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Forecasting Philippine Monthly Inflation Using TRAMO/SEATS

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The study aims to explore the feasibility of adopting for inflation forecasting a sophisticated expert system normally used in routine outlier detection and deseasonalization of time series. Known as TRAMO/SEATS expert system, this twin program is a fully automatic procedure that extracts the trend-cycle, seasonal, irregular and certain transitory components of high frequency time series via the so-called ARIMA-model-based method. The results of the study reveal the feasibility of the use of the technique for routine inflation forecasting. The automatic model building capability of TRAMO/SEATS is exploited to arrive at an ex-ante model that has the ability to generate optimal forecasts. The results show the ability of the final model to forecast inflation with remarkable accuracy.

Keywords: Inflation, inflation rates, economic forecasts, economic forecasting, forecasting techniques

One of the most important preconditions for successful implementation of the current monetary policy framework adopted by the Bangko Sentral ng Pilipinas (BSP) known as Inflation Targeting is the development of reliable quantitative models that can accurately track and predict the direction and magnitude of general price levels (Department of Economic Research, Bangko Sentral ng Pilipinas [DER-BSP], 2007). As mandated by its charter, the BSP's foremost job is to promote price stability conducive to balanced and sustainable economic growth (Republic Act No. 7653). BSP executes this task by regulating money supply which in turn impact on the demand for goods and services, thus influencing inflation. Under inflation targeting, the BSP explicitly announces to the public an inflation figure it will endeavor to attain over a specified period using all of the policy instruments at its disposal. Most of these instruments involve the modification of key policy interest rates controlled by BSP. If the BSP fails to achieve the announced target, it is required to explain to the public the reason for such failure and to announce measures it will undertake to steer inflation back to target level.

In setting inflation targets, monetary authorities rely extensively on the capability of their forecasting models to accurately predict future price levels. Most of these models are large scale structural econometric models [e.g., BSP's Single Equation Model (SEM) and Multi-Equation Model (MEM), Cruz (2009), or the Mariano Model (Mariano, 1985)] capable of anticipating long term over-all price movements. Other theory-based econometric models like the NAIRU Phillips Curve model and its other variants (e.g., Fisher, Liu, &

Zhou, 2002; Stock & Watson, 1999; 2007; Gordon, 1997) which suggest that unemployment is an excellent predictor of future inflation are also being used extensively. For shorter forecast horizons, the models/methods of choice are either simple ad-hoc extrapolative procedures (e.g., moving averages, percent change extrapolation or simple rules-of-thumb heuristics) or a-theoretic univariate models [e.g., trend analysis, exponential smoothing, statistical time series decomposition and Univariate ARIMA (Autoregressive Integrated Moving Average) Box-Jenkins models]. Multi-equation non-structural models like Vector Autoregressive (VAR) and micro founded dynamic stochastic general equilibrium (DSGE) models have also been tried to forecast inflation. The predictive accuracy of these models, however, vary widely, with some, even falling short of the forecasting performance of the Random Walk (or the no-change extrapolation) model.

This study attempts to explore the feasibility of applying an expert system capable of automatically generating reliable models in the context of forecasting and signal extraction of unobserved time series components. This state-of-the-art system, called the TRAMO/SEATS program, developed by Bank of Spain mathematicians Gomez and Maravall (1996) calls for the modeling of univariate time series as being spawned by some data generating process driven by influential data points and an ARIMA model-based white noise.

The plan of the study is to first give a descriptive account of the recent Philippine inflation scenario before analytically examining the statistical properties of the monthly inflation series. The theoretical underpinnings of the featured modeling technique will then be presented, followed by a discussion of the methodological framework of the study. Concluding remarks will follow the presentation of the empirical results.

RECENT INFLATION SCENARIO IN THE PHILIPPINES

After witnessing an unprecedented peacetime inflation of 50.32% in 1984, many Filipinos thought that they have seen the worst, especially when, in the two consecutive years of 1986 and 1987 under the democratic space provided by the Aquino government, inflation fell to an annual average of 0.80% in 1986 and 3.9% in 1987 (Yap, 1996). True enough, for the following decades – 1990s and 2000s – average annual inflation did not even go past the 20% mark. As seen in Table 1, during a long 15-year span from 1995 to 2009, inflation remains at single digit annual average. Economic analysts and politicians attribute these inflation figures to sound economic fundamentals, but some economists, particularly the central bank authorities, ascribe these to sensible monetary programming.

Table 1

Annual Average Inflation Rates (In Percent), 1970-2009

Year	Inflation	Year	Inflation	Year	Inflation	Year	Inflation
1970	15.00	1980	18.09	1990	12.18	2000	3.97
1971	21.59	1981	13.29	1991	19.33	2001	6.78
1972	8.41	1982	10.20	1992	8.68	2002	3.01
1973	16.38	1983	9.95	1993	6.73	2003	3.48
1974	34.07	1984	50.32	1994	10.41	2004	5.97
1975	7.18	1985	23.11	1995	6.83	2005	7.68
1976	8.76	1986	0.80	1996	7.50	2006	6.28
1977	9.95	1987	3.72	1997	5.58	2007	2.77
1978	7.33	1988	8.81	1998	9.22	2008	9.29
1979	17.67	1989	12.20	1999	5.99	2009	3.35

Source: Philippine Statistical Yearbook, Various Issues.

DATA FOR THE STUDY

The modeling framework of the study calls for the use of a data frequency higher than a year, and with the number of observations substantial enough to make meaningful inference despite large number of parameters to be estimated. The monthly inflation series available at the National Statistics Office (NSO) Web site (http://www.census.gov.ph) is just the ideal time series data for the study. To make the analysis cover some of the more exciting periods of the country's economic history, the 20-year period from January 1990 to December 2009 is used as the sample period, involving 240 monthly observations.

The raw data for the inflation series is exhibited in Table 2 and are pictorially presented as line graph in Figure 1. Over most of the sample period, it appears that monthly inflation fluctuates around a slightly downward sloping linear trend line, with some episodes of short-term spikes, the most recent run of which was the six-month span (June to November) in 2008 when crude oil prices reached record highs. As can be gleaned from the line graph, seasonality is not prominently recognizable, however, in some years, peaks and troughs apparently coincide in certain months. To provide a non-linear perspective on the general direction the inflation series is taking, a cutting-edge trend indicator known as Hodrick-Prescott Filter is employed. The line graph of the smoothed (filtered) inflation series is superimposed on the original series in the figure to highlight the general direction the series is taking. Also presented is the implied cyclical fluctuation of monthly inflation over the sample period.

Table 2
Monthly Inflation Data, January 1990 to December 2009

Year	Jan.	Feb.	March	April	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.
1990	12.3	12.0	12.5	12.7	12.3	11.6	12.0	10.3	10.4	11.8	12.9	15.3
1991	18.5	20.2	20.8	20.4	20.5	20.3	20.0	21.1	20.9	18.8	17.2	13.2
1992	10.8	9.1	8.8	8.6	8.9	9.0	8.9	8.3	8.2	8.2	8.0	7.4
1993	7.5	7.3	6.9	6.7	6.1	6.0	6.1	6.3	6.6	6.9	7.0	7.4
1994	10.9	12.1	11.5	11.7	11.5	11.0	10.4	10.7	9.3	8.9	8.5	8.4
1995	5.8	5.0	5.6	5.6	6.3	6.6	6.4	6.8	8.8	8.8	8.1	8.1
1996	8.5	8.7	8.7	8.9	8.0	8.0	7.8	7.3	5.3	5.4	6.5	6.9
1997	5.6	5.3	5.4	5.1	5.0	5.6	5.4	5.3	5.8	5.9	6.4	6.2
1998	6.5	7.6	8.1	8.3	9.7	10.0	10.1	9.9	9.9	9.8	10.7	10.0
1999	10.5	9.0	7.7	7.1	5.8	4.9	4.8	4.7	4.9	5.0	3.6	3.9
2000	2.2	2.5	2.8	3.3	3.4	3.8	4.2	4.4	4.2	4.6	5.7	6.5
2001	7.5	7.4	7.6	7.4	7.4	7.2	7.4	7.0	6.8	6.1	5.0	4.5
2002	3.7	3.2	3.5	3.5	3.5	2.9	2.6	3.0	2.7	2.6	2.4	2.5
2003	2.8	3.2	3.0	3.3	3.4	3.9	3.7	3.4	3.6	3.6	3.9	3.9
2004	4.1	4.0	4.2	4.3	4.5	5.4	6.6	6.8	7.2	7.7	8.2	8.6
2005	8.4	8.5	8.5	8.5	8.5	7.6	7.1	7.2	7.0	7.0	7.1	6.7
2006	6.7	7.6	7.6	7.1	6.9	6.7	6.4	6.3	5.7	5.4	4.7	4.3
2007	3.9	2.6	2.2	2.3	2.4	2.3	2.6	2.4	2.7	2.7	3.2	3.9
2008	4.9	5.4	6.4	6.8	9.6	11.4	12.2	12.4	11.8	11.2	9.9	8.0
2009	7.1	7.3	6.4	4.8	3.3	1.5	0.2	0.1	0.7	1.6	2.8	4.4

Source: National Statistics Office (www.census.gov.ph).

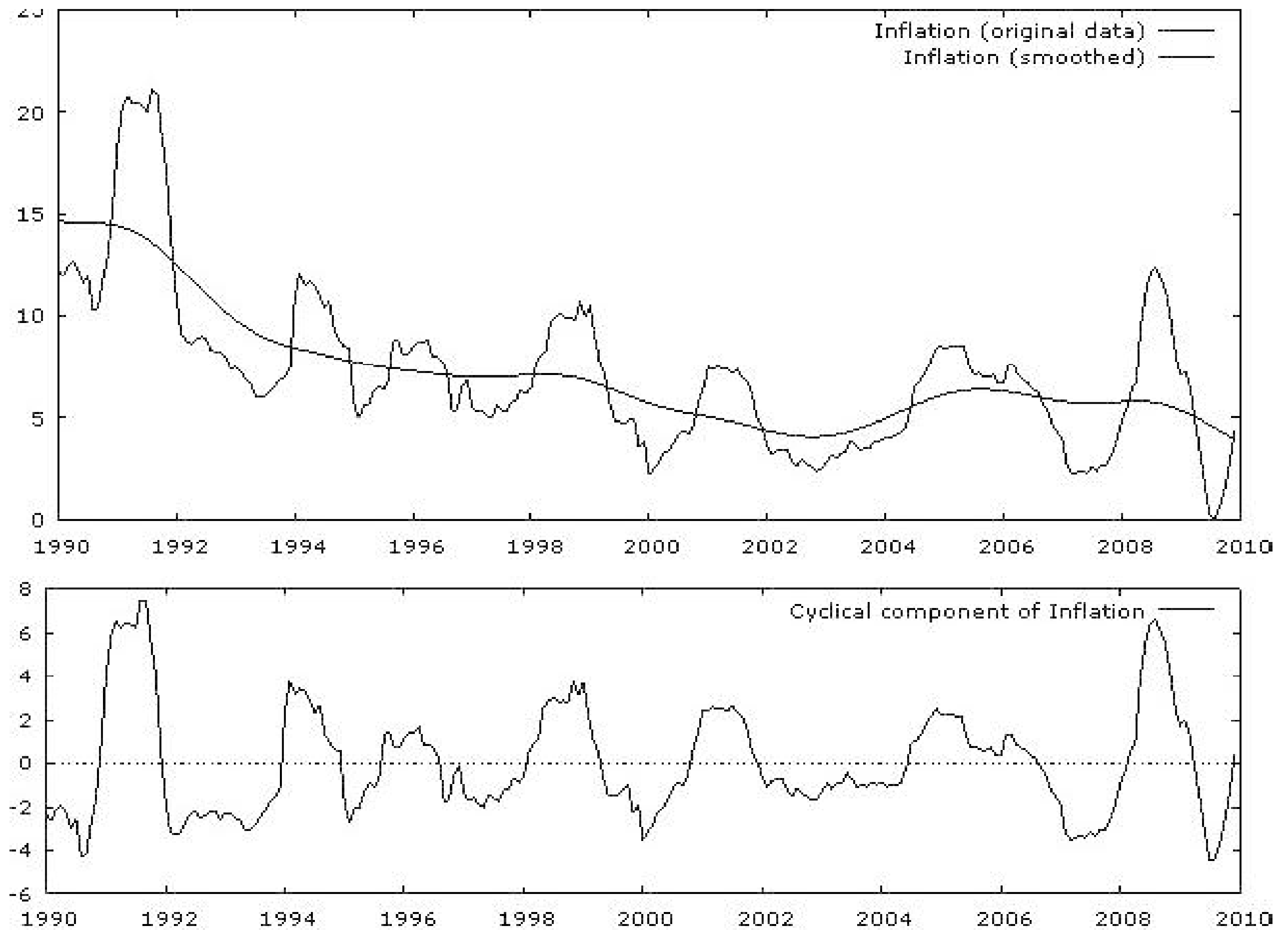

Figure 1. Monthly inflation for the Philippines, January 1990 to December 2009.

THE TRAMO-SEATS SYSTEM

One particular challenge among data analysts is to uncover the components comprising any observed time series in order to have a clearer picture of how the variable unfolds over time. These unobserved elements are the secular trend (the general direction the series is heading), seasonality (tendency of the series to peak and dip regularly year after year), cyclical fluctuations and the irregular variations that characterize the data. A good number of analytical tools ranging in complexity from ad-hoc decomposition methodologies to highly sophisticated time series modeling techniques are being used for this purpose. Among the most widely used by western European data agencies like the Eurostat (1999), European Central Bank (2000) Banca d'Italia (1999), and Banco de Espana (1999) is the twin programs know as the TRAMO/SEATS expert system – a fully automatic procedure that extracts the trend-cycle, seasonal, irregular and certain transitory components of high frequency time series via the so-called ARIMA-model-based (**AMB**) method. The system is composed of two programs, the TRAMO (**T**ime series **R**egression with **A**RIMA noise, **M**issing observations and **O**utliers) and the SEATS (**S**ignal **E**xtraction in **A**RIMA **T**ime **S**eries). TRAMO is a program for estimation and forecasting of regression models with possibly non-stationary ARIMA noise and any sequence of missing values. It interpolates the missing values, identifies and corrects for various categories of outliers and estimates special effects like trading day, Easter and intervention-type factors that often characterize high-frequency time series. SEATS is the program designed to handle the estimation of the aforementioned unobserved components of the data following the AMB methodology. The programs are structured to be used together for in-depth analysis of one or more series. TRAMO pre-adjusts the series for signal extraction by SEATS. Hence, SEATS is completely dependent on the regression model developed by TRAMO although it can handle data analysis independent of TRAMO in certain routine signal extraction tasks done at various international data agencies (e.g., Eurostat and European Central Bank).

In this study, the TRAMO program will be used in modeling the monthly Philippine inflation series from January 1990 to December 2009 in a fully automatic manner in order to generate ex-ante inflation forecasts for a full-year planning horizon. It is expected that the TRAMO program will be able to produce an ARIMA model that can be used for routine forecasting of inflation series for potential adoption by BSP in its inflation target setting. The SEATS program will only be used to validate the reasonableness of the specifications of the forecasting model developed by TRAMO and to extract, if there are any, seasonality, cyclical fluctuations and other unobserved components of the inflation series. The cutting-edge software called TRAMO-SEATS for Windows (TSW Beta Ver. March 2009) will be used in the automation of the model-building task.

THREE INFLATION FORECASTING MODELS AUTOMATICALLY GENERATED BY TRAMO/SEATS

In the pursuit of the most desirable inflation forecasting model with ARIMA-based noise, three distinct models were generated by the TRAMO/SEATS expert system based on different input assumptions. Using the monthly headline inflation time series over the period January 1990 to December 2009, the models were generated by the TSW software. Parameter estimates computed through exact maximum likelihood procedure via Kalman Filter, together with their respective standard errors and other goodness-or fit indicators are examined for their relative desirability.

Model 1

The first model was generated using the following input assumptions: The program tests for the log/level specification and performs automatic model identification and outlier detection. Three types of outliers are considered: additive outliers, transitory changes and level shifts; the level of significance is set by the program and depends on the length of the series. The full model is estimated by exact maximum likelihood. The model is decomposed and optimal estimators and forecasts of the components are obtained, as well as their mean squared error. These components are the trend-cycle, seasonal, irregular and (perhaps) transitory component. If the model does not accept an admissible decomposition, it is replaced by a decomposable one.

Model 2

Tested for the log/level specification, performs automatic model identification and outlier detection. The model is decomposed and optimal estimators and forecasts of the components are obtained, as well as their mean squared error. These components are the trend-cycle, seasonal, irregular and (perhaps) transitory component. But unlike Model 1, a pretest is made for the presence of Trading Day, Leap Year and Easter effects, with the first effect using a one parameter specification (working / non-working days).

Model 3

This was generated using automatic modeling through the TRAMO routine without passing through SEATS. Outlier detection was not activated and identification of candidate models for automatic selection done via the iterative Box-Jenkins procedure.

EMPIRICAL RESULTS

The empirical implementation of the above models resulted in three different estimated **Tramo/Seats** models presented below. These estimated models employed the full sample period January 1990 to December 2009. All results are generated by TSW Beta Ver. March 16, 2009, with auxiliary modeling using EViews 6.0 and Gretl 1.87.

Model 1

Inflation = 2 Outliers + $ARIMA(1,1,0)0,0,1)_{12}$ for level series, without intercept, without trading day correction and without Easter correction. Outliers are December 1991 (*Out1* - a level shifter) and April 2008 (*Out2* - an additive outlier)

If Y_t = Inflation during month *t*; X_t = AMB error and ε_t = pure white noise

B = Backshift operator ($BY_t = Y_{t-1}$) and $\Delta = 1 - B$ (differencing operator)

$$Y_t = -2.58Out1_t - 1.26Out2_t + X_t \qquad (1)$$
(-6.64) (-5.36)

with AMB error model

$$(1 - 0.4553B)\Delta X_t = (1 - 0.7925B^{12})\varepsilon_t \qquad (2)$$
(-7.73) (-15.79)

Model 2

Inflation = 4 Outliers + $ARIMA(0,1,1)0,1,1)_{12}$ for level series, without intercept, without trading day and Easter corrections. Outliers are December 1991 (*Out1* - Level Shifter), January 1995 (*Out2* - Level Shifter), January 2000 (*Out3* - Transitory Component) and January 1994 (*Out4* - Level Shifter).

$$Y_1 = -2.8716Out1 - 2.2859Out2 - 2.1422Out3 + 2.4892Out4 + X_t \qquad (3)$$
(-4.55) (-3.61) (-3.86) (3.93)

$$\Delta\Delta^{12} X_t = (1 + 0.4565B)(1 - 0.9850B^{12})\varepsilon_t \qquad (4)$$
(7.73) (-86.00)

Model 3

Inflation = ARIMA$(0,1,1)0,1,1)_{12}$ for level series, with intercept. Automatic modeling only on the AMB noise component using TRAMO, no automatic outlier detection. Modeling via SEATS waived.

$$\Delta Y_t = 0.00378 + (1 + 0.4157B)(1 - 0.9850B^{12})\varepsilon_t \qquad (5)$$
(0.30) (6.89) (-86.00)

COMPARATIVE PERFORMANCE OF THE MODELS

When the three models are implemented over the sample period of January 1990 to December 2009, the comparative performance of the models may be assessed through a number of goodness-of-fit indicators and in-sample forecasting efficiency. The figures needed for the empirical performance evaluation of the models are shown in Table 3 and Table 4. Graphical analysis of the models' comparative in-sample performance may be made using Figure 2, Figure 3, and Figure 4.

Table 3
Model Specifications and Goodness-of-fit Indicators

Model Specifications and Indicators of Fit	Model 1	Model 2	Model 3
Dependent Variable in Level =1; Logarithm = 0	1	1	1
Intercept (yes=1, No=0)	0	0	1
Autoregressive Order (p)	1	0	0
Differencing Order (d)	1	1	1
Moving Average Order (q)	0	1	1
Seasonal Autoregressive Order (P)	0	0	0
Seasonal Differencing Order (D)	0	1	1
Seasonal Moving Average Order (Q)	1	1	1
Standard Error of Residuals	0.54465	0.69469	0.78685
Bayesian Information Criterion (BIC)	-1.14046	-0.61195	-0.42105
Ljung-Box Q Statistics	19.37	68.49	59.60
Bowman-Shenton Normality test	300	65.00	289.70
Skewness Test Statistic (SK)	5.57	-2.28	-0.91
Kurtosis Test Statistic (KUR)	16.40	8.93	8.24
Box-Pierce Q	0.548	0.00	0.00
Box-Pierce Q^2	7.234	42.06	26.13
Run's Test (t – value)	1.30	1.48	2.67
Durbin Watson Statistic	2.0227	1.7740	1.7483
Number of Outliers	2	4	0
Number of Iterations	2	13	12
Number of Function Evaluations	7	80	37

Table 4
In-Sample Forecasting Performance of the Models

Forecasting Performance Indicators	Model 1	Model 2	Model 3
Mean Error	-0.00172	-0.03358	-0.03734
Mean Squared Error	0.32333	0.62852	0.82302
Root Mean Squared Error	0.56862	0.79279	0.90720
Mean Absolute Error	0.40042	0.55073	0.58388
Mean Percentage Error	0.12802	-0.54243	-0.98437
Mean Absolute Percentage Error	7.4472	12.1930	12.9080
Theil's U	0.28337	0.94577	0.93756
Bias proportion, UM	9.1443×10^{-6}	0.00179	0.00169
Regression proportion, UR	0.00534	0.05892	0.07230
Disturbance proportion, UD	0.99465	0.93928	0.92598

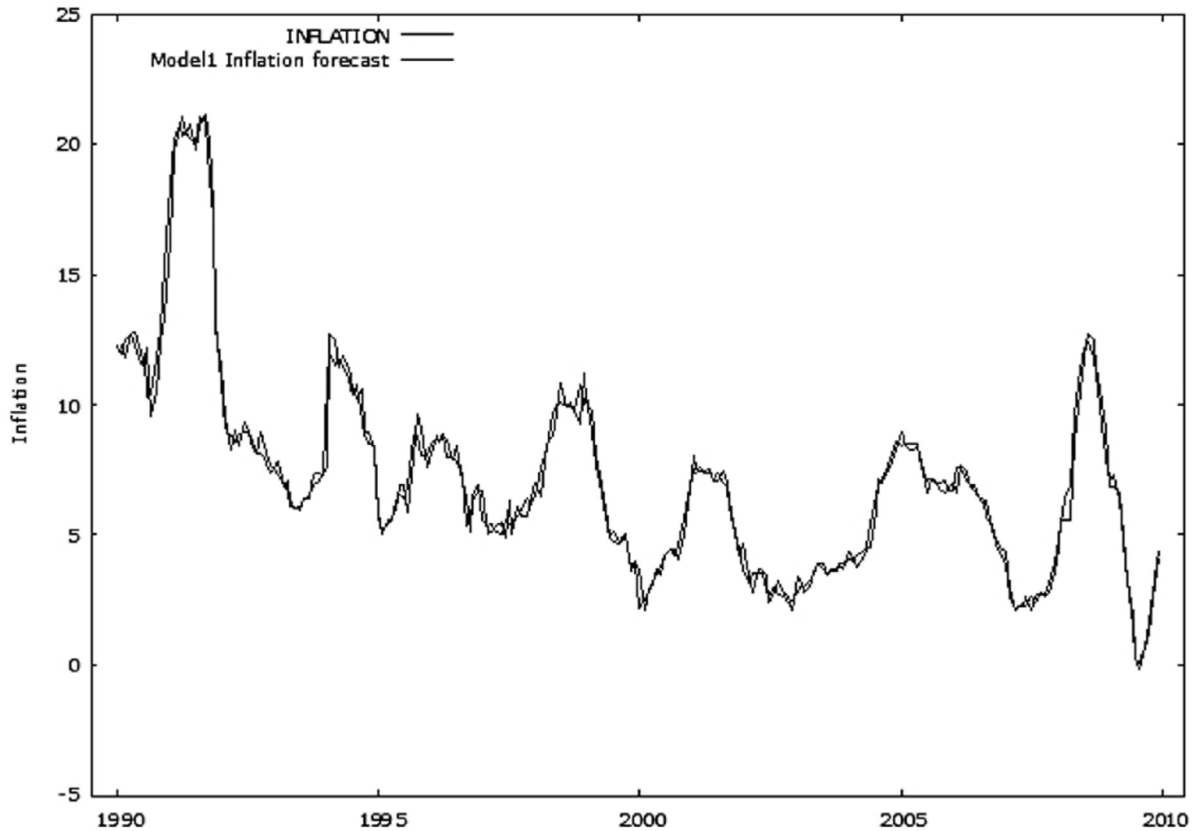

Figure 2. Forecast simulation using Model 1.

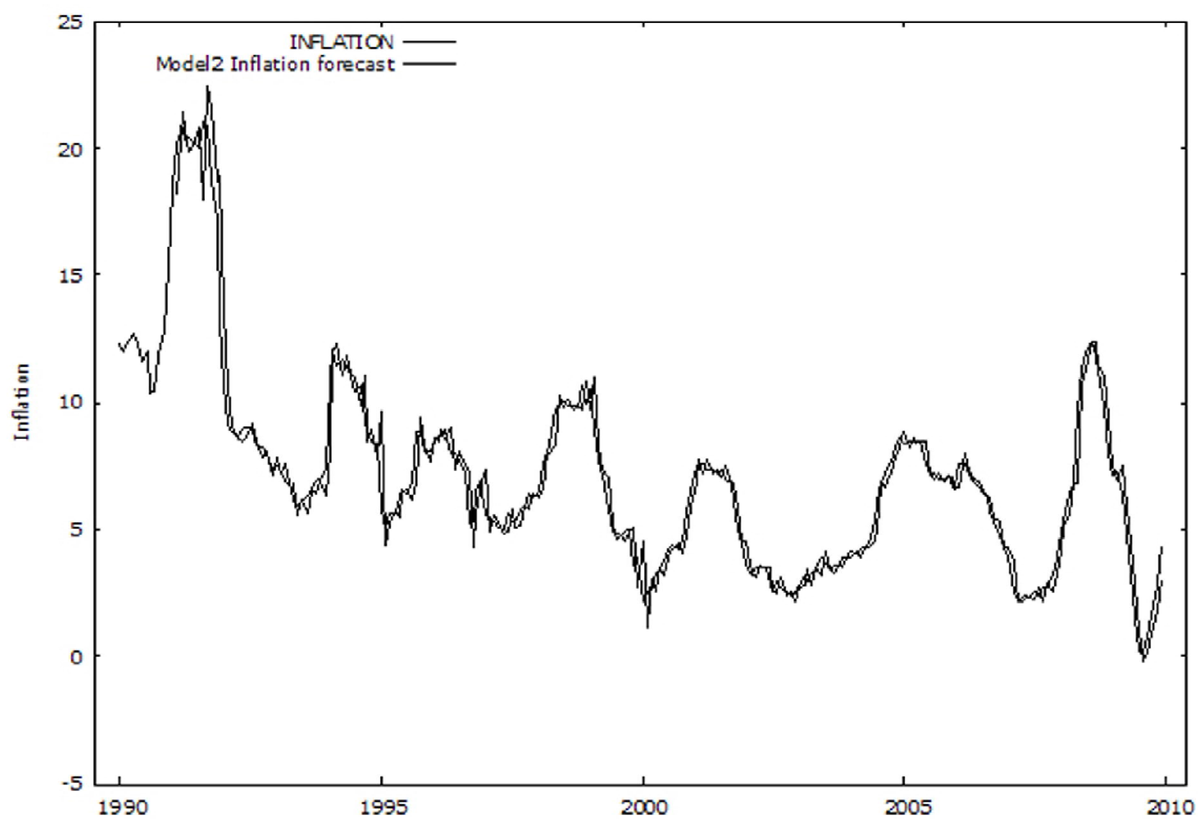

Figure 3. Forecast simulation using Model 2.

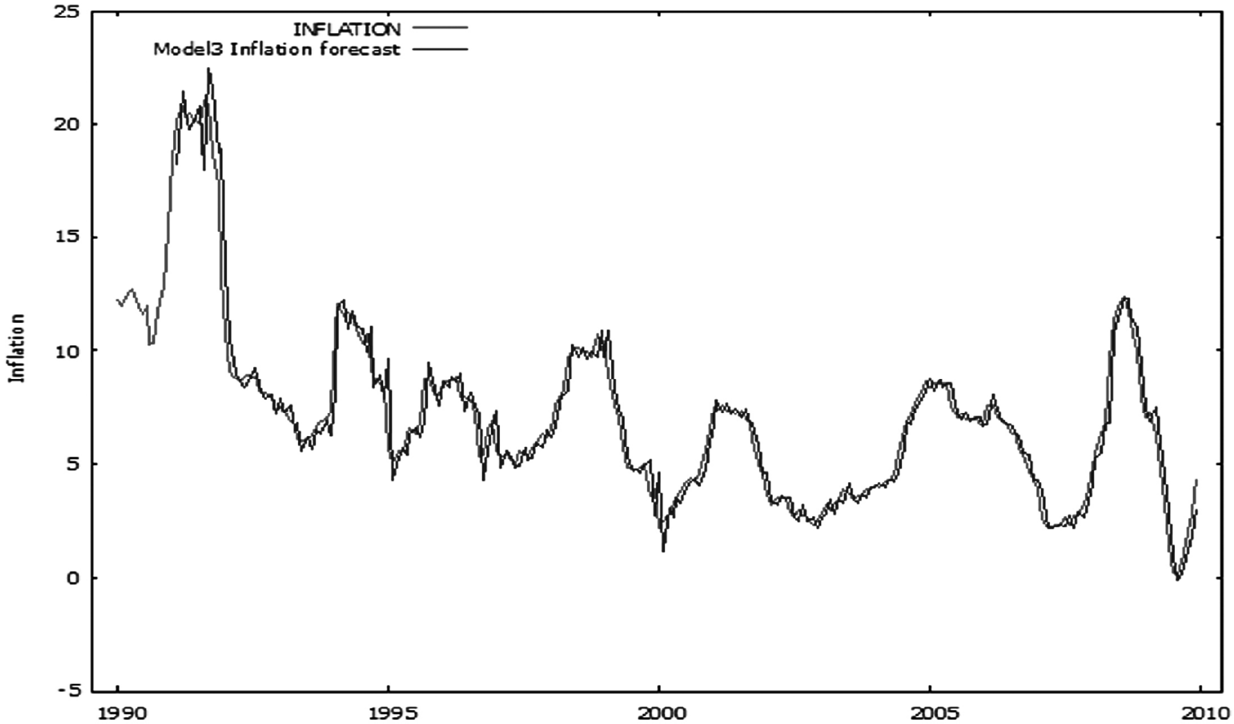

Figure 4. Forecast simulation using Model 3.

DISCUSSION OF THE EMPIRICAL RESULTS

The figures presented in the summary tables (Table 3 and Table 4) as well as the forecast simulations using in-sample data generated by the three models vis-à-vis the actual inflation data (as shown by the graphs in Figures 2, 3 and 4) underscored the relative superiority of Model 1 over the two other models. Most of the goodness-of-fit indicators shown in Table 3 indicate Model 1's adherence to the requirements of desirable time series model, except for the result of the Bowman-Shenton Normality test of residuals. The test implied that the distribution of the residuals of Model 1 is far from normal but with pronounced fatter tails. With regards to the information provided by the Bayesian Information Criterion (BIC), Model 1 is truly a class in itself as it produced a BIC which is almost twice negative as the closest model's BIC figure, indicating its preponderance of information content in explaining, parsimoniously the trajectory of the inflation series than the other models.

Moving to the figures presented in Table 4, the same conclusion can be inferred. All indicators of forecasting performance reveal the relative dominance of Model 1 over the other alternative models. The most pre-eminent among the performance measures is the MAPE (Mean Absolute Percentage Error) with Model 1's MAPE figure of 7.45% is almost 5 percentage points less than the second best performing model. The results of the analysis is clear: Model 1 completely dominates Model 2 and Model 3 in terms of in-sample forecasting performance and goodness-of-fit indicators, hence it is the model of choice that will generate for us the 12-period ahead ex-ante inflation forecasts covering the entire year of 2010. Table 5 presents the results of this forecast generation. It is interesting to note that the 95% confidence interval out-of-sample ex-ante forecast for inflation rate for January and February 2010 situate the actual inflation rate for this two periods of 4.4% and 4.2% respectively, highlighting the feasibility of our forecast generation via Model 1.

Table 5
Ex-Ante Forecasts for the Entire Year 2010 Generated by Model 1

Month	Inflation Forecast	Standard Error	Margin of Error at 95% Confidence	Lower 95% Confidence Forecast	Upper 95% Confidence Forecast
January	4.94	0.5447	1.07	3.87	6.01
February	4.87	0.9617	1.88	2.99	6.75
March	5.14	1.3209	2.59	2.55	7.73
April	5.47	1.6377	3.21	2.26	8.68
May	5.68	1.9030	3.73	1.95	9.41
June	6.18	2.1456	4.20	1.98	8.16
July	6.60	2.3654	4.64	1.96	11.24
August	6.66	2.5673	5.03	1.63	11.69
September	6.67	2.7548	5.40	1.27	12.07
October	6.40	2.9305	5.74	0.66	12.14
November	6.16	3.0963	6.07	0.09	12.23
December	5.91	3.2537	6.38	-0.47	12.29

CONCLUDING REMARKS

Price stability has been the foremost objective of all monetary policies crafted by the government since the time it adopted the inflation targeting framework. The BSP, by virtue of its power to control the amount of money in circulation and setting policy interest rates, has been tasked to operationalize this type of transmission mechanism by announcing explicit inflation target it will endeavor to achieve over a given period of time. In setting this all important inflation objective, the BSP has to be guided by a reliable inflation forecasting model that would make the inflation target both realistic and achievable.

Inflation data for 240 monthly observations encompassing the period January 1990 to December 2009 were employed in the modeling exercise. The results show the ability of the model to forecast inflation with remarkable accuracy. Even turning points were adequately anticipated by the system. In the end, the study produced forecasts for the yet to happen period January 2010 to December 2010. It is hoped that the Bangko Sentral ng Pilipinas and other government or private instrumentalities involved in inflation forecasting will include the modeling framework presented in this paper in their forecasting methodology arsenal.

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