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An Early Warning System for Inflation in the Philippines Using Markov-Switching and Logistic Regression Models*

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ABSTRACT

With the adoption of the BangkoSentralngPilipinas (BSP) of the Inflation Targeting (IT) framework in 2002, average inflation went down in the past decade from historical average. However, the BSP's inflation targets were breached several times since 2002. Against this backdrop, this paper develops an early warning system (EWS) model for predicting the occurrence of high inflation in the Philippines. Episodes of high and low inflation were identified using Markov-switching models. Using the outcomes of regime classification, logistic regression models are then estimated with the objective of quantifying the possibility of the occurrence of high inflation episodes. Empirical results show that the proposed EWS model has some potential as a complementary tool in the BSP's monetary policy formulation based on the in-sample and out-of sample forecasting performance.

Keywords: Inflation Targeting, Markov Switching Models, Early Warning System

I. Introduction

Price stability or the condition of low and stable inflation is a universal goal shared by monetary authorities all over the world. Price stability is important because empirical evidence show that high and volatile rates of inflation distort the decisions that people make about consumption, investment, savings and production. These distortions, in turn, lead to inefficient allocation of resources, and ultimately contribute to slower economic growth. In addition, high inflation erodes the purchasing power of the domestic currency, thus affecting the lower-income households to a greater extent than any other sector of the society. Monetary authorities, therefore, help promote sustainable economic growth by keeping inflation low and stable.

Since January 2002, the BangkoSentralngPilipinas (BSP) has adopted inflation targeting (IT) as its framework for monetary policy formulation. Under the IT framework, monetary

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authorities take a forward-looking view and calibrate their policy rates to manage deviations of future expected inflation or output levels from their respective targets. State-of-the-art statistical models provide monetary authorities reliable forecasts on the future path of inflation and output.[3] The forecasts are complemented by the policymakers' forward-looking assessment of inflation pressures. Risks to the inflation outlook, both upside and downside, are assessed using the widest possible array of information and tools.

With the adoption of the IT framework, the BSP was able to bring down the inflation rate from historical average. Cruz and Dacio (2013) estimate that average inflation (using 2006-based series) went down from 6.9 percent in the seven years before IT was adopted to 4.4 percent over the period 2002 to 2012. Nonetheless, the BSP's inflation targets were breached in seven of the 11 years that the IT framework had been adopted in the Philippines. Since there is no single model that could accurately forecast the inflation path or address all policy issues concerning monetary authorities, the BSP periodically reviews its existing suite of forecasting models as well as develop new tools to keep up with new developments in modern monetary economics.[4]In addition to forecasting models, therefore, statistical models that could help policymakers measure and assess the risks to the inflation objective may prove to be useful in the monetary policy formulation process.

This paper aims to contribute to the literature by developing an early warning system (EWS) for predicting the occurrence of high inflation in the Philippines. The proposed early warning system model for predicting high inflation employs the limited dependent variable approach. Episodes of high inflation were identified using the Markov-switching model which allows the shift from a low inflation to a high inflation regime to occur endogenously rather than being imposed by the researcher. The paper then identifies a class of domestic and external macroeconomic indicators which have leading indicator properties for switching between inflation regimes.

The end-goal of the paper is to develop models that could help quantify the possibility of the future occurrence of high inflation. While the models are not intended to forecast inflation for some forecast horizon, they could complement the existing toolkit of the BSP in the assessment of the inflation environment and the risks to the inflation outlook.

The organization of the paper is as follows: Section 2 reviews some of the relevant research works on inflation regimes; Section 3 describes in detail the methodology adopted in the paper; Section 4 discusses the inflation indicators used in the model; Section 5 presents the empirical results as well as the evaluation of the proposed models; and the last section concludes.

II. Predicting Regime Shifts of Inflation

A monitoring tool called the early warning system consists of a precise definition of a crisis and a mechanism for generating predictions of crises (Edison, 2003). The development of early warning systems for use in economic policy formulation relates mainly to the prediction of

[3] Cruz &Dacio, 2013
[4] Ibid.

financial crises. There are various types of financial crises typically studied, including currency crises, banking crises, sovereign debt crises, private sector debt crises, and equity market crises.

However, the literature on the development of an EWS-like system to predict high and volatile inflation has been fairly limited. The studies which have attempted to do so use variants of Markov-switching models and limited dependent variable regression models. The macroeconomic variables considered as explanatory variables for some of these studies tend to be very limited as well.

In an early work, Evans and Wachtel (1993) analyze the sources of uncertainty that affects the dynamics of inflation and agents' inflationary expectations collected in surveys. On the assumption that inflation can either follow a random walk process or an autoregressive process, they note that that the switch between these two regimes explains the presence of discrete jumps in the US inflation during the postwar period. Simon (1996) of the Reserve Bank of Australia applies the methodology of Markov-switching models to describe the inflation process in Australia. He notes that the distinctive feature of the approach is the use of very simple equations for inflation within a framework that allows for discrete 'regime shifts' or shift points in time. Amisano and Fagan (2010) employ a similar approach in their analysis of the relationship between money growth and inflation. They develop a time-varying transition probabilities Markov switching model in which inflation is characterized by two regimes, high and low inflation. In the study, the probability of shifting from one regime to the other depends on a measure of lagged money growth.

Meanwhile, Landrito, Carlos and Soriano (2011) implement a univariate Markov-switching Autoregressive model to identify periods of high and low inflation over the period 1995-2009 in the Philippines. The study shows that when the country is in a state of 'high' inflation, the average inflation rate is 6.64 percent while in times of low inflation, the average inflation rate is 4.43 percent. It is interesting to note that the study's estimated average inflation during the low inflation regime is on the upper bound of the current inflation target range of the BSP of 3-5 percent. This may be attributed to the fact that periods of high inflation prior to the BSP's adoption of the IT framework in 2002 are included in the analysis.

A recent work by Mitra and Erum (2012) proposes a different approach to setting up an early warning prediction system for high inflation. The proposed warning system uses historical values of a set of economic variables as inputs and builds an elitist genetic algorithms-based artificial neural network (ANN) model for quantifying the possibility of high inflation within a fixed period of time window. In building the neuro-genetic model, the paper uses elitist generational genetic algorithms for optimizing the architecture of the ANN. The output of the proposed EWS is in terms of probability, quantifying the possibility of occurrence of an incidence of high inflation within a chosen period of time. Their results suggest a promising performance of the proposed neuro-genetic warning system, which is capable of generating accurate early warning signals of an impending high inflation.

III. Model Specification

This paper considers a qualitative response model in setting up an early warning system for high inflation in the Philippines. The approach is in line with the literature on early warning systems for the various types of financial crises.

3.1 Markov-switching model

In identifying episodes of high inflation, the paper employs the Markov-switching model which does not distinguish *ex ante* between high and low inflation episodes. The inflation process is described as being governed by two different regimes and the switches between them are based on a probabilistic process, so that shifts occur endogenously rather than being imposed by the researcher.

This study uses a two-regime MS-AR model in which the transition is driven by a two-state Markov chain. We let y_t be the inflation rate time series. Then, y_t follows a two-regime MS(2)-AR(p) model if

$$y_t = \begin{cases} c_1 + \sum_{i=1}^{p} \phi_{1,i} y_{t-i} + a_{1t} \ \ if \ S_t = 1 \\ c_2 + \sum_{i=1}^{p} \phi_{2,i} y_{t-i} + a_{2t} \ \ if \ S_t = 2. \end{cases} \tag{1}$$

The process $\{S_t\}$ assumes values $\{1,2\}$ to signify the regime at time t. In particular, $S_t = 1$ denotes a low inflation regime while $S_t = 2$ signifies a high inflation regime. The series $\{a_{1t}\}$ and $\{a_{2t}\}$ are sequences of iid random variables with mean zero and finite variance. The process $\{S_t\}$ is a stationary, aperiodic and irreducible Markov chain, defined by transition probabilities between the two states:

$$p_{ij} = p_{j|i} = P(S_t = j | S_{t-1} = i), \qquad i,j = 1,2 \tag{2}$$

The probability p_{ij} refers to the probability that the Markov chain will move from state i at time $t-1$ to state j at time t. A small value of p_{ij}means that the model tends to stay longer in state i. Meanwhile, its reciprocal $1/p_{ij}$ indicates the expected duration of the process to stay in state *i*.

The process is assumed to depend on the past values of y_t and S_t only through S_{t-1}. When the process is in any given state, it may move to the other state in the next transition, or it may stay in its current state since the process $\{S_t\}$ is assumed to be irreducible and aperiodic.

Franses and van Dijk (2000) note that for the p_{ij}s to define proper probabilities, they should be nonnegative while it should also hold that $p_{11} + p_{12} = 1$and $p_{21} + p_{22} = 1$.The transition probabilities can be written in the form of a transition probability matrix:

$$P = \begin{bmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{bmatrix} \tag{3}$$

Since only the time series of interest is observed, not the Markov process, the estimation of Markov-switching models are not straightforward. Following the discussion of Franses and van Dijk (2000), under the assumption that $a_{s_t,t}$ in Eq. (1) are normally distributed, the density of $y_t$conditional on the regime s_t and the information set I_{t-1} is a normal distribution with mean $\phi_{s_t,0} + \sum_{i=1}^{p} \phi_{s_t,i} y_{t-i}$ and variance σ^2,

$$f(y_t|s_t = j, I_{t-1}; \theta) = \left(\frac{1}{\sqrt{2\pi\sigma^2}}\right) exp\left\{\frac{-\left(y_t - \left(\phi_{s_t,0} + \sum_{i=1}^{p} \phi_{s_t,i} y_{t-i}\right)\right)^2}{2\sigma^2}\right\} \tag{4}$$

Given that the state s_t is unobserved, the conditional log likelihood for thet^{th} observations $l_t(\theta)$is given by $l_t(\theta) = \ln f(y_t|\, I_{t-1}; \theta)$ or the log of the density of y_t conditional only upon the history I_{t-1}. The density $f(y_t|I_{t-1}; \theta)$ can be obtained from the joint density of y_t and s_t as follows:

$$\begin{aligned} f(y_t|I_{t-1}; \theta) &= f(y_t, s_t = 1|I_{t-1}; \theta) + f(y_t, s_t = 2|I_{t-1}; \theta) \\ &= \sum_{j=1}^{2} f(y_t|s_t = j, I_{t-1}; \theta \cdot P(s_t = j|I_{t-1}; \theta) \end{aligned} \tag{5}$$

To compute the density in Eq. (5), the conditional probabilities of being in either regime given the history of the process, $P(s_t = j|I_{t-1}; \theta)$, needs to be quantified. In addition, Franses and van Dijk (2000) note that to develop the maximum likelihood estimates of the parameters in the model, we need to estimate three types of probabilities of each of the regimes occurring at time t. These are *forecast* (estimate of the probability that the process is in regime j at time t given all observations up to time $t-1$), *inference* or *filtered* (given all observations up to and including time t) and *smoothed* (given all observations in the entire sample) inference of the regime probabilities.

Hamilton (1990) notes that the maximum likelihood estimates of the transition probabilities are given by

$$\widehat{p_{ij}} = \sum_{t=2}^{n} P(\, s_t = j, s_{t-1} = \frac{i\big|I_n; \hat{\theta})}{\sum_{t=2}^{n} P(s_{t-1} = i\big|I_n; \hat{\theta})}, \tag{6}$$

where$\hat{\theta}$ denotes the maximum likelihood estimates of θ. In addition, the estimates $\hat{\theta}_j$can be obtained from a weighted least squares regression of $y_t$on x_t, with weights given by the smoothed probability of regime j occurring.

An iterative procedure, which is an application of the Expectation Maximization (EM) algorithm developed by Dempster, Laird and Rubin (1977), may be used to estimate the parameters of the Markov switching model. In the EM algorithm, each iteration increases the value of the likelihood function, which guarantees that the final estimates can be considered ML estimates. An alternative maximization method is developed by Lawrence and Tits (2001). Called the feasible sequential quadratic programming, the method ensures that the parameters stay within the feasible region. Meanwhile, McCulloch and Tsay (1994) consider a Markov Chain Monte Carlo method to estimate a general MS-AR model. The MS-AR model can be generalized to the case of more than two states though the computational intensity increases rapidly.

3.2 Dependent Variable Specification

In specifying the dependent variable in the qualitative response model, one can take the "contemporaneous" approach in which the dependent variable takes the value 1 if HI_t is equal to 1 in the dating techniques discussed above. That is, if we let H_t indicate an episode of high inflation, then,

$$H_t = \begin{cases} 1, if\ HI_t = 1 \\ 0, otherwise. \end{cases} \tag{7}$$

An alternative approach takes a forward-looking view in which the contemporaneous variable H_t is transformed into a forward variable. This alternative model predicts whether an inflation crisis or an event of high inflation event will occur within the specific time period defined by the researcher.

3.3 Logistic Regression Model

In setting up the EWS model for inflation, we model the probability of being in the state of high inflation using the logistic regression model. Following the discussion of Kedem and Fokianos (2002), we consider a binary time series $\{Y_t\}$ taking the values 0 or 1 to denote a low inflation regime and a high inflation regime, respectively. We let $\mathbf{Z}_{t-1} = (Z_{(t-1)1}, \ldots, Z_{(t-1)p})'$ be the corresponding p-dimensional vector of past explanatory variables or covariates, $t = 1, \ldots, T$, and refer to $\mathbf{Z}_t$ as the covariate process. It is also convenient to think of $\mathbf{Z}_{t-1}$ as already including the past values of the response variable $(Y_{t-1}, Y_{t-2}, \ldots)$. We denote by S_{t-1} the σ-field generated by $Z_{t-1}, Z_{t-2}, \ldots$,

$$S_{t-1} = \sigma\{Z_{t-1}, Z_{t-2}, \ldots\}. \tag{8}$$

In addition, let us denote by $\mu_t = E[Y_t|S_{t-1}]$ the conditional expectation of the response given the past. Our interest is the estimation of the conditional success probability

$$P_{\boldsymbol{\beta}}(Y_t = 1|S_{t-1}), \tag{9}$$

where$\boldsymbol{\beta}$ is a p-dimensional vector, and S_{t-1} represents all that is known to the observer at time $t-1$ about the time series and the covariate information. According to Kedem and Fokianos (2002), the response process $\{Y_t\}$ may be stationary or non-stationary and the time dependent random covariate vector process $\{\mathbf{Z}_{t-1}\}$ may represent one or more time series and functions thereof that influence the evolution of the primary series of interest $\{Y_t\}$.

To ensure that the model in Eq. (9) yields proper probability estimates, we need to choose suitable inverse links $h \equiv F$ that map the real line onto the interval $[0,1]$. We denote by π_t the probability of success given F_{t-1}. That is, we write Eq. (9) as

$$\pi_t(\boldsymbol{\beta}) = \mu_t(\boldsymbol{\beta}) = P_{\boldsymbol{\beta}}(Y_t = 1|S_{t-1}) = F(\boldsymbol{\beta}'\mathbf{Z}_{t-1}), \tag{10}$$

where F is a continuous and strictly increasing function, returning a value which ranges from 0 to 1,$\boldsymbol{\beta}$ is a column vector parameter of the same dimension p as the covariate process $\mathbf{Z}_{t-1}$.

The choice of the function F would determine the type of binary model. The typical candidate for F is the standard logistic cumulative distribution function which leads to the general logistic regression model given by,

$$\pi_t(\boldsymbol{\beta}) = P_{\boldsymbol{\beta}}(Y_t = 1|S_{t-1}) = \frac{1}{1+\exp(-\boldsymbol{\beta}'\mathbf{Z}_{t-1})}, \qquad (11)$$

where again, $\boldsymbol{\beta}$ is a column vector parameter of the same dimension p as the covariate process $\mathbf{Z}_{t-1}$. Alternatively, the inverse link may be defined by $F \equiv \Phi$, where Φ is the standard normal cumulative distribution function. In empirical applications, logit and probit models typically yield similar results (Nyberg, 2010).[5]

Kedem and Fokianos (2002) provide a comprehensive discussion of the estimation $\boldsymbol{\beta}$ using maximum partial likelihood estimation (MPLE). They also show that the MPLE $\hat{\beta}$ is almost surely unique for sufficiently large N and as $N \to \infty$, $\hat{\beta} \to \beta$ in probability. An asymptotic $100(1-\alpha)\%$ prediction interval is given by

$$\pi_t(\beta) = \pi_t(\beta) \pm z_{\frac{\alpha}{2}} \frac{f(\boldsymbol{\beta}'\mathbf{Z}_{t-1})}{\sqrt{N}} \sqrt{\mathbf{Z}_{t-1}\mathbf{G}^{-1}(\beta)\mathbf{Z}_{t-1}}. \qquad (12)$$

IV. Data Description

This section describes briefly the key variables of interest for an IT central bank. The sample period used in the estimation work is January 2002, when IT was adopted by the BSP, until December 2012.

4.1 Main Variable of Interest

Inflation rate is the annual rate of percentage change or the year-on-year change in the Consumer Price Index (CPI), which is a general measure of the average retail prices of commodities commonly purchased by households. CPI is reckoned from a base year and weighted by the consumption pattern or basket of the households. This study uses the year 2006-based inflation rate from the National Statistics Office (NSO).

4.2 Explanatory Variables

Considering the theoretical drivers of inflation as well as the modern practice of central banks in the monetary policy formulation, representative indicator variables are chosen from the following sectors: real output, liquidity, financial, and international commodity prices. Also included as an explanatory is the BSP's RRP rate, which is the BSP's main policy instrument in managing the inflation environment.

[5] Kedem and Fokianos (2002) also discuss log-log and complementary log-log as common links for binary time series.

Real Output Indicator. The importance of **output gap** in inflation forecasting may be viewed as originating largely from the demand-pull theory of inflation. The output gap is the difference between actual real Gross Domestic Product (GDP) and potential GDP as a percent of potential GDP. A positive output gap is an inflationary gap, indicating that the growth of aggregate demand is outpacing the growth of aggregate supply. Meanwhile, a negative output gap is also called a recessionary gap which could result in deflation. A number of studies focused on the relevance of output gap in the BSP's monetary policy framework, including those of Debelle and Lim (1998), Yap (2003), and McNelis and Bagsic (2007). In this paper, the potential output estimate is taken to be the trend component of actual GDP, which is extracted using the Census X-12 time series decomposition.

Liquidity Indicator. From the monetary theory of Friedman, a measure of money supply called **M3 or broad money liabilities or domestic liquidity** is included as one of the key explanatory variables in this paper. Domestic liquidity has been traditionally included in inflation forecasting models, as discussed by Mariano, Dakila and Claveria (2003) and Cruz (2009). Sustained growth in liquidity could boost demand for goods and services and increase inflation. M3includes national currency outside depository corporations, transferable deposits, other deposits, and securities other than shares included in broad money (deposit substitutes). This paper uses a measure called M3-to-GDP gap which is the percent difference between the seasonally-adjusted M3-to-GDP ratio and the trend of M3-to-GDP ratio obtained using Census X-12.

Financial Indicator. Asset prices, such as equity prices, are relevant for IT central banks as the build-up of asset market imbalances contributes to financial stability risks that can adversely affect both domestic economic activity and the inflation outlook. A surge in equity prices, for instance, may reflect the substantial inflow of foreign capital which could lead to overall increase in asset price inflation. In addition, vulnerabilities in the financial sector can weaken the traditional transmission channels of monetary policy. This paper uses the **Philippine Stock Exchange Composite Index (PSEi)** as the indicator variable for the financial sector.PSEi is a weighted aggregative index that provides a definite measure of the country's stock market performances.

Foreign exchange market indicator. The foreign exchange market is important for IT central banks due to its traditional impact on import prices. In line with the cost-push inflation theory, a weakening of the domestic currency increases the prices of imported goods and therefore could lead to higher inflation. This paper uses the **peso-dollar rate or the foreign exchange rate**, whichrefers to the guiding rate for the exchange of one US dollar (the country's intervention currency) for pesos. The foreign exchange rate is included as a key explanatory variable in the BSP's single-equation model (SEM) as noted by Cruz (2009) and in the structural long-term inflation forecasting model (LTMM) developed by Mariano et al. (2003). In this paper, the foreign exchange rate is expressed as the exchange rate gap or the deviation of the foreign exchange rate from the estimated trend using Census X-12.

International Commodity Prices. In accordance with the cost-push inflation theory, the world prices of key commodity imports, both food and non-food, have direct effects on domestic commodity prices. The benchmark prices of key cereal grains (in US$ per MT) and crude oil (in US$ per barrel), which are published by the World Bank in its monthly pink sheet reports, are used in this paper. **International rice prices** refer to the indicative price of Thai rice, 5 percent broken based on weekly surveys of export transactions while **international wheat prices** refer to the price of benchmark US wheat no. 1, hard red winter, export price delivered at the US Gulf port for prompt or 30 days shipment. Meanwhile, **international oil prices** refer to the price of Dubai Fateh crude oil.

Fiscal. As implied by the demand-pull theory of inflation, changes in fiscal policy can affect aggregate demand which may, in turn, affect either the output or the price level. Hence, excessive government spending relative to government revenue, which results in fiscal deficit, can be an upside risk to inflation. In this paper, **government expenditure,** expressed as a proportion of nominal GDP, is used.

BSP Policy Rate. The **reverse repurchase (RRP) rate** is the BSP's key policy rate. RRPs are typically contracted between the BSP and the banks, allowing the BSP to siphon off liquidity from the banking system on a temporary basis (as compared to the long-term effect of a change in reserve requirements). Increases in the RRP rate aim to temper inflation through the different channels of monetary policy.

4.3 Data Transformation

Table 1 describes the estimation and transformation performed on the crisis indicators. Various types of transformations are applied to ensure that the indicators are stationary and free from seasonal effects. Seasonal adjustment (SA) and trend estimation are performed using Census X-12 ARIMA multiplicative procedure. In case the indicator variable has no seasonal pattern and is non-trending, its level form is maintained.

Table 1. Summary of variable estimation and transformation procedures

Indicator	Estimation/Transformation
REAL OUTPUT	
Output Gap	The quarterly real GDP data is first transformed to monthly frequency using ECOTRIM. Then, the potential output is estimated by applying Census X12 time series to the SA GDP data. The output gap is estimated as the percentage deviation of the SA GDP from the trend.
LIQUIDITY	
M3-to-GDP ratio gap	The M3-to-GDP ratio is obtained by dividing the M3 level by the nominal monthly GDP, which is estimated using ECOTRIM. The procedure in estimating the output gap is then applied to the resulting M3-to-GDP ratio.
FINANCIAL	
Stock Index	No SA, no detrending; Data are expressed in terms of natural logarithm.
FOREIGN EXCHANGE	
₱/US$ Exchange rate	The series is expressed as deviation from trend.
INTERNATIONAL COMMODITY PRICES	
Rice	No SA, no detrending. The series is expressed as 12-month percentage changes or as year-on-year growth rates.
Wheat	No SA, no detrending. The series is expressed as 12-month percentage changes or as year-on-year growth rates.
Dubai crude oil	No SA, no detrending. The series is expressed as 12-month percentage changes or as year-on-year growth rates.
FISCAL	
Expenditure-to-GDP ratio	The expenditure-to-GDP ratio is obtained by dividing the level of government revenue by the nominal annual GDP. The series is expressed in natural logarithm.
POLICY RATES	
RRP rate	No SA, no detrending.

Headline inflation as well as the crisis indicator variables are tested for the presence of unit roots using the Dickey-Fuller-GLS (DF-GLS) procedure developed by Elliot, Rothenberg and Stock (1996). Following the suggestion of Schwert (1989), a lag length of 13 months, which is based on the formula $p_{max} = (12 * (\frac{T}{100})^{\frac{1}{4}})$, is used.The results are shown in Table 2.

Table 2. Results of the Test for Stationarity

Indicator	DF-GLS Test Statistic*		Conclusion	Code for transformed stationary series
	Trend	Constant and Trend		
Headline Inflation	-2.40	-2.56	Non-stationary; I(1)	DINF
REAL OUTPUT				
Output Gap	-1.91	-12.53	Stationary	YGAP
LIQUIDITY				
M3-to-GDP ratio gap	-8.17	-9.78	Stationary	M3
FINANCIAL				
Stock Index	1.28	-1.66	Non-stationary; I(1)	PSEI
EXTERNAL				
₱/US$ Exchange rate	-10.10	-10.42	Stationary	FOREX
INTERNATIONAL COMMODITY PRICES				
Rice	-3.47	-3.54	Stationary	IRICE
Wheat	-2.93	-3.15	Stationary	IWHEAT
Dubai crude oil	-2.74	-3.35	Stationary	DUBAI
FISCAL				
Revenue-to-GDP ratio	-0.77	-1.05	Stationary	EXPEND
POLICY RATES				
Policy Rate	0.73	-1.87	Non-stationary; I(1)	POLICYRATE

*For the DF-GLS Test, the null hypothesis is presence of unit root (non-stationary). The critical values at the 10 percent significance level are as follows: Equation with intercept= -1.615075; Equation with trend and intercept=-2.7110.

V. Discussion of Results

This section first describes the results of the inflation regime identification via a Markov switching model. This is followed by a discussion of the EWS model using logistic regression.

5.1 Regime Identification using the Markov-switching model

The estimation of the Markov switching model parameters was done in OxMetrics. The inflation rate series is scaled, i.e., multiplied by 100, following the recommendation of Doornik and Hendry (2009). They note that it is often beneficial to scale the data prior to non-linear estimation.

Four two-regime Markov switching models, MS-AR(1) to MS-AR(4), are estimated using different lags. Model selection is performed using the Akaike Information Criterion (AIC) and various diagnostic tests, including normality and linearity tests. The results in Table 3 suggest that of the four MS-AR models, it may be prudent to exclude MS-AR(1) from the list of potential models. This is because it has relatively distant AIC value and the residuals appear to be not normally distributed. For the MS-AR(2), MS-AR(3) and MS-AR(4) models, the AIC values are close to each other with relatively behaved residuals. It may be noted also that linearity is rejected across models suggesting that the use of non-linearity adds to the linear, constant parameter model. Following the principle of parsimony, the MS-AR(2) is chosen to be the final model.[6]

Table 3. Diagnostic Tests – MS-AR models

Tests		**Models**			
		AR(1)	**AR(2)**	**AR(3)**	**AR(4)**
AIC		10.440	10.207	10.216	10.192
Linearity test (Likelihood Ratio)	Test Stat	34.970	16.001	17.676	21.096
	P-Value	0.000	0.014	0.014	0.007
Normality test (Chi-Square)	Test Stat	7.175	3.594	1.459	0.929
	P-Value	0.028	0.166	0.482	0.930
ARCH 1-1 test (F)	Test Stat	10.186	1.427	0.654	0.008
	P-Value	0.002	0.234	0.420	0.930
Portmanteau test (Chi-Square)	Test Stat	71.085	62.325	48.568	37.825
	P-Value	0.000	0.004	0.079	0.386

The estimated parameters of the MS-AR(2) model are shown in Table 4. The values shown are rounded to the first three decimal places. Results show that the mean inflation in state 0 using the formula $c/(1-\Phi_1-\Phi_2)$ is 2.89 percent while that in state 1 is 5.75 percent. This implies that state 0 refers to a low inflation regime while state 1 refers to a high inflation regime. It is also worth noting that the average inflation for state 1 is higher than the upper bound of the current inflation target range of the BSP of 5 percent.

[6] Based on the diagnostic tests alone, MS-AR(4) model should be chosen because it is able to satisfy the assumption of no serial correlation, aside from normality and homoskedasticity. However, the resulting regime classification appears to be erratic with regimes lasting only 1 month. This may not be a reasonable result considering the inflation trends in the Philippines.

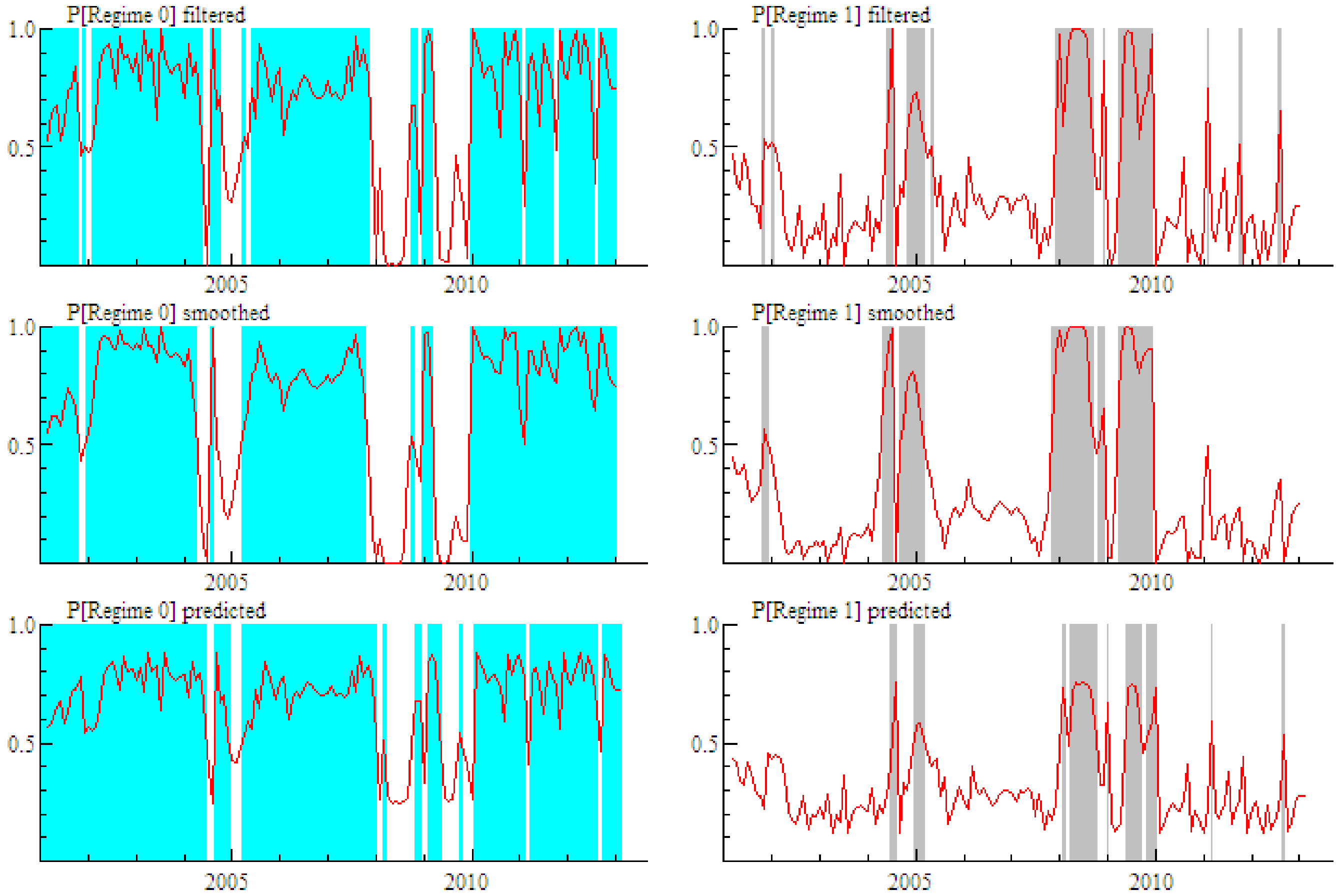
Table 4. Estimation Results of a Markov Switching Model with Two Lags for Inflation

State 0 (Low Inflation)					
Parameter	c_1	Φ_1	Φ_2	σ_1	p_{01}
Estimate	16.583	1.105	-0.162	33.254	0.116
Standard Error	11.460	0.114	0.112	2.912	
State 1 (High Inflation)					
Parameter	c_2	Φ_1	Φ_2	σ_2	p_{10}
Estimate	55.243	1.898	-0.994	32.141	0.246
Standard Error	17.040	0.096	0.104	4.428	

Based on the transition probabilities of the Markov-Switching model, the probability that the country will shift from a “high inflation” state to “low inflation” state($p_{10} = 0.246$) is about twice the probability of shifting from a low inflation regime to a high regime ($p_{01} = 0.116$). Another interesting result is the expected duration of a state which is estimated as the reciprocal of the transitional probability. The expected duration of a period of low inflation is estimated to be 8.6 months while that of high inflation is about 4.1 months. This implies that, on average, once the Philippines enters a period of “high” inflation, it will stay in that state for about 4 months. The estimated duration of low inflation is about 9 months, more than twice that of high inflation. Overall, the relatively low probability of shifting from a low inflation regime to a high inflation regime and the duration of a low inflation regime lend support to the effectiveness of monetary policy in managing inflation in the Philippines.

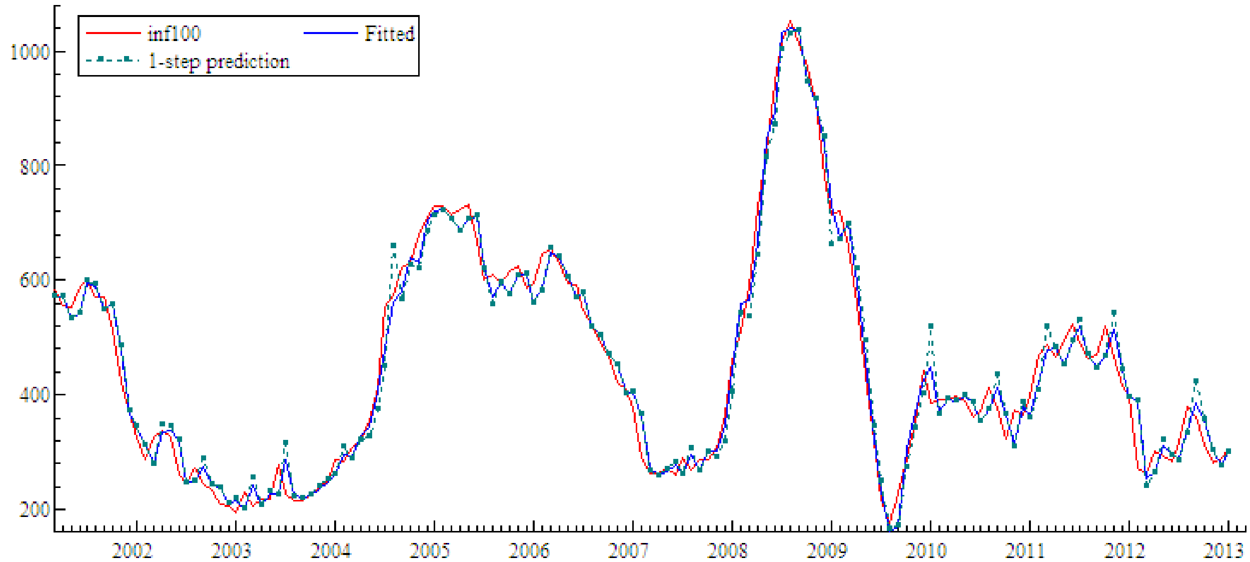
The filtered, smoothed and forecast probabilities for each of the regimes are shown in Figure 1. It may be observed that low inflation periods dominate high inflation periods. This is consistent with the earlier results that the expected duration of low inflation is more than twice that of high inflation.

Figure 1. Filtered, smoothed and forecast probabilities for each state



The fitted conditional mean shown in Figure 2 appears to predict well the actual inflation series. This suggests that the Markov switching model has performed relatively well in tracking the inflation values for both the peaks and the troughs.

Figure 2. Actual Inflation vs. Conditional Mean



The results of the Markov-switching model may be used to classify the months into low inflation or high inflation periods depending on the probabilities (Table 5). Oxmetrics uses smoothed probabilities in identifying the periods of low and high inflation.

Table 5. Dating of high and low inflation episodes based on the results of the Markov-switching model

Low Inflation	High Inflation
Jan 2002 - Apr 2004	May 2004 - Jul 2004
Apr 2005 - Oct 2007	Sep 2004 - Mar 2005
Oct 2008 - Oct 2008	Nov 2007 - Sep 2008
Jan 2009 - Mar 2009	Nov 2008 - Dec 2008
Jan 2010 - Dec 2012	Apr 2009 - Dec 2009

5.3 Logistic Regression

The logistic regression model is considered in setting up an early warning system for high inflation in the Philippines. The probabilities resulting from the logit model could provide a fair assessment about the possible onset of inflation crisis in the Philippines. Based on the regime classification from the Markov-switching model, an episode of high inflation is tagged 1 while an episode of low inflation is labeled as 0. Model selection is done using the goodness of fit criterion AIC.

The results of the logistic regression model are shown in Tables 6. The signs of the coefficients of the crisis indicators are consistent with theoretical expectations. The world prices rice as well as equity prices and domestic liquidity are estimated to be positively associated with Philippine inflation. This implies that a surge in the values of these indicators increases the probability that the country will enter a high inflation regime. Meanwhile, the BSP's policy rate is found to be negatively associated with inflation, suggesting that adjustments in monetary policy settings are properly transmitted to the economy through the various transmission mechanisms. It may be noted that the other indicators are not included in the final model because their coefficients are insignificant or have theoretically-incorrect signs.

Table 6. Estimated Logit Model

Variable	Coefficient	Std. Error	z-statistic	Prob.
C	-2.964	0.499	-5.936	0.000
M3(-7)	1.032	0.422	2.443	0.015
POLICYRATE(-4)	-6.773	2.540	-2.667	0.008
POLICYRATE(-5)	-5.317	3.172	-1.677	0.094
POLICYRATE(-6)	-6.218	2.691	-2.311	0.021
PSE(-4)	9.878	4.833	2.044	0.041
IR(-1)	0.069	0.019	3.663	0.000
AIC	0.775			
LR statistic	59.364			
Prob(LR statistic)	0.000			

5.4 Evaluation of the Performance of the Logit-based EWS model

Logit models could provide probability estimates resulting in one of the following scenarios:

Table 7. Probabilities of correct and incorrect crisis prediction

	High inflation	**Low inflation**
Signal Issued	P(1,1) = Correct call of crisis [A]	P(1,0) = Type II error or wrong signal [B]
No Signal Issued	P(0,1)=1-P(1,1)= Type I error or Missing Signal [C]	P(0,0)=1-P(1,0)= Correct call of non-event [D]

In Table 7, Event A represents the occasion when the model indicates a crisis when a high inflation event indeed occurs. Event B refers an event when a signal issued by the model is not followed by the occurrence of high inflation, i.e., wrong signal. It is also possible that the model does not signal a crisis (low estimated probability) but a crisis in fact occurs, i.e., missing signal, (Event C). Finally, Event D indicates a situation in which the model does not predict a crisis and no crisis occurs. In this paper, a threshold value of 0.5 is used to indicate whether the probabilities can already be interpreted as crisis signals.

To assess the performance of the EWS model, we utilize various performance criteria as suggested in Kaminsky et al. (1998).

1. Percent of crisis correctly called (PCCC) : $\frac{A}{A+C}$
2. Percent of non-crisis correctly called (PNCCC) : $\frac{D}{B+D}$
3. Percent of observations correctly called (POCC): $\frac{A+D}{A+B+C+D}$
4. Adjusted noise-to-signal ratio (ANSR): $\frac{B}{B+D} / \frac{A}{A+C}$
5. Probability of an event of high inflation given a signal (PRGS): $\frac{A}{A+B}$
6. Probability of an event of high inflation given no signal (PRGNS): $\frac{C}{C+D}$
7. Percent of false alarms to total alarms (PFA): $\frac{B}{A+B}$

Results shown in Table 8 suggest that the model has some potential as an EWS tool. Based on the in-sample forecasts, the model is able to correctly predict 50 percent of high inflation and 95 percent of low inflation events. Overall, 83 percent of observations are correctly predicted by the model. Moreover, the probability of a high inflation event given a signal is relatively high at 76 percent while the proportion of false alarms is relatively low at 24 percent.

An acceptable performance of a model within the sample does not imply good performance out of sample. In the evaluation of the out-of-sample forecasts, the EWS model is re-estimated using the sample period 2002-2007. The interest is to forecast the inflation regimes in 2008 and 2009 during and in the aftermath of the global commodity crisis. It may be noted that the forecast period is limited to 24 months in consideration of the policy horizon of the BSP as well as of the general forecast limitations of econometric models. Results in Tables 9 show that the probability of an event of high inflation given a signal stands at 79 percent, even higher than the in-sample equivalent of 76 percent. In addition, the proportion of false alarms for the out-of sample forecasts falls to 21 percent from 24 percent in the in-sample forecasts.

Table 8. Forecasts of the EWS model*

In-Sample		ACTUAL				
		High Inflation		Low Inflation		Total
PREDICTED	High Inflation	16	(50.0%)	5		21
	Low Inflation	16		88	(94.6%)	104
	Total	32		93		125
Out-of-Sample		ACTUAL				
		High Inflation		Low Inflation		Total
PREDICTED	High Inflation	11	(55.0%)	3		14
	Low Inflation	9		1	(25.0%)	10
	Total	20		4		24

*The first set of numbers represents counts while figures in parentheses represent percentages of correctly-predicted observations with respect to the two inflation regimes.

Table 9. Forecasting Performance of the EWS model

	In-Sample	Out-of-Sample
PCCC	50.0	55.0
PNCCC	94.6	25.0
POCC	83.2	50.0
ANSR	10.8	136.4
PRGS	76.2	78.6
PRGNS	15.4	90.0
PFA	23.8	21.4

The previous analysis is based on the choice of a threshold value of 0.5 to indicate whether the probabilities can already be interpreted as crisis signals. Bussiere and Fratzscher (2002) note that the lower the chosen threshold is, the more signals the model will send, but having the drawback of also raising the number of wrong signals (Type II errors).Meanwhile, increasing the threshold level reduces the number of wrong signals, at the expense of raising the number of missing crisis signals, that is, the absence of a signal when a crisis actually occurred (Type I errors). They add that from a policymakers' point of view, Type II errors may be less worrisome because they tend to be less costly from a welfare perspective than Type I errors. For these reasons, it may be prudent to consider a threshold value which is less than 0.5, in line with the policy bias put forth by Bussiere and Fratzscher (2002). In this paper, we use an alternative threshold value of 0.3 in evaluating the performance of the model.

Results shown in Table 10 point to an improvement in the in-sample forecasting performance of the model. Based on the in-sample results, the proportion of high inflation episodes correctly predicted by the model rises to 75 percent from 50 percent as a result of the lowering of the threshold. However, there appears to be some trade-offs in the use of the lower threshold with respect to out-of-sample forecasts. The probability of a high inflation event given a signal remains relatively high at 73 percent but lower compared to 79 percent which was recorded when the threshold value of 0.5 is used. In addition, the proportion of false alarms for the out-of sample forecasts rose slightly to 27 percent from 21 percent.

Table 10. Forecasting Performance of the EWS model

	In-Sample		Out of Sample	
	Threshold value		Threshold value	
	0.5	**0.3**	**0.5**	**0.3**
PCCC	50.0	75.0	55.0	55.0
PNCCC	94.6	89.2	25.0	0.0
POCC	83.2	85.6	50.0	45.8
ANSR	10.8	14.3	136.4	181.8
PRGS	76.2	70.6	78.6	73.3
PRGNS	15.4	8.8	90.0	100.0
PFA	23.8	29.4	21.4	26.7

5.5 Marginal Effects

To help in quantifying the possibility of the occurrence of an incidence of high inflation, we also compute for the marginal effects of the explanatory variables. The direction of the effect of a change in X_j depends on the sign of the coefficient β_j, i.e., positive values of β_j imply that increasing X_j would increase the probability of the response. However, unlike the typical regression models where the dependent variable is continuous, the estimated coefficients cannot be interpreted as marginal effects on the binary dependent variable. Some researchers use the average of all the values of the explanatory variables as the representative values to estimate the marginal effects. However, Bartus (2005) argues that marginal effects computed at means are not good approximations of average marginal effects. He recommends the estimation of the average marginal effect which is the average of each observation's marginal effect. The average marginal effect may be more realistic in that it evaluates all observations and not just those at the means which can be biased approximations.

Results shown in Table 11 imply that a one-percentage-point increase in the price inflation of the benchmark rice 1 month ago increases the probability that the country will be in a high inflation state by 0.7 percentage point. A one-percent increase in the value of the stock index 4 months ago and in domestic liquidity (relative to trend) seven months ago raises the probability of a high inflation episode by about 1.0 percentage point and 0.1 percentage point, respectively. Meanwhile, the BSP's policy rate seems to have persistent effects on domestic inflation as suggested by the significance of lags 4, 5 and 6 in the model. In the case of the longer lag, a one-percentage-point increase in the BSP's RRP rate six months ago decreases the probability that the country will be in a high inflation state by about 63.5 percentage points. This result points to the potency of policy rate adjustments by the BSP to manage inflation.

Table 11. Marginal effects

Variables	Marginal Effects
M3(-7)	0.105
POLICYRATE(-4)	-0.692
POLICYRATE(-5)	-0.543
POLICYRATE(-6)	-0.635
PSEI(-4)	1.009
IRICE(-1)	0.007

VI. Conclusion

This paper develops an early warning system (EWS) model for predicting the occurrence of high inflation in the Philippines to complement the BSP's existing suite of inflation forecasting models. Episodes of high and low inflation were identified using a Markov-switching model. Using the outcomes of the regime classification, a logistic regression model is then estimated with the objective of quantifying the possibility of the occurrence of high inflation episodes.

Results show that Philippine inflation may be modeled by a two-state MS-AR(2), with the estimated average inflation rate for the high inflation regime exceeding the upper bound of the current inflation target range of the BSP. The empirical results also suggest that it is more likely for the country to be in a state of low inflation than in a state of high inflation at least under the inflation targeting framework of the BSP. In addition, the estimated duration of low inflation is more than twice that of high inflation. Overall, the results of the Markov-switching model lend support to the effectiveness of the BSP's monetary policy instruments in managing inflation in the Philippines.

Meanwhile, results from the logistic regression model show that the indicators which are significantly related to domestic inflation include world prices of rice as well as equity prices and domestic liquidity. The policy rate of the BSP turns out to be significant as well, supporting the earlier results on the effectiveness of the BSP in steering inflation back to the target. Empirical results suggest that the EWS model has some potential as a complementary tool in the BSP's monetary policy formulation based on the in-sample and out-of sample forecasting performance.

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