, 2017).

Given a lag length, l, which corresponds to reasonable beliefs about the longest time over which one of the variables could help predict the other, consider the bivariate regressions of the form:

$$\begin{aligned} y_t &= \alpha_0 + \alpha_1 y_{t-1} + \cdots + \alpha_l y_{t-l} + \beta_1 x_{t-1} + \cdots + \beta_l x_{t-l} + \epsilon_t \\ x_t &= \alpha_0 + \alpha_1 x_{t-1} + \cdots + \alpha_l x_{t-l} + \beta_1 y_{t-1} + \cdots + \beta_l y_{t-l} + u_t \end{aligned} \qquad (3.2.2.1)$$

for all possible pairs of (x, y) series in the group.

The reported F-statistics are the Wald statistics for the joint hypothesis for each equation:

$$\beta_1 = \beta_2 = \cdots = \beta_t = 0 \qquad (3.2.2.2)$$

The null hypothesis is that x does not Granger-cause y in the first regression and that y does not Granger-cause x in the second regression.

3.2.3 Threshold Autoregressive Model (TAR)

Consider a simple AR(p) model for a time series $\mathrm{y_t}$:

$$y_t = \mu + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots + \emptyset_p y_{t-p} + \sigma\epsilon_t \qquad (3.2.3.1)$$

where $\emptyset_i (i = 1, 2, \ldots, p)$ are the AR coefficients, $\epsilon_t \sim WN(0, 1)$ and $\sigma > 0$ is the standard deviation of disturbance term.

The model parameters $\emptyset = (\mu, \emptyset_1, \emptyset_2, \ldots, \emptyset_P)$ and σ are independent of time t and remain constant (Hansen, 2000). To capture nonlinear dynamics, TAR models allow the model parameters to change according to the value of a weakly exogenous threshold variable z_t:

$$y_t = \boldsymbol{X}_t \emptyset^{(j)} + \sigma^{(j)} \epsilon_t \; if \; r_{j-1} < z_t \leq r_j \qquad (3.2.3.2)$$

where $X_t = (1, y_{t-1}, y_{t-2}, \ldots, y_{t-p}), j = (1, 2, \ldots, k)$ and $-\infty = r_0 < r_1 < \cdots < r_k = \infty$.

In essence, the $k - 1$ non-trivial thresholds $(r_1, r_2, \ldots, r_{k-1})$ divide the domain of the threshold variable z_t into k different regimes. In each different regime, the time series y_t follows a different AR(p) model.

In the context of the study, the inflation rate model is defined of the form:

$$INF = f(X_1, X_2) \qquad (3.2.3.3)$$

where INF is the Inflation Rate, X_1 is the price of Diesel, and X_2 is the price of Rice.

Consider the regression equation below which is the standard linear model of equation (3.2.3.3):

$$INF = \alpha_0 + \beta_1 X_1 + \beta_2 X_2 + e_t \qquad (3.2.3.4)$$

However, as discussed above, a myriad of recent studies predicts the presence of threshold effects associated with rates of inflation above or below certain critical values. Thus, discussed below are peculiar econometric issues pertaining to the estimation and inference of economic models with threshold effects.

The TAR model presents tests for threshold effects, threshold parameter estimation, and the identification of threshold parameter asymptotic confidence intervals. The concept behind these tests by Hansen (2000) is that an exogenously given variable, which may or may not be a regressor, is used to split the sample into two regimes. More distinctly, consider a two-regime structural equation in a TAR model:

$$y_t = \begin{cases} \theta_1' x_t + e_{1t}, & if\ DIESEL_t < k \\ \theta_1' x_t + e_{1t}, & If\ DIESEL_t \geq k \end{cases} \qquad \begin{matrix} (3.2.3.5) \\ (3.2.3.6) \end{matrix}$$

where $DIESEL$ is the regime-splitting threshold variable, y_t is the dependent, and x_t is explanatory variables, e_{1t} is the error term white-noise properties, and k is the threshold value or parameter.

Prior knowledge of k permits an OLS estimation, however since the threshold value is not known a priori, it has to be estimated in addition to other parameters. It is important to note that when the threshold variable is greater than the threshold parameter, the model estimates equation (3.2.3.5). Conversely, the model estimates equation (3.2.3.6) when the reverse is the case.

The post estimation sum of squared residuals (SSR) can be written as:

$$S_1(k) = \hat{e}_t(k)' \hat{e}_t(k) \qquad (3.2.3.7)$$

The least squares technique is recommended by Hansen (2000) in estimating the threshold parameter k, and Munir and Mansur (2009) note that the minimization of SSR as a function of the expected threshold value is the easiest approach to implementing Hansen's recommendation. Thus, the optimal threshold value can be written as:

$$\hat{k} = \arg\min S_1(k) \qquad (3.2.3.8)$$

Conditional on $\hat{k}$, the regression equation is linear in θ and δ', giving rise to the conditional OLS estimates of $\hat{\theta}(k)$ and $\delta'(k)$ by regression of dependent variable on explanatory variables. Following Khan and Senhadji (2001) and the foregoing procedure, the linear equation (3.2.3.4) can be expressed as a nonlinear equation under a two-regime TAR model as follows:

$$INF = \begin{cases} \alpha_0 + \beta_1 DIESEL + \beta_3 RICE + \epsilon_t & if\ DIESEL_t < k \\ \alpha_0 + \beta_2 DIESEL + \beta_3 RICE + \epsilon_t & if\ DIESEL_t \geq k \end{cases} \tag{3.2.3.9}$$

where $DIESEL$ = log difference of the price of Diesel and $RICE$ = log difference of the price of Rice.

The two variables, $DIESEL$ and $RICE$, are expected to be positively signed. From equation (3.2.3.9), the optimal threshold value can be determined by obtaining the threshold value that minimizes the RSS. The threshold variable which will be used in the analysis is $DIESEL$, since the one of the primary goals of this paper is to investigate the threshold effects of $DIESEL$ in inflation.

For the test on the number of threshold and number of regimes, *EViews* uses the methodologies of Bai and Perron (1998), and not the fixed regressor bootstrap testing proposed by Hansen (1999). The threshold values are estimated sequentially by finding an initial threshold value that minimizes the residual sums of squares, then searching for additional values given the initial value that minimize the SSR until the desired number of thresholds, possibly determined through testing, is obtained. Specifically, this study used Sequential L+1 breaks vs. L where the number of thresholds is not known and the maximum number of thresholds allowed was set to five.

3.2.4 Markov-Regime Switching Model (MSW)

The Markov-Regime Switching model of Hamilton (1989) is one of the popular nonlinear time series models in the literature. This model is constructed by combining two or more dynamic models using a Markovian switching mechanism (Kuan, 2002). The MSW posits that two or more regimes could have prevailed over the course of the time series. However, it differs from models with imposed breaks such as Threshold Regression, because the timing of breaks in MSW is entirely endogenous. The breaks are not explicitly imposed, but inferences are drawn on the basis of probabilistic estimates of the most likely state prevailing at each point in history. The estimates of parameters for the most likely regimes are generated using maximum likelihood techniques. With the parameters identified, it is then possible to estimate the probability that the variable of interest, in this case inflation, is following one of the alternative regimes. This involves identifying where in the probability distribution of each regime the observation falls at each point in time (Simon, 1996).

To start, consider a classical linear regression model given by:

$$y_t = x_t'\beta + \epsilon_t \tag{3.2.4.1}$$

where the data are independently and identically normally distributed such that $\epsilon_t \sim i.i.d.N(0, \sigma^2)$ for $t = 1, \ldots, T$.

The key assumption in model (3.2.4.1), however, is that the parameters are constant through time, which would not be true if some sort of structural break occurred in the series and the model suddenly changed. One alternative is to make the structural break endogenous to the model since in many cases the timing of the shift may not be known. By this, inferences about the process that drives these shifts can be made. Models that shift between various densities allow to incorporate structural breaks in the estimation procedure (Paliouras, 2007). Instead of assuming a single density for the data, regime (or state) switching models assume that the observations come from a mixture of r parametric distributions given by:

$$Y_t = \begin{cases} f(y_t|\theta_1, \mathcal{F}_{t-1}), & if\ S_t = 1 \\ f(y_t|\theta_2, \mathcal{F}_{t-1}), & if\ S_t = 2 \\ \vdots & \vdots \\ f(y_t|\theta_r, \mathcal{F}_{t-1}), & if\ S_t = r \end{cases} \tag{3.2.4.2}$$

where θ_i contains the parameters of the model i and $\theta_i \neq \theta_{ij}$ if $i \neq j$.

Here, S_t is an unobserved discrete state variable that determines the conditional distribution of Y_t, which is time dependent. Moreover, $\mathcal{F}_{t-1} = \sigma(X_t, X_{t-1}, \ldots, X_{t-p}, Y_{t-1}, \ldots, y_{t-p})$ is the sigma algebra generated by the known vector of exogenous random variables or known functions of random variables, or more simply the information known up to time $t-1$.

The number of states r is unknown but most applications assume that $r = 2$ or $r = 3$. This study assumes that there are only two states, $r = 2$ such that inflation follows a two regime or two state ($S_t = 0$ or $S_t = 1$) Markov-switching process. With two states, the linear model in (3.2.4.2) becomes:

$$
\begin{aligned}
y_t &= x_t'\beta_{S_t} + \epsilon_t \quad \epsilon_t \sim i.i.d. N(0, \sigma_{S_t}^2) \\
\beta_{S_t} &= \beta_1 S_t + \beta_0 (1 - S_t) \\
\sigma_{S_t}^2 &= \sigma_1^2 S_t + \sigma_0^2 (1 - S_t)
\end{aligned}
\tag{3.2.4.3}
$$

Thus, under regime $S_t = i$ the parameters are given by $\theta_i = (\beta_i, \sigma_{S_t}^2)$. However, the state vector S_t is not known a *priori*, so distributional assumptions about probability of being in a given state must be made. Let $p_{ij} = P(S_t = i|\mathcal{F}_{t-1}; \gamma)$ with the restrictions $p_{ij} \geq 0$ and $\sum_{i=1}^{r} p_{ij} = 1$, where γ contains the parameters associated with the probability law of S_t. To complete the model, the properties of the process S_t need to be specified.

One novel feature of the Markov switching model is that the switching mechanism is controlled by an unobservable state variable that follows a first-order Markov chain, where the current value of the state variable depends on its immediate past value. In particular, the Markovian state variable yields random and frequent changes of model structures, and its transition probabilities determine the persistence of each regime. While the threshold model also possesses similar features, the Markov switching model is relatively easy to implement because it does not require choosing a priori the threshold variable. Instead, the regime classification in this model is probabilistic and determined by data (Kuan, 2002).

As such, a structure may prevail for a random period of time, and it will be replaced by another structure when a switching takes place (Kuan, 2002). This implies that the current regime S_t only depends on the regime one period ago, S_{t-1} and not on past values of y or x (Franses & van Dijk, 2000). That is, the likelihood is calculated for each possible state. The probability that a particular state is prevailing is obtained by dividing the likelihood of that state by the total likelihood for both states. Thus, the sum of all the probabilities will equal one. With this estimate of the probabilities, it is common to infer that a state is prevailing when the probability estimate for that state is greater than 50%.

Some of the values may lie close to zero or one tend to occur, making identification of the prevailing state relatively easy. Hence, the transition probabilities of moving from one state of inflation to another state of inflation are defined as:

$$\begin{aligned} P(S_t = 0|S_{t-1} = 0) = p_{00} \\ P(S_t = 1|S_{t-1} = 0) = p_{10} \\ P(S_t = 0|S_{t-1} = 1) = p_{01} \\ P(S_t = 1|S_{t-1} = 1) = p_{11} \end{aligned} \qquad (3.2.4.4)$$

Therefore, p_{ij} is equal to the probability that the Markov chain moves from state i at time $t-1$to state j at time t. As such, the probability that regime i at time $t-1$ is followed by regime j at time t. Obviously, for the p_{ij}'s to define proper probabilities, the values should be nonnegative, while it should also hold that $p_{00} + p_{01} = 1$ and $p_{10} + p_{11} = 1$.

Also of interest in the MSW models are the unconditional probabilities that the process is in each of the regimes, that is, $P(S_t = i)$ for $i = 0, 1$. Using the theory of ergodic Markov chains it is straightforward to show that for the MSW model these unconditional probabilities are given by:

$$\begin{aligned} P(S_t = 0) = \frac{1 - p_{11}}{2 - p_{00} - p_{11}} \\ P(S_t = 1) = \frac{1 - p_{00}}{2 - p_{00} - p_{11}} \end{aligned} \qquad (3.2.4.5)$$

Furthermore, another interesting feature of the MSW is the expected duration the series spends in a state. Let D_i denote the duration of state i. D_i follows a geometric distribution, then the expected duration is computed as:

$$E[D_i] = \frac{1}{1 - p_{ii}} \qquad (3.2.4.6)$$

The closer p_{ii} is to 1, the higher is the expected duration of state i.

This study deviates from the standard univariate models of inflation used in previous applications of the MSW methodology. Significant exogenous explanatory variables such as $DIESEL$ and $RICE$ will be included to improve the model and capture information on the nature of inflation uncertainty. $DIESEL$ will searve as the state-dependent variable, while $RICE$ will be assigned as a state-independent parameter. Therefore, the final MSW model is given by:

$$INF = \begin{cases} \alpha_0 + \beta_1 DIESEL + \beta_3 RICE + \epsilon_t & if\ S_t = 0 \\ \alpha_0 + \beta_2 DIESEL + \beta_3 RICE + \epsilon_t & if\ S_t = 1 \end{cases} \quad (3.2.4.7)$$

where $DIESEL$ = log difference of the price of Diesel, and $RICE$ = log difference of the price of Rice.

3.2.5 Diagnostic Tests

Diagnostic tests on the residuals were performed to determine the final TAR and MSW models for the Headline inflation and the Bottom 30% Inflation. These tests include the Jarque-Bera Test for Normality, the White's Test for Heteroskedasticity and the Breusch-Godfrey Lagrange Multiplier Test for Serial Autocorrelation. Each of these tests were discussed in detail in following subsections.

3.2.5.1 Jarque-Bera Test for Normality

Jarque-Bera is a test statistic for testing whether the series is normally distributed. The test statistic measures the difference of the skewness and kurtosis of the series with those from the normal distribution (EViews User Guide, 2017). The statistic is computed as:

$$Jarque - Bera = \frac{N}{6}\left(S^2 + \frac{(K-3)^2}{4}\right) \quad (3.2.5.1.1)$$

where S is the skewness, and K is the kurtosis.

Under the null hypothesis of a normal distribution, the Jarque-Bera statistic is distributed as χ^2 with 2 degrees of freedom.

3.2.5.2 White's Test for Heteroscedasticity

White's (1980) test is a test of heteroscedasticity. The null hypothesis is homoscedasticity against the alternative hypothesis of heteroscedasticity of unknown, general form. The test statistic is computed by an auxiliary regression, where the squared residuals are regressed on all possible (nonredundant) cross products of the regressors. Consider the following regression:

$$y_t = b_1 + b_2 x_t + b_3 z_t + e_t \qquad (3.2.5.2.1)$$

where b are the estimated parameters and e_t the residual.

The test statistic is then based on the auxiliary regression:

$$e_t^2 = \alpha_0 + \alpha_1 x_t + \alpha_1 z_t + \alpha_3 x_t^2 + \alpha_4 z_t^2 + v_t \qquad (3.2.5.2.2)$$

EViews output reports three test statistics from the test regression. First is the *F-statistic* which is a variable test for the joint significance of all cross products, excluding the constant. It is presented for comparison purposes. The NR^2 statistic is White's test statistic, computed as the number of observations multiplied by the centered R^2 from the test regression. The exact finite sample distribution of the F-statistic under the null hypothesis is not known, but White's test statistic is asymptotically distributed as a χ^2 with degrees of freedom equal to the number of slope coefficients, excluding the constant, in the test regression. The third statistic, an LM statistic, is the explained sum of squares from the auxiliary regression divided by $2\sigma^4$. This is also distributed as chi-squared distribution with degrees of freedom equal to the number of slope coefficients, minus the constant, in the auxiliary regression. White also describes this approach as a general test for model misspecification, since the null hypothesis underlying the test assumes that the errors are both homoscedastic and independent of the regressors, and that the linear specification of the model is correct. Failure of any one of these conditions could lead to a significant test statistic. Conversely, a non-significant test statistic implies that none of the three conditions is violated (User Guide, 2017).

3.2.5.3 Breusch-Godfrey Lagrange Multiplier Test for Autocorrelation

Serial correlation is defined as correlation between the observations of residuals. It can be caused by a missing variable, an incorrect functional form, or the pure serial correlation that frequently arises in the time series data. In order to test for autocorrelation, the study will utilize the Breusch-Godfrey Lagrange multiplier Test. The null hypothesis of the test is that there is no serial correlation in the residuals up to the specified order. Consider the linear regression model:

$$y_t = \beta_1 x_{1t} + \cdots + \beta_k x_{kt} + u_t \tag{3.2.5.3.1}$$

where the covariates $x_1$through x_k are not assumed to be strictly exogenous and u_t is assumed to be i.i.d. and to have finite variance. The process is also assumed to be stationary.

Estimating the parameters in (3.2.5.3.1) by OLS obtains the residuals $\hat{u}_t$. Next, another OLS regression is performed of $\hat{u}_t$on $\hat{u}_{t-1}, \ldots, \hat{u}_{t-p}$ and the other regressors:

$$\hat{u}_t = \gamma_1 \hat{u}_t + \cdots + \gamma_p \hat{u}_{t-p} + \beta_1 x_{1t} + \cdots + \beta_k x_{kt} + \epsilon_t \tag{3.2.5.3.2}$$

where ϵ_t stands for the random-error term in this auxiliary OLS regression.

The Breusch–Godfrey test is an LM test of the null hypothesis of no autocorrelation versus the alternative that u_t follows an $AR(p)$ or $MA(p)$ process. It is based on the auxiliary regression (3.2.5.3.2), and it is computed as NR^2, where N is the number of observations and R^2 is the simple R^2 from the regression. This test and Durbin's alternative test are asymptotically equivalent. The test statistic NR^2 has an asymptotic χ^2 distribution with p degrees of freedom.

3.2.6 Akaike Information Criterion

The Akaike Information Criterion (AIC) is a model selection tool (Hu, 2007). AIC is given by the formula:

$$AIC = -2 * log\mathcal{L}(\hat{\theta}|y) + 2k \qquad (3.2.6.1)$$

where $\mathcal{L}$ is the likelihood function, $\hat{\theta}$ is the maximum likelihood estimate of θ and k is the number of estimated parameters (including the variance).

To use AIC for model selection, the model giving smallest AIC is chosen over the whole set of candidates. AIC attempts to mitigate the risk of over-fitting by introducing the penalty term $2k$, which grows with the number of parameters. The lower AIC score signals a better model. This filters out unnecessarily complicated models, which have too many parameters to be estimated accurately on a given data set of size N. AIC has preference for more complex models compared to Bayesian Information Criterion (BIC) (Hu, 2007).

4 RESULTS AND DISCUSSION

This section first describes the trends in inflation rate, in price of diesel and in price of rice. Subsequently, these variables were tested for the stationarity. This is followed by the discussion of the Threshold Autoregressive models and the Markov Regime Switching models.

4.1 Trends in Inflation

In 2017, the inflation was posted at 3.20% which is within the national government's announced target range of 2.0% and 4.0% for the year. In 2016 and 2015, inflation fell below the target range, while inflation was way above in 2008 due to the surge in the international prices of oil and food commodities resulting in higher domestic rice and pump prices of fuel (BSP, 2017). Nonetheless, inflation was stable and within targets from 2009 until 2014.

Figure 1. Monthly Inflation from January 2008 to April 2018

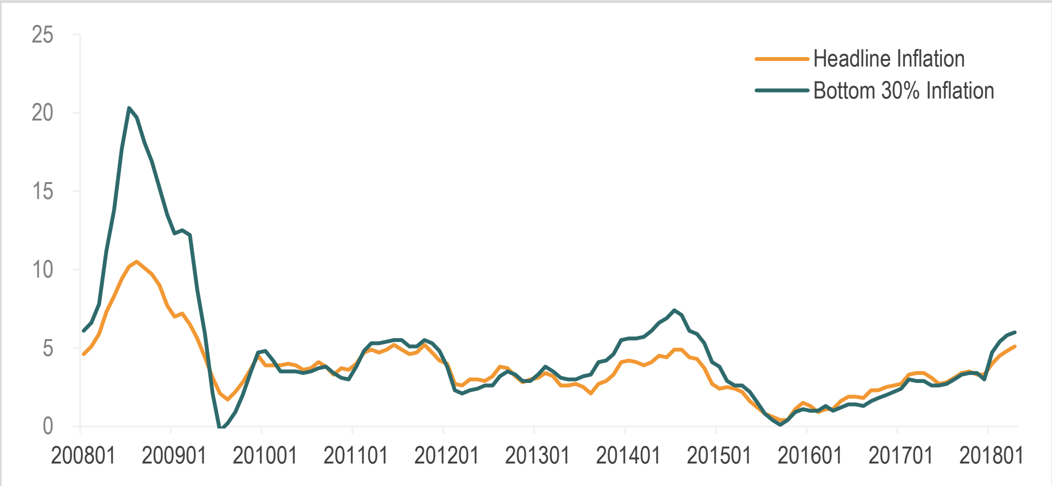


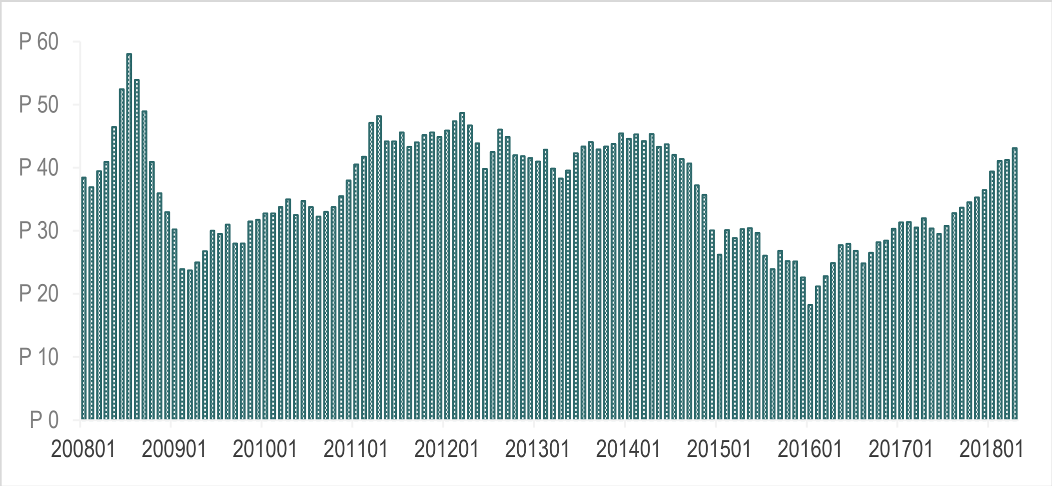
Table 1: Actual Inflation vs. Target Inflation

Year	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Actual Inflation	8.30	4.20	3.80	4.60	3.20	3.00	4.10	1.40	1.80	3.20
Target Inflation	4.0±1	3.5±1	4.5±1	4.0±1	4.0±1	4.0±1	4.0±1	3.0±1	3.0±1	3.0±1
Actual vs. Target	Higher	Within	Within	Within	Within	Within	Within	Below	Below	Within

4.2 Trends in Price of Diesel

Figure 2 shows the trend in the prices of fuel, particularly of diesel during the period January 2008 to April 2018. During the period covered, price of diesel was at its peak during the months of July 2008 at about PHP58.01 per liter. Although prices started to continuously decline from March 2014 to January 2016, it has started to ramp up thereafter. These changes in prices are expected to greatly affect not only the sectors which are directly dependent on diesel but also other sectors of the economy (Reyes et al, 2009).

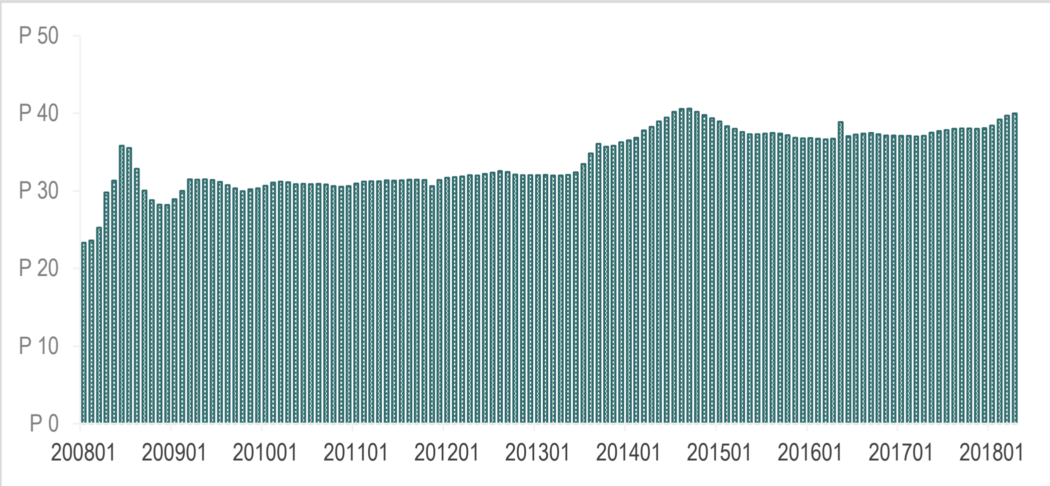
Figure 2. Monthly Price of Diesel from January 2008 to April 2018



4.3 Trends in Price of Rice

In terms of prices, retail prices of rice show a fairly stable trend during the period of January 2009 to June 2013 as shown in Figure 3. However, rice prices significantly increased starting July 2013. During the period covered in this study, price of rice was at its highest in September 2014. In particular, retail price of ordinary rice reached its peak at about PHP40.58 per kilogram.

Figure 3. Monthly Price of Rice from January 2008 to April 2018



4.4 Unit Root Tests

Inflation Rate, price of Diesel and price of Rice were first tested for the presence of unit roots using Dickey-Fuller – GLS. Table 2 summarizes the test statistics for the test equations with (1) intercept and (2) intercept and trend. For the DF-GLS, the null hypothesis is the presence of unit root which indicates non-stationarity. At 1% significance level, the critical values are -2.5840 for the equation with constant, and -3.5536 for the equation with constant and linear trend. Results showed that only Bottom 30% inflation has no unit root. Headline Inflation, price of Diesel (in log) and price of Rice (in log) have unit roots, and are, therefore, non-stationary.

Table 2: DF-GLS Unit Root Tests on Variables

Variable	DF-GLS Test Statistics		Conclusion
	Intercept	Trend and Intercept	
Headline Inflation	-2.5412	-2.9710	Non-stationary; I(1)
Bottom 30% Inflation	-3.3791	-3.9496	No unit root
Diesel (in log)	-1.6170	-1.6190	Non-stationary; I(1)
Rice (in log)	-0.3518	-2.7108	Non-stationary; I(1)

**the critical values at 1% significance level are: (1) Equation with Constant = -2.5840, and (2) Equation with Constant and Linear Trend= -3.5536.*

In addition, all the variables at level showed evidence of seasonality. Therefore, transformations for the variables were applied to ensure that the indicators are stationary and are free from seasonal effects at 1% significance level (see Appendix Table A09-A12). Specifically, Headline Inflation and Bottom 30% Inflation were de-trended using first difference, while first differences of logged values were generated for price of Diesel and price of Rice. Consequently, for better interpretation in the discussion of results, differenced Headline Inflation and differenced bottom 30% Inflation will be referred to as change in Headline Inflation and change in Bottom 30% Inflation, respectively. The first difference of logged values of the price of Diesel and the price of Rice will be referred to as growth in price of Diesel and growth in price of Rice, respectively.

Table 3: Variable Codes, Transformations and Interpretation

Variable	Code	Transformation	Interpretation
Headline Inflation	INF_H	D(INF_H)	Change in Headline Inflation
Bottom 30% Inflation	INF_P	D(INF_P)	Change in Bottom 30% Inflation
Diesel	DIESEL	DLOG(DIESEL)	Growth in Price of Diesel
Rice	RICE	DLOG(RICE)	Growth in Price of Rice

4.5. Granger Causality Test

Granger Causality Test was employed to determine existing relationships among the variables. At 10% significance level, the test results detailed in Appendix Table A13 indicate: (1) one-way causality from growth in price of Diesel to change in Headline Inflation, (2) one-way causality from growth in price of Rice to change in Headline Inflation, and (3) one-way causality from change in Bottom 30% Inflation to change in Headline Inflation.

4.6. Threshold Autoregressive (TAR) Models

TAR models were generated for the Headline Inflation and the Bottom 30% Inflation using price of Diesel as the threshold variable. Test for the number of thresholds and regimes was done using Bai-Perron tests of L+1 vs. L sequentially determined thresholds. The threshold value was then estimated endogenously through the model. The variances were allowed to be heterogeneous across breaks. Models with specified threshold value were also fitted and the model which minimizes the Akaike Criterion (AIC) was selected. Lag effects were also added to improve the model.

4.6.1 Headline Inflation TAR Models

Bai and Perron (1998) Test was performed to test for multiple breaks. It starts by testing the null hypothesis of no break against the alternative hypothesis of one break, followed by two breaks, until five breaks. If evidence of at least one break is found, it will then employ the sequential testing procedure to determine the number of breaks.

The Bai-Perron Test identified two regimes with one threshold value for the change in Headline Inflation TAR model without lag effects. Notably, there were no regimes and threshold values determined for the TAR-AR(1) and TAR-AR(2) models. Thus, the TAR model without lag effects was selected. The results are shown in Table 4.

Table 4: Bai-Perron Test on Number of Thresholds and Regimes of the Change in Headline Inflation Models

Threshold Test	F-Statistic	Scaled F-Statistic	Critical Value**
TAR			
0 vs. 1*	8.6598	8.6598	8.5800
1 vs. 2	1.5541	1.5541	10.1300
Sequential F-Statistic Determined Thresholds			1
Threshold Value			30.05
TAR-AR(1)			
0 vs. 1	3.4890	6.9781	11.4700
Sequential F-Statistic Determined Thresholds			0
Threshold Value			NONE
TAR-AR(2)			
0 vs. 1	2.7274	8.1823	13.9800

Sequential F-Statistic Determined Thresholds	0
Threshold Value	NONE

**significant at 5% level*
***Bai-Perron (Econometric Journal, 2003) critical values*

The results of TAR for the change in Headline Inflation were summarized in Table 5. The model estimated PHP30.05 as the threshold value of the price of Diesel for the Headline Inflation model. TAR models were also generated using the following specified threshold values: PHP 30, PHP 31, PHP 32, PHP 33, PHP 34 and PHP 35. All the models showed significant effect of growth in price of Diesel for Diesel prices above the threshold value. Growth in price of Rice, which is a state-independent variable, is also significant across all models. The models were then compared using the Akaike Information Criterion and the model with estimated threshold (PHP 30.05) was chosen since it has the lowest AIC among the Headline Inflation TAR models.

Table 5: Threshold Autoregressive Models for Change in Headline Inflation

Dependent Variable: D(INF_H)							
Threshold	**Estimated**	**Specified**					
	PHP 30.05	**PHP 30**	**PHP 31**	**PHP 32**	**PHP 33**	**PHP 34**	**PHP 35**
Diesel Below Threshold							
DLOG(Diesel)	-0.7220	-0.1892	0.2412	0.4874	0.7117	0.6752	0.6246
Diesel Above Threshold							
DLOG(Diesel)	3.0590*	2.4819*	2.8099*	2.6411*	2.4235*	2.5256*	2.6784*
Non-Threshold Variables							
DLOG(Rice)	4.5807*	4.9757*	4.6431*	4.7513*	4.9476*	4.8707*	4.7587*
C	-0.0311	-0.0312	-0.0281	-0.0225	-0.0240	-0.0230	-0.0215
Akaike Info Criterion	1.2575	1.3000	1.3041	1.3153	1.3249	1.3225	1.3187

**significant at 5% level*

From the final Headline Inflation TAR model shown in Table 6, a threshold value of PHP 30.05 is identified. The growth in price of Diesel is significant only in Regime 2 – when price of Diesel is above the threshold. That is, if diesel price is at least PHP 30.05, a

10% growth in price of Diesel will give a 0.3059 percentage point change in Headline Inflation. It is also worth pointing out that within the first regime where the price of Diesel is below the threshold, the coefficient of the growth in price of Diesel is not significant. This, however, is not a problem since it is actually consistent with the expectation of the study. The growth in price of Rice is significant and positive which is a clear evidence of the importance of price of Rice, being a staple food, on the change in Headline Inflation. As such, if the price of Rice grew by 10%, the change in Headline Inflation will increase by 0.4581 percentage point.

Table 6: Threshold Autoregressive Model for Change in Headline Inflation with PHP30.05 as the Threshold Value

Dependent Variable: D(INF_P)				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**p-value**
Diesel < 30.05				
DLOG(Diesel)	-0.7220	1.0464	-0.6899	0.4916
Diesel >= 30.05				
DLOG(Diesel)	3.0590	0.7686	3.9798	0.0001*
Non-Threshold Variables				
DLOG(Rice)	4.5807	2.2762	2.0124	0.0464*
C	-0.0311	0.0599	-0.5196	0.6043
		Log Likelihood		-73.3361
		F-Statistic		11.3621
		Prob(F-Statistic)		0.0000*
		Akaike Info Criterion		1.2575
		Jarque-Bera**		0.0590
		Breusch-Godfrey**		0.0000*
		White**		0.7588

**significant at 5% level; **p-value*

Furthermore, diagnostic tests of the residuals revealed that the residuals follow normal distribution and are homoscedastic. However, results of the Breusch-Godfrey test showed presence of serial autocorrelation, thus standard errors robust to autocorrelation were generated.

4.6.2 Bottom 30% Inflation TAR Models

Three TAR models of the change in Bottom 30% Inflation were estimated, namely, TAR without lag effects, TAR-AR(1) and TAR-AR(2). Results of the Bai-Perron test, detailed in Tables 7, did not support existence of regimes and threshold for the change in Bottom 30% Inflation model without lag effects. On the other hand, when the lag effects were added, the test identified a threshold value of PHP 30.25 for both the TAR-AR(1) model and the TAR-AR(2) model.

Table 7: Bai-Perron Test on Number of Thresholds and Regimes of the Change in Bottom 30% Inflation Models

Threshold Test	F-Statistic	Scaled F-Statistic	Critical Value**
TAR			
0 vs. 1	7.3694	7.3694	8.5800
Sequential F-Statistic Determined Thresholds			0
Threshold Value			NONE
TAR-AR(1)			
0 vs. 1*	8.7733	17.5466	11.4700
1 vs. 2	3.4123	6.8246	12.9500
Sequential F-Statistic Determined Thresholds			1
Threshold Value			30.25
TAR-AR(2)			
0 vs. 1*	5.3167	15.9501	13.9800
Sequential F-Statistic Determined Thresholds			1
Threshold Value			30.25

**significant at 5% level*
***Bai-Perron (Econometric Journal, 2003) critical values*

The fitted models for TAR-AR(1) and TAR-AR(2) are shown in Tables 8 and 9, respectively. Model selection was performed using the Akaike Information Criterion and some residual diagnostic tests, including normality, homoscedasticity and serial autocorrelation. The results indicate that the two models satisfied these diagnostic tests except for normality. Notably, TAR-AR(1) has relatively lower AIC value compared to TAR-AR(2). Therefore, following the principle of AIC, the TAR-AR(1) model is chosen.

Table 8: Threshold Autoregressive Model for the Change in Bottom 30% Inflation of the Poor with PHP30.25 as the Threshold Value

Dependent Variable: D(INF_P)				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**p-value**
Diesel < 30.25				
DLOG(Diesel)	-1.8285	1.3562	-1.3483	0.1802
D(INF_P)(-1)	0.8254	0.1167	7.0728	0.0000*
Diesel >= 30.25				
DLOG(Diesel)	3.6755	1.0091	3.6424	0.0004*
D(INF_P)(-1)	0.4370	0.0601	7.2699	0.0000*
Non-Threshold Variables				
DLOG(Rice)	12.8942	1.9485	6.6174	0.0000*
C	-0.0368	0.0527	-0.6988	0.4861
			Log Likelihood	-100.2865
			F-Statistic	52.5985
			Prob(F-Statistic)	0.0000*
			Akaike Info Criterion	1.7424
			Jarque-Bera**	0.0000*
			Breusch-Godfrey**	0.3485
			White**	0.9698

**significant at 5% level; **p-value*
where D(INF_P)(-1) is lag 1 of INF_P.

Table 9: Threshold Autoregressive Model for Bottom 30% Inflation with PHP30.25 as the Threshold Value

Dependent Variable: D(INF_P)				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**p-value**
Diesel < 30.25				
DLOG(Diesel)	-1.8463	1.3714	-1.3462	0.1809
D(INF_P)(-1)	0.8053	0.1591	5.0614	0.0000*
D(INF_P)(-2)	0.0369	0.1748	0.2110	0.8333
Diesel >= 30.25				
DLOG(Diesel)	3.3669	1.0168	3.3113	0.0012*
D(INF_P)(-1)	0.5575	0.0882	6.3185	0.0000*
D(INF_P)(-2)	-0.1454	0.0776	-1.8741	0.0635

Non-Threshold Variables				
DLOG(Rice)	12.5274	2.0131	6.2228	0.0000*
C	-0.0273	0.0530	-0.5139	0.6083

Log Likelihood	-98.6202
F-Statistic	37.1285
Prob(F-Statistic)	0.0000*
Akaike Info Criterion	1.7623
Jarque-Bera**	0.0000*
Breusch-Godfrey**	0.3085
White**	0.9734

**significant at 5% level; **p-value*
where D(INF_P)(-1) and D(INF_P)(-2) are lag 1 and lag 2 of INF_P, respectively.

Using the TAR-AR(1) model, a set of TAR models for change in Bottom 30% Inflation were also generated with the following specified threshold values: PHP 30, PHP 31, PHP 32, PHP 33, PHP 34 and PHP 35. The results were summarized in Table 10 below. All the models showed significant lag effects in both regimes. Rice is also significant across all models. Results suggest that out of all the models, the model with estimated threshold PHP 30.25 has the least AIC value. Therefore, this was chosen as the final model for the change in Bottom 30% Inflation.

Table 10: Threshold Autoregressive Models for Change in Bottom 30% Inflation

Dependent Variable: D(INF_P)							
Threshold	**Estimated**	**Specified**					
	PHP 30.25	**PHP 30**	**PHP 31**	**PHP 32**	**PHP 33**	**PHP 34**	**PHP 35**
Diesel Below Threshold							
DLOG(Diesel)	-1.8285	-1.7639	-1.5735	-0.9027	-0.8403	-0.8840	-0.8898
D(INF_P)(-1)	0.8254*	0.6845*	0.8149*	0.7082*	0.7009*	0.7047*	0.7052*
Diesel Above Threshold							
DLOG(Diesel)	3.6755*	1.8455	3.6125*	2.6856*	2.7328*	2.9332*	3.0564*
D(INF_P)(-1)	0.4370*	0.5817*	0.4410*	0.5021*	0.5031*	0.4937*	0.4911*
Non-Threshold Variables							
DLOG(Rice)	12.8942*	13.0634*	12.8413*	12.8775*	12.8726*	12.7939*	12.7192*
C	-0.0368	-0.0686	-0.0352	-0.0427	-0.0469	-0.0433	-0.0406
Akaike Info Criterion	1.7424	1.8646	1.7624	1.8576	1.8605	1.8545	1.8525

**significant at 5% level*
where D(INF_P)(-1) is lag 1 of INF_P.

Based on Table 10, the final model identified PHP 30.25 as the threshold value of the price of Diesel. All the variables yielded significant coefficients except for the growth price of Diesel under the below threshold regime. D(INF_P)(-1) or the lagged one of the change in Bottom 30% Inflation is a useful predictor of the current change in Bottom 30% Inflation as it bears a significant and positive effect. According Pasaogullari & Meyer (2010), inflation tends to be a relatively persistent process, which means that past values are helpful in forecasting future inflation. In line with the expectations of the study, the growth in the price of Diesel has no significant effect on Bottom 30% Inflation when the price of Diesel is below the threshold, while it has a significant positive effect in the second regime. This indicates that the commodities typically consumed by the bottom 30% households are dependent on the price of Diesel. As highlighted by Reyes et al (2009), the impact of higher fuel prices can either be a direct effect of higher prices of petroleum products consumed by the household or an indirect effect on the prices of other goods and services consumed by the households that use fuel as an intermediate input. Lastly, the growth in the price of Rice stands as a significant variable in the change in Bottom 30% Inflation, and it bears a positive sign. In essence, the significance of Rice shows that the poor are highly sensitive to price changes in Rice as it is a staple food.

In summary, crucial to this finding first of all is that the current price of Diesel lies above the identified thresholds of PHP 30.05 for change in Headline Inflation, and PHP 30.25 for change in Bottom 30% Inflation. This suggests that the current increases in the diesel price will have significant positive effect on the inflation rate. Interestingly, the change in Headline Inflation model has a slightly lower threshold value for Diesel price (PHP 30.05) than the change in Bottom 30% Inflation model (PHP 30.25). In general, the findings thus lead to suggest that Diesel price has indeed threshold effects on inflation. The results also affirm the significant impact of growth in the price of Rice on inflation.

4.7 Markov Regime-Switching (MSW) Models

Markov Regime-Switching models were fitted for the change in Headline Inflation and the change in Bottom 30% Inflation. The error variances were allowed to be regime-specific in the models. Lag effects were added and model selection was done using the Akaike Criterion (AIC) and normality test. Robust standard errors were generated to account for heteroscedasticity and serial autocorrelation. Furthermore, the transition probabilities and expected durations were estimated for the final models.

4.7.1 Headline Inflation MSW Models

Three two-regime MSW models of change in Headline Inflation were generated: MSW without lag effects, MSW-AR(1) and MSW-AR(2). The AIC values and the results diagnostics tests of these models are summarized and compared in Table 11. Since the MSW model without lag effects has a relatively distant AIC value from the other models, this model was excluded from the potential models. MSW-AR(1) and MSW-AR(2) have relatively close AIC values, however, the normality of the residuals is rejected in both models. In view of parsimony, the MSW-AR(1) is chosen as the final model.

Table 11: Markov Regime-Switching Models for Change in Headline Inflation

	MSW	MSW-AR(1)	MSW-AR(2)
Log Likelihood	-68.1266	-51.9866	-50.3945
Akaike Info Criterion	1.2378	1.0162	1.0313
Jarque-Bera**	0.0137*	0.0281*	0.0006*

**significant at 5% level; **p-value*

The parameter estimates of the MSW-AR(1) model are shown in Table 12. Results indicate that Regime 1 is the "Low Inflation" state, while Regime 2 refers to the "High Inflation" state. All the variables are significant except for the growth in price of Diesel in Regime 1. As such, growth in price of Diesel has no significant effect at low levels of inflation, but has a significant positive effect in high inflationary period. First lag of the change in Headline Inflation, D(INF_H)(-1), helps to predict the change in Headline Inflation with a positive coefficient. Meanwhile, growth in price of Rice remains to have significant positive effect in both regimes – a 10% growth in the price of Rice will increase the change in Headline Inflation by 0.4777 percentage point. Using the estimates of the log standard deviation in the low and high inflation regimes, the implied standard deviations are 0.5553 and 0.3090, respectively. This indicate that the high inflationary regime has a relatively low variance and that the low inflationary regime is more volatile.

Table 12: Markov Regime-Switching Model for Change in Headline Inflation

Variable	Coefficient	Std. Error	z-Statistic	p-value
Dependent Variable: D(INF_P)				
Regime 1				
DLOG(Diesel)	-1.3798	1.0428	-1.3231	0.1858
D(INF_H)(-1)	0.6824	0.1572	4.3403	0.0000*
LOG(Sigma)	-0.5883	0.1534	-3.8355	0.0001*
Regime 2				
DLOG(Diesel)	1.4766	0.5157	2.8633	0.0042*
D(INF_H)(-1)	0.3564	0.1145	3.1142	0.0018*
LOG(Sigma)	-1.1743	0.0811	-14.4729	0.0000*
Common				
DLOG(Rice)	4.7765	1.5653	3.0515	0.0023*
C	0.0073	0.0367	0.2002	0.8413
		Log Likelihood		-51.9866
		Akaike Info Criterion		1.0162

**significant at 5% level*
where D(INF_H)(-1) is lag 1 of INF_P.

One feature of the MSW models is the transition probabilities between high and low inflation regimes. The results from Table 13 indicate a great chance (89%) of a low inflation regime succeeding a low inflationary period. Furthermore, a minimal chance (11%) is estimated of a high inflation period succeeding a previously low inflation period. The greatest expectation is for a high inflation era to succeed itself (97%), and only about 3% chance is given for a high inflation regime to give way to a low inflationary period.

Table 13: Transition Probabilities for Change in Headline Inflation

Probability	1 - Low Inflation	2 - High Inflation
1 - Low Inflation	0.8856	0.1144
2 - High Inflation	0.0283	0.9717

Another interesting result is the expected duration of the high and the low inflation regimes. These are shown in Table 14. Results imply an expected duration of about 35 months for high inflationary periods while lower inflation is expected to last for a much shorter period - merely 9 months.

Table 14: Expected Duration for Change in Headline Inflation

	1 - Low Inflation	2 - High Inflation
Duration	8.7396	35.3680

The predicted, filtered and smoothed probabilities for the regimes are presented in Figures 4 - 6. It is evident that the high inflation periods dominate the low inflation periods. This is consistent with the expected duration results that the high inflation regime will stay longer than the low inflation regime.

Figure 4. Predicted Regime Probabilities for Change in Headline Inflation

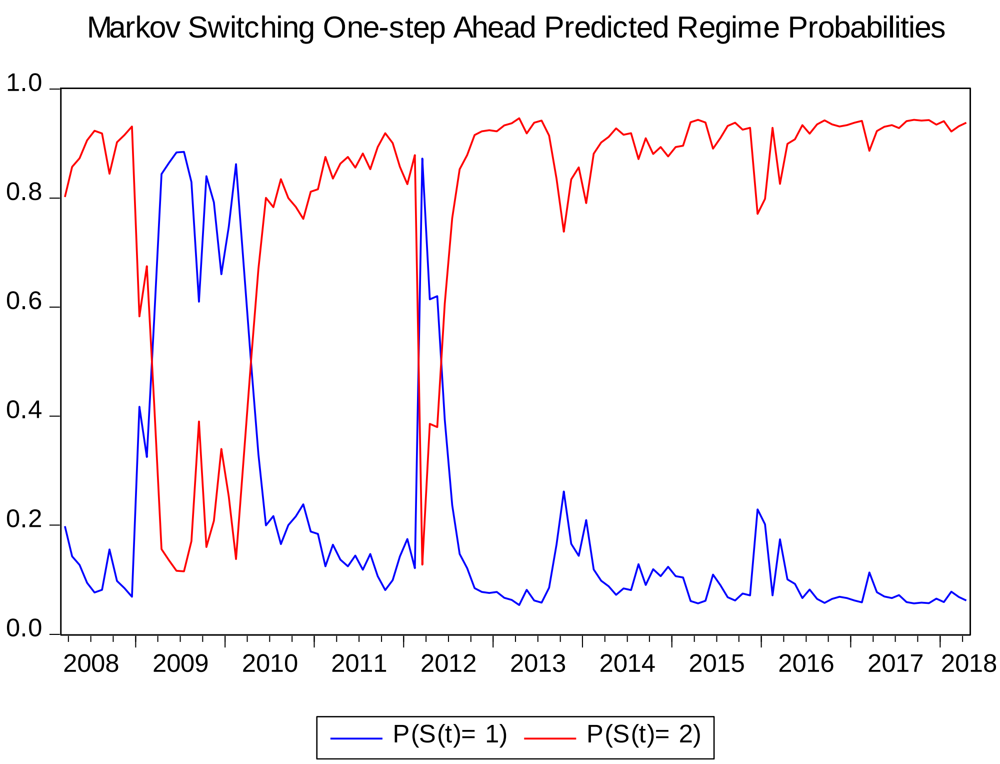


Figure 5. Filtered Regime Probabilities for Change in Headline Inflation

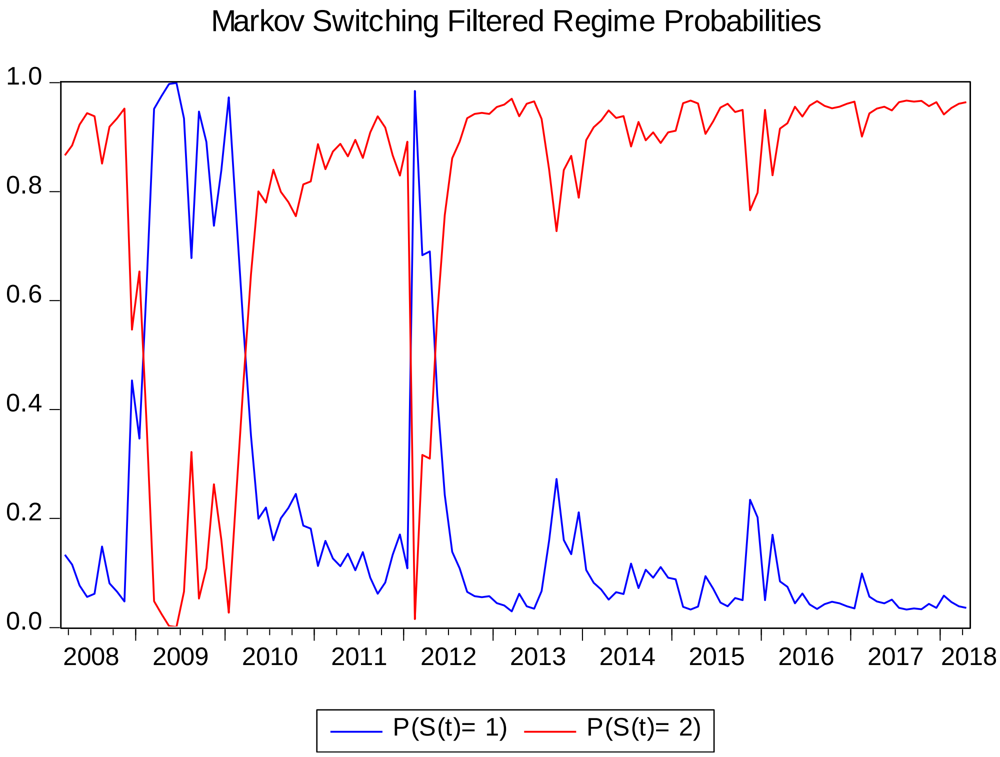
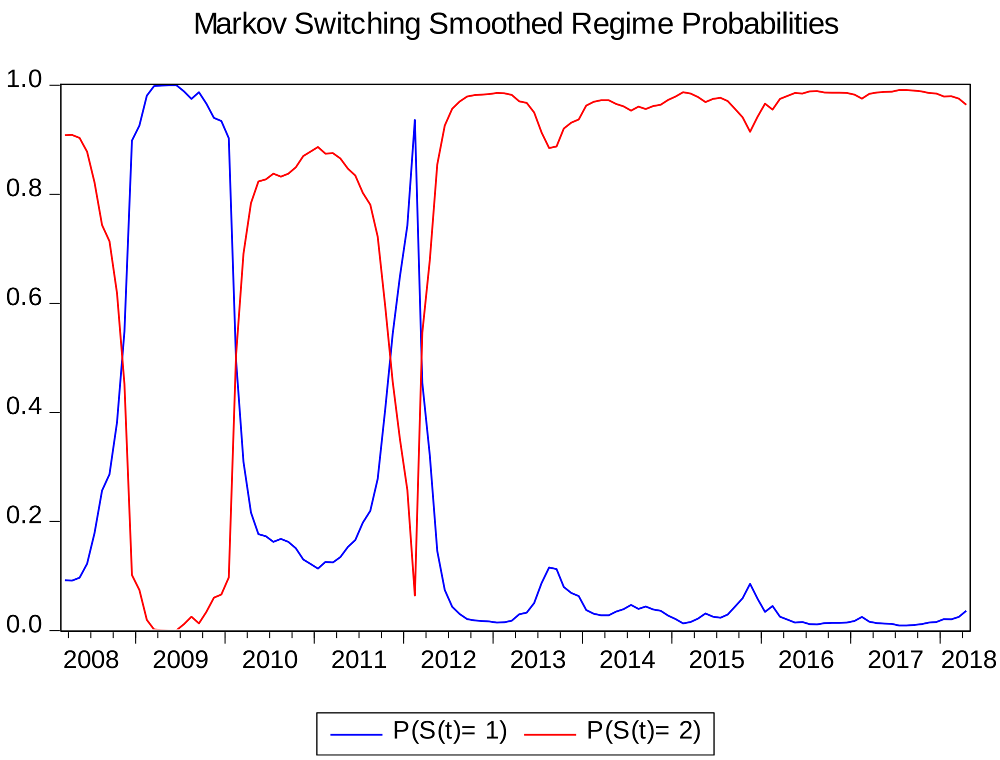


Figure 6. Smoothed Regime Probabilities for Change in Headline Inflation



4.7.2 Bottom 30% Inflation MSW Models

Similar to change in Headline Inflation, three two-regime MSW models were generated for the change in Bottom 30% Inflation. These include MSW without lag effects, MSW-AR(1) and MSW-AR(2). The AIC values and the result of normality test are summarized in Table 15. Normality of the residuals is rejected in all the models. Robust standard errors were generated to account for heteroscedasticity and serial autocorrelation. The MSW model without lag effects was excluded from the potential models since it has the highest AIC value. Considering the AIC value and the consistency with literature of the parameter estimates, the MSW-AR(2) was chosen as the final model.

Table 15: Markov Regime-Switching Models for Change in Bottom 30% Inflation

Variable	MSW	MSW-AR(1)	MSW-AR(2)
Log Likelihood	-109.2027	-83.9417	-78.3202
Akaike Info Criterion	1.9057	1.5400	1.4929
Jarque-Bera*	0.0000*	0.0000*	0.0000*

**p-value*

Based on Table 16, Regime 1 is characterized as the "Low Inflation" state and Regime 2 is the "High Inflation" state. All the variables in the model obtained significant parameter estimates, except for the growth in price of Diesel in Regime 1. Specifically, growth in price of Diesel has a positive effect in the High Inflation regime, but has no significant effect within the Low Inflation regime. That is, a 10% growth in the price of Diesel will increase the change in Bottom 30% Inflation by 0.1574 percentage point. While D(INF_P)(-1) or the lag 1 of change in Bottom 30% Inflation has significant positive effect in both regimes, D(INF_P)(-2) or the lag 2 of change in Bottom 30% Inflation has a significant negative effect. This, again, suggests inflation being dependent on its past value. On the other hand, the growth in price of Rice has positive effect in both regimes. This again highlights the impact of the price of Rice on the inflation of the poor being highly dependent on food items, particularly rice. Furthermore, the estimates of the log standard deviation show that the low is more volatile with a corresponding standard deviation of 0.8192 as compared to the high inflation regimes with a standard deviation of 0.2836.

Table 16: Markov Regime-Switching Model for Change in Bottom 30% Inflation

Dependent Variable: D(INF_P)				
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**p-value**
Regime 1				
DLOG(Diesel)	-4.5425	2.1245	-2.1381	0.0325
D(INF_P)(-1)	1.4502	0.1363	10.6399	0.0000*
D(INF_P)(-2)	-0.5315	0.1245	-4.2673	0.0000*
LOG(Sigma)	-0.1994	0.1365	-1.4607	0.1441
Regime 2				
DLOG(Diesel)	1.5738	0.6380	2.4666	0.0136*
D(INF_P)(-1)	1.6111	0.0572	28.1582	0.0000*
D(INF_P)(-2)	-0.6457	0.0636	-10.1454	0.0000*
LOG(Sigma)	-1.2603	0.1177	-10.7064	0.0000*
Common				
DLOG(Rice)	15.3729	1.5485	9.9276	0.0000*
C	0.1208	0.0618	1.9537	0.0507
		Log Likelihood		-80.3760
		Akaike Info Criterion		1.5144

**significant at 5% level*
where D(INF_P)(-1) and D(INF_P)(-2) are lag 1 and lag 2 of INF_P, respectively.

Based on the transition probabilities of the model in Table 17, the probability that the country will shift from a high inflation regime to low inflation regime is only about 9%. Note that there is considerable state dependence in the transition probabilities with a relatively higher probability of remaining in the origin regime – 91% for the high inflation regime and 78% in low inflation regime.

Table 17: Transition Probabilities for Change in Bottom 30% Inflation

Probability	1 - Low Inflation	2 - High Inflation
1 - Low Inflation	0.7809	0.2191
2 - High Inflation	0.0914	0.9087

The corresponding expected durations in a regime are presented in Table 18. The expected duration of the high inflation regime is approximately 11 months, while that of the low inflation regime is about 5 months. Thus, when the Bottom 30% Inflation enters the high inflation regime, it will stay in that state for about a year.

Table 18: Expected Duration for Change in Bottom 30% Inflation

	1 - Low Inflation	2 - High Inflation
Duration	4.5640	10.9469

Figures 7 - 9 show the predicted, filtered and smoothed probabilities for the regimes. Since high inflation regime is expected to stay longer than the low inflation regime, figure below shows that high inflation periods tend to rule over the low inflation periods.

Figure 7. Predicted Regime Probabilities for Change in Bottom 30% Inflation

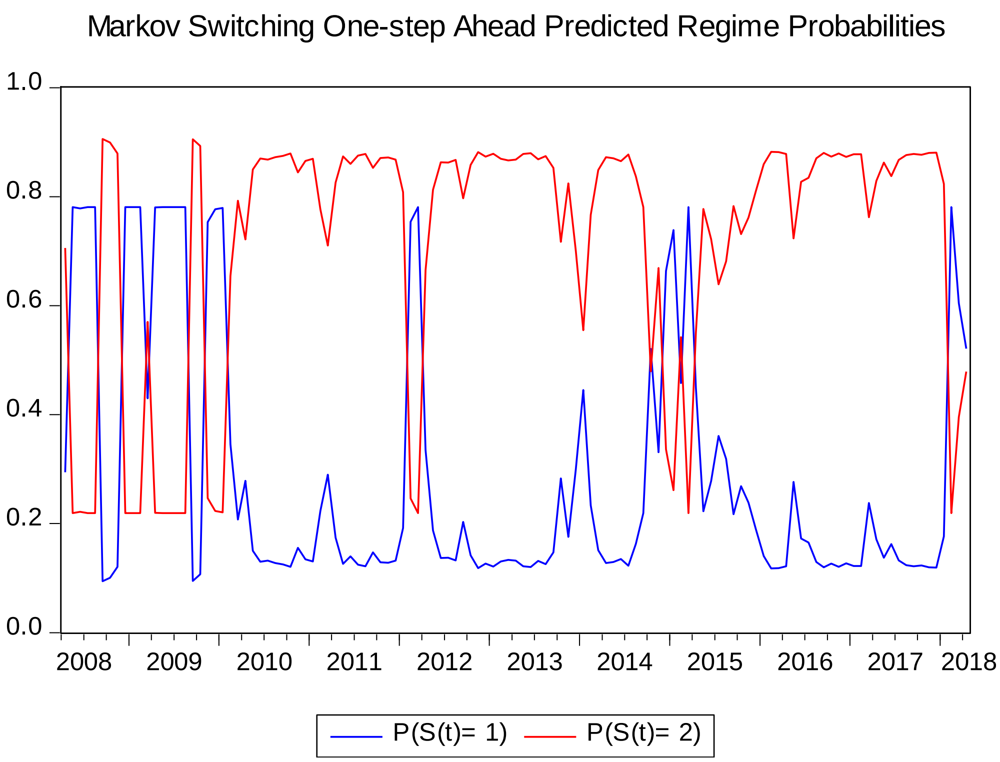


Figure 8. Filtered Regime Probabilities for Change in Bottom 30% Inflation

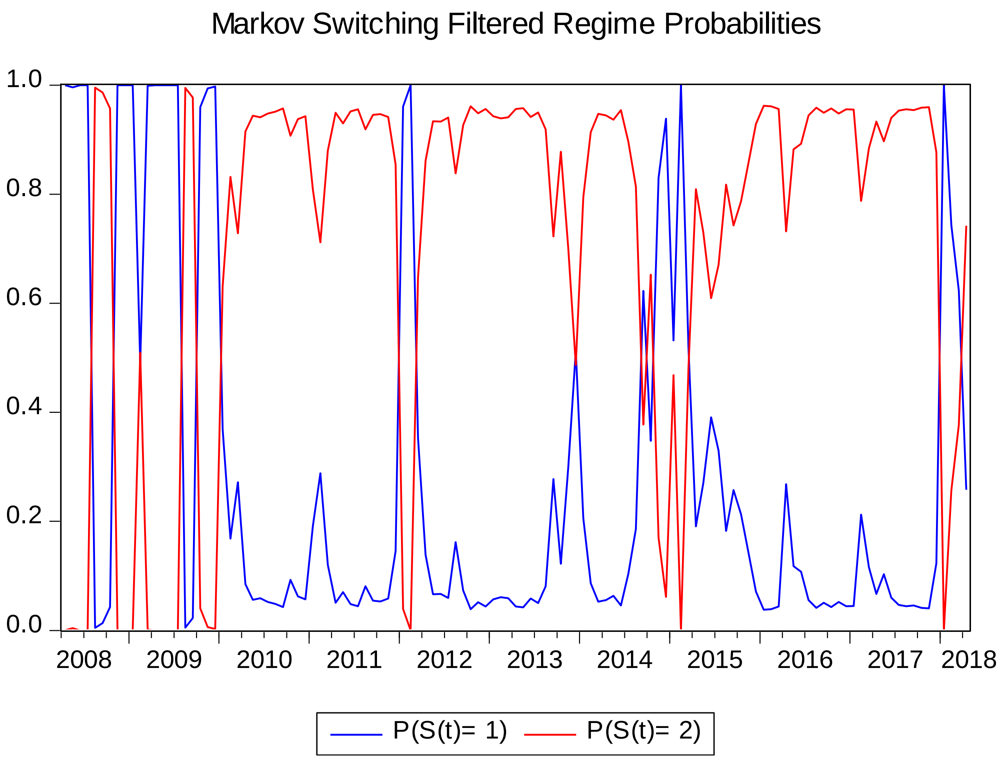
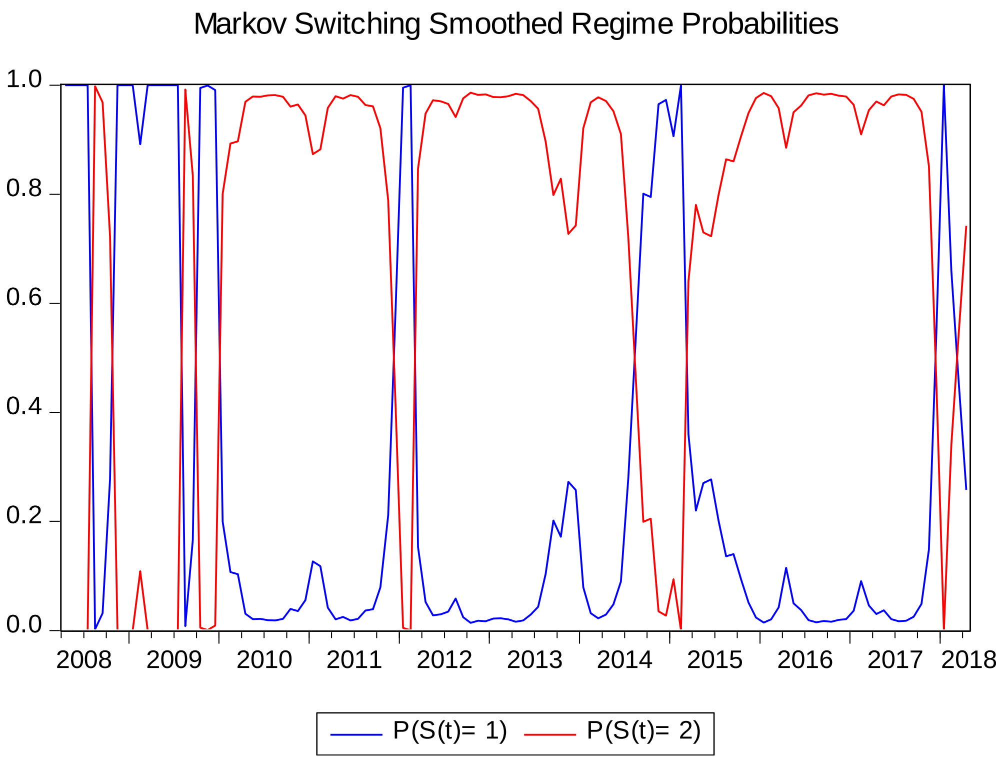


Figure 9. Smoothed Regime Probabilities for Change in Bottom 30% Inflation



In general, the results of the Markov Regime-Switching models for Headline Inflation and Bottom 30% Inflation show that Diesel has significant positive effect in the High Inflation regime for both the Headline Inflation and the Bottom 30% Inflation models. Rice has positive significant effect in both models.

4.8. Impact of the Diesel Excise Tax on Inflation Rate

The impact of the imposed diesel excise tax on the inflation rate was determined using the results of the Threshold Autoregression and Markov Regime-Switching. Diesel, which was not taxed before, is now taxed PHP2.50 per liter under the TRAIN Law. Including the value added tax, price increase for diesel totaled to PHP2.80. This translates to 9.3% of the average diesel price prior to TRAIN (see Table 19 below).

Table 19: Diesel Excise Tax

TRAIN Excise Tax on Diesel	2.5
Value Added Tax	0.3
Total Price Increase	2.8
Average Price of Diesel in 2017	32
Price Increase Percentage	9.3%

The impact was then calculated using the significant coefficient estimates of the growth in price of Diesel from the TAR and MSW models. The computed values are shown in Table 20. Since the current price of diesel is above the identified threshold using the TAR models, the imposed excise tax will add a 0.29 percentage point impact on the change in Headline Inflation and a 0.34 percentage point impact on the change Bottom 30% Inflation. Moreover, given the current trend and state of inflation, the excise tax is expected to give a 0.14 and a 0.15 percentage point increase on the change in Headline Inflation and on the change in Bottom 30% inflation, respectively, using the results of the MSW models.

Table 20: Impact of the Diesel Excise Tax on Change in Inflation

	Headline Inflation				Bottom 30% Inflation			
	TAR Model		**MSW Model**		**TAR Model**		**MSW Model**	
	Below Threshold	Above Threshold	Low Inflation	High inflation	Below Threshold	Above Threshold	Low Inflation	High inflation
Coefficient	NA	3.06	NA	1.48	NA	3.68	NA	1.57
Impact	NA	0.29	NA	0.14	NA	0.34	NA	0.15

**NA = growth in price of Diesel is not significant*

5 CONCLUSION AND RECOMMENDATIONS

Given the current scale of poverty in the Philippines and the high impact of inflation on the poor households, inflation studies deserve more attention especially now that the Philippines is at the onset of TRAIN Law. Therefore, this paper aimed to study inflation rate in the Philippines using Threshold Autoregressive Model (TAR) and Markov Regime-Switching Model (MSW). Specifically, this study modeled inflation as a regime-switching process, in which inflation is characterized by two regimes – low and high inflation where switches between them (1) are triggered by a threshold or (2) evolve according to a Markov chain.

Using the Diesel price as the threshold variable, the TAR model for the change in Headline Inflation identified a threshold value of PHP 30.05, which is slightly lower than estimated threshold of PHP 30.25 in the change in Bottom 30% Inflation model. Findings suggest that Diesel price has indeed threshold effects on inflation, with Diesel being significant when its price is above the threshold. Therefore, the current price increases in Diesel will have significant effect on the inflation rate. The results also affirm that growth in price of Rice has a significant positive impact on inflation.

The results of Markov Regime-Switching models showed that growth in price of Diesel has a significant positive effect within the high inflationary regime, while Rice remains to have positive significant effect in both models. There is also a considerable state dependence in the transition probabilities with a relatively higher probability of remaining in the origin regime. The highest expectation is for a high inflation regime to succeed itself - 97% for change in Headline Inflation and 91% for change in Bottom 30% Inflation. Furthermore, there is only a minimal chance for a high inflation regime to give way to a low inflationary period. The corresponding expected durations indicate that Headline Inflation is expected to stay in the high inflationary period for 35 months. Similarly, when Bottom 30% Inflation enters the high inflation regime, it will stay in that state for about 11 months. The low inflation regimes for both models are expected to last for a much shorter period.

As the current price of diesel is above the identified thresholds, the imposed excise tax will have a 0.29 percentage point and a 0.34 percentage point impact on the change in Headline Inflation and on the change in Bottom 30% Inflation, respectively, based on the results of the TAR models. Moreover, using the results of the MSW models and given the current trend and state of inflation, the excise tax is expected to have a 0.14 percentage point and a 0.15 percentage point impact on the change in Headline Inflation and on the change in Bottom 30% Inflation, respectively.

In general, findings of this study confirm the significant effect of increasing prices of diesel and rice on Inflation. It is thus highly relevant for policymakers to monitor inflation and direct government policies toward stabilizing prices and providing safety nets to poor households. In addition, the study mainly focused on the impact of prices of diesel and rice on inflation. It would be interesting to explore certain other factors that were not considered in the study. It also recommended to expand the data period and study inflation amidst the TRAIN implementation to help the government, as enforcers of the tax reform package, to properly evaluate the TRAIN so that strengthening and reorientation of the program to address problems can be achieved. Further studies to determine threshold values of inflation to set inflation targets using the Threshold Autoregression would also be good direction for future research. Finally, future studies on inflation may also consider exploring other nonlinear models.

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