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**Forecasting Inflation Rate in the Philippines:  
Linear vs Markov-Switching Model**

by

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## **ABSTRACT**

Forecasting inflation remains as a veritable challenge especially in an environment where market forces are given a greater reign in price determination. A Markov-switching model presents an alternative to take into account market changes that can possibly cause changes in parameter estimates of models and, ultimately, improve forecasting accuracy. This paper evaluates the performance of a Markov-switching model in forecasting inflation in the Philippines. Results show that the Markov-switching model outperforms a naïve random walk model in terms of forecasting accuracy; But it pales in comparison to the forecasting precision of a linear model. In terms of directional forecasting, the linear model remains the best followed by the random walk and the Markov-switching models, respectively.

## **Introduction**

Forecasting inflation rate is of interest to everyone. Economic policy makers forecast inflation rate as a guide to policy making. Firms use inflation forecasts as one of the key inputs in financial projections. Workers impute inflation forecasts in determining wages that they ask from their employers.

Yet, forecasting inflation remains as a veritable challenge. It is humbling to note that a naïve random walk model, which predicts that the one-period-ahead inflation forecast is equal to the previous inflation, outperforms highly developed models of inflation (Fisher, et. al., 2002 and Atkeson and Ohanian, 2001). Thus, in practice, statistical models of inflation are usually complemented by “anecdotal and other ‘extra-model’ information, and professional judgment” (Bernanke, 2007). In some cases, skepticism is cast on the value of statistical models in forecasting inflation.

On the part of those who are engaged in developing statistical models, the superior forecasting performance of the random walk model presents a challenge in developing alternative statistical models. Such challenge becomes even more in an environment where market forces are given a greater reign in price determination. Besides, there have been changes in the conduct of monetary policy which seems to affect the behavior of inflation (Fisher, et. al., 2002).

In this paper, we evaluate the merits of using Markov-switching modeling techniques in forecasting inflation in the Philippines. This family of models takes into account possible non-linear relationships which may improve forecasting. The Phillips relation is estimated based on the assumption the relationship between inflation and unemployment shifts between two states determined by transition probabilities that follow a Markov process. The out-of-sample forecast of the model is compared to those of the random walk model and a linear model of the Phillips relation over the estimation period.

Results show that the Markov-switching model outperforms a naïve random walk model in terms of forecasting accuracy; But it pales in comparison to the forecasting precision of a linear model. In terms of directional forecasting, the linear model remains the best followed by the random walk and the Markov-switching models, respectively.

Section two is a review of the common models of inflation: namely the random walk model and those that are based on alternative versions of the Phillips relation. Section three presents an empirical framework in estimating a Markov-switching Phillips relation. Section four discusses the approach in evaluating the forecasting performance of the alternative models. Section five shows the data, results, and analysis. Section six concludes the paper.

## **1. Inflation Models**

There is a host of models used in forecasting inflation. In this paper, we focus on two statistical models: the naïve random walk model and models based on the Phillips relation.

### **1.1. Random Walk Model of Inflation**

The naïve random walk model is based on the martingale hypothesis which posits that expected value of variable is best predicted by its current value. Applied to inflation forecasting, the hypothesis states that the expected inflation rate in a given period is equal to the inflation rate in the previous period. Thus,

$$(1) \quad E_{t-1}\pi_t^4 = \pi_{t-1}^4$$

where  $E_{t-1}$  is the expectations operator conditional on information at date t-1 and  $\pi_t^4$  is the inflation rate at quarter t defined as 100 times the change in the natural logarithm of the quarterly price index  $p_t$ ,

$$(2) \quad \pi_t^4 = 100(\ln p_t - \ln p_{t-4})$$

In the random walk model, the projected inflation at quarter t denoted as  $\hat{\pi}_t^4$  is equal to the conditional forecast of inflation. Thus,

$$(3) \quad \hat{\pi}_t^4 = \pi_{t-1}^4$$

## 1.2. Models based on the Phillips Relation

At the forefront of structural models of inflation are those based on the Phillips relation which establishes the negative relationship between inflation rate and unemployment rate. In its original form, the Phillips relation is given by:

$$(4) \quad \pi_t^4 = \alpha - \beta u_t$$

where  $u_t$  is the unemployment rate at quarter t and  $\alpha$  and  $\beta$  positive parameters. Implicit in this specification is the assumption that the expected inflation is equal to zero following the behavior of inflation in the Europe and the US prior to the 1960s. Thus, the Phillips relation can be generalized by

$$(5) \quad \pi_t^4 = \hat{\pi}_t^4 + \alpha - \beta u_t$$

If the expected inflation is proportional to the previous period inflation (i.e.,  $\hat{\pi}_t^4 = \theta \pi_{t-1}^4$ ) and the random walk holds (i.e.,  $\theta = 1$ ), equation (5) can be stated as:

$$(6) \quad \pi_t^4 - \pi_{t-1}^4 = \alpha - \beta u_t$$

In this modified version of the Phillips relation, unemployment rate affects not the inflation rate per se but the change in inflation rate.

Now, the empirical estimation of the Phillips relation has taken various forms. In this study, relation is adapted from a model of Fisher et. al., (2002):

$$(7) \quad \pi_t^4 - \pi_{t-1}^4 = \alpha - \beta u_t + \gamma(L)(\pi_t - \pi_{t-1}) + \varepsilon_t$$

where  $\gamma(L)$  is the number of lags in the change in one-period inflation rate,  $\Delta\pi_t$ , defined by

$$(8) \quad \pi_t = 100(\ln p_t - \ln p_{t-1})$$

It is taken that  $\gamma(L)$  is equal to four, representing the number of quarters in a year. The unemployment rate,  $u_t$ , represents an indicator of economic activity.

## 2. Empirical Framework

Traditionally, the Phillips relation is estimated using an ordinary least squares method which assumes a linear relationship between the change in inflation and the explanatory variables, namely the lagged change in one-period inflation rate and unemployment rate. However, changes in the market environment and the shifts in conduct of monetary policy provide a basis to believe that the Phillips relation changes with the latent state of the economy.

Markov-switching models provide an alternative approach to account for a possible non-linear Phillips relation. This family of models was initially employed by Hamilton (1989) in characterizing business cycles in the US. Quarterly percentage changes in the real GDP of the US from 1953 to 1984 were fitted in a fourth-order autoregression model based on the following specification:

$$(9) \quad \Delta y_t - \mu(s_t) = \alpha_1[\Delta y_{t-1} - \mu(s_{t-1})] + \dots + \alpha_4[\Delta y_{t-4} - \mu(s_{t-4})] + u_t$$

where

$\Delta y_t$ : log rate of change in real GDP times 100

$\mu(s_t)$ : conditional mean that changes between two states

$$\mu(s_t) = \begin{cases} \mu_1 > 0 & \text{if } s_t = 1 \text{ ("expansion")} \\ \mu_2 < 0 & \text{if } s_t = 2 \text{ ("contraction")} \end{cases}$$

$$u_t \sim \text{NID}(0, \sigma^2)$$

The state,  $s_t$ , is assumed to follow a Markov chain process described by transition probabilities  $\Pr(s_t = j | s_{t-1} = i) = p_{ij}$ , where  $\sum_{j=1}^2 p_{ij} = 1$ . These transition

probabilities are generally summarized in a matrix  $P$  given by:  $P = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix}$

In this matrix,  $p_{12}$  is the transition probability from expansion to contraction and  $p_{21}$  is the transition probability from contraction to expansion. The elements  $p_{11}$  and  $p_{22}$  indicate the probability that expansion and contraction will respectively remain.

Krolzig (1997, 2000) generalized Hamilton's specification to a multi-country model of business cycles in the form of a Markov-switching vector autoregression (VAR) model to incorporate co-movements in economic growth rates. He also provided for the exogenous variables in the model and the possibility of a state-dependent variance-covariance matrix. Thus, the conditional mean, the parameter estimates and the variance-covariance matrix may change with the realized state  $s_t$ .

In this paper, we specify a two-state Markov switching model of inflation rate. The model is specified to allow conditional mean, parameter estimate and the variance to change with the realized state.

### 3. Evaluating Forecasting Models

The science of forecasting inflation rate is generally benchmarked against a naïve random walk model since the literature is rich in empirical support that the naïve model outperforms both structural and time series models. (Atkeson and Ohanian, 2001). The root mean square error (RMSE) of inflation forecasts based on the random walk model will be compared to those of the Markov switching model and an ordinary linear model of the Phillips relation. The root mean square error is defined as the square root of the average of the squared differences between actual inflation and the predicted inflation.

$$(10) \quad \text{RMSE} = \left( \frac{1}{T} \sum_{t=1}^T [\pi_t^4 - \hat{\pi}_t^4]^2 \right)^{1/2}$$

To facilitate the analysis, the relative RMSE is computed. This is defined as the ratio of the RMSE of the Phillips curve models to the RMSE of the random walk model. A ratio of less than one suggests that the former models are superior in forecasting accuracy; A ratio of greater than one suggest otherwise. One minus the relative RMSE multiplied by 100 gives the percentage difference in RMSE between the structural models and the random walk model.

The predicted inflation of the Markov-switching model and linear model are estimated using a 15-year rolling regression. Using a sample that spans from 1983 to 2006, eight 15-year regression runs were undertaken to generate one-year-ahead forecasts from 1999 to 2006.

The underlying assumption in this approach is that each year, the latest available information is incorporated in re-estimating the model while the distant observations beyond the fifteen-year fixed estimation period are dropped. It also assumes that the data are available at the end of each year and the forecaster has the luxury of having the revised data used in the estimation of the new model.

In addition to the relative forecasting accuracy of the Phillips curve models, this paper also evaluates the effectiveness of the Phillips models capturing directional changes in inflation. Following the approach of Fisher et. al., (2002) the predicted and actual direction of change is measured by  $\hat{D}_t^4$  and  $D_t^4$  which are respectively defined as:

$$(11) \quad \hat{D}_t^4 = \begin{cases} +1 & \text{if } \hat{\pi}_{t+1}^4 > \pi_t^4 \\ -1 & \text{otherwise} \end{cases}$$

$$(12) \quad D_t^4 = \begin{cases} +1 & \text{if } \pi_{t+1}^4 > \pi_t^4 \\ -1 & \text{otherwise} \end{cases}$$

The performance of the models in capturing the directional change is measured by the percentage of the directional change predictions (PDCP) that are correct over the forecast period. This measure is defined as:

$$(13) \quad PDPC = \frac{1}{T} \sum_{t=1}^T I\{\hat{D}_{t+1}^4 = D_{t+1}^4\}$$

where  $I = 1$  if  $\{\hat{D}_{t+1}^4 = D_{t+1}^4\}$  and zero otherwise. The higher the PDCP suggests that there are more directional changes that are captured by the model.

### **Data, Results And Analysis**

In this study, inflation rate is based on the Consumer Price Index (CPI) with 2000 as the base year. The unemployment rate is taken from the quarterly Labor Force Survey conducted by the National Statistics Office.

The forecast of the random walk model is based on the inflation of the previous period as provided by equation (4). The forecast of the linear model is based on the OLS estimate of the Phillips relation given by equation (7).

In the case of the Markov-switching model, there are two Phillips relations that are estimated following the assumption that there are two states. Thus, the assumption may be based on either one of these equations (MS1 and MS2, respectively). Alternatively, the choice on which equation to use in forecasting can be based on the predominant state during the estimation period (MS OBS) or the state at the end of the estimation period (MS EOP). The former assumes that the predominant state will prevail over the forecast period; the latter assumes that the state at the end of the estimation period will persist over the forecast period.

Among the forecasts of the Markov switching model, the MS EOP yields the best forecasting accuracy. This is better than that of the random walk model but pales in comparison to the linear model. In terms of directional forecasting, the linear model

remains the best followed by the random walk and the Markov-switching models, respectively. In sum, the linear model proves to be the best model in forecasting inflation in the Philippines. Chart 1 shows its ability to track the general movements in inflation rate overtime.

Table 1. Summary of Results

	Naïve	Linear	MS1	MS2	MS OBS	MS EOP
RMSE	1.87	1.59	3.84	1.82	3.15	1.74
Rel RMSE	1.00	0.85	2.05	0.97	1.68	0.93
DPC	27	28	25	22	21	24
PDPC	84%	88%	78%	69%	66%	75%

## Conclusion

In this paper, we evaluate a Markov-switching model of inflation in forecasting. Results show that it does not surpass the performance of a simple linear model in forecasting the magnitude of inflation and in predicting the direction of change. Incessant search to improve the science of forecasting continues. Meanwhile, the practice forecasting remains more of an art than a science: “extra-model” information and professional judgment continue to play an important role.

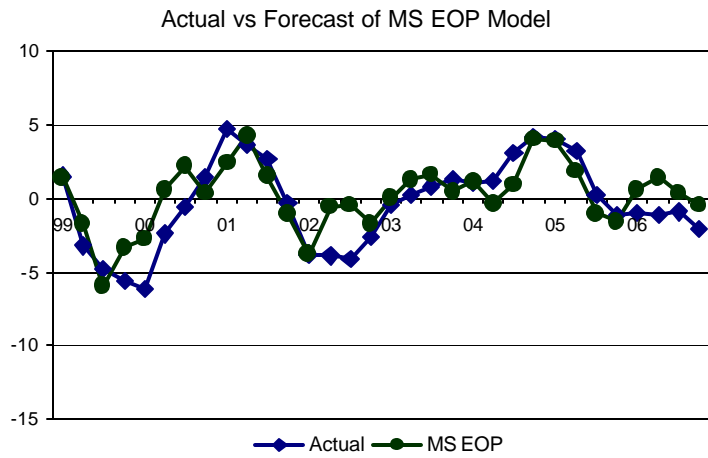
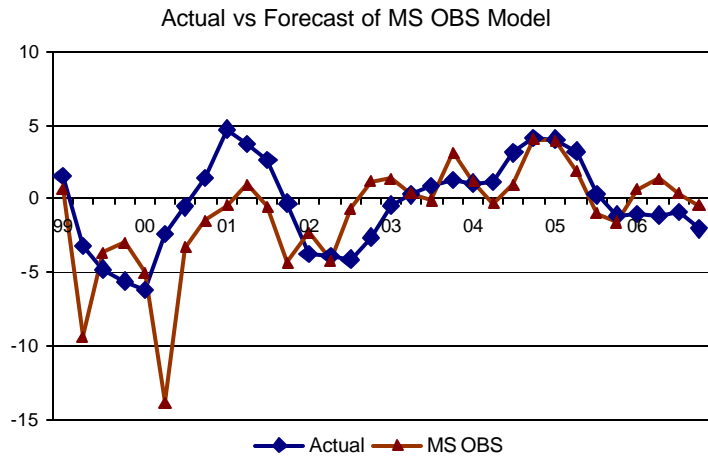
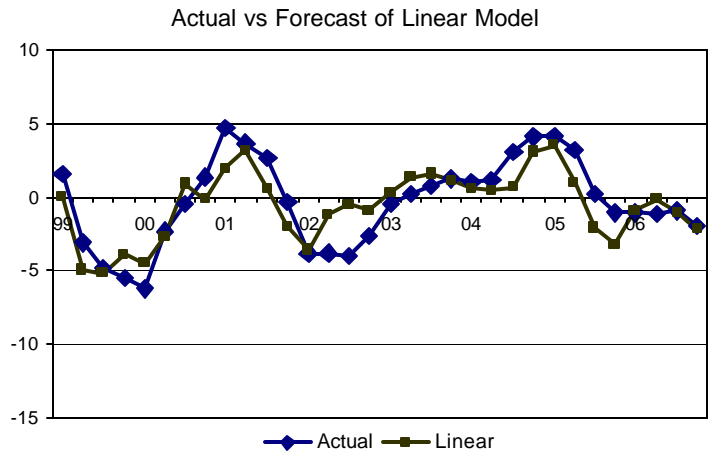


Chart 1: Actual vs Forecasts

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