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Forecasting Inflation: A Disaggregated Approach Using ARIMA Models

By Joan Christine S. Allon[1]

The monetary authorities of a large number of countries recognize that price stability, that is, an environment of low and stable inflation rate, is the main contribution that monetary policy can give to economic growth. In the case of the Philippines, price stability is the ultimate objective of monetary policy under the inflation targeting (IT) framework which was adopted in 2002.[2] This shift required not only a change in the conduct of monetary policy but also the institution of key elements necessary to support the new framework.[3]

One such necessary structure is the ability to forecast the future course of inflation in a precise and timely manner. Monetary authorities like the Bangko Sentral ng Pilipinas (BSP) have to undertake pre-emptive actions and neutralize inflationary or deflationary pressures that could threaten the stability of prices in the future. Naturally, such monetary action takes the forecasts of the future path of inflation as an important input. Thus, inflation forecasting is an essential component in the formulation of appropriate forward-looking monetary policy.

In the BSP, there are continuing efforts to develop and improve further its suite of economic models used for forecasting and policy analysis. This helps enhance the institutional capacity to conduct economic research. A step towards improving the forecasting capability of the BSP is to augment existing structural forecasting models (i.e. Single Equation Model and the Multi-Equation Model) with a modest yet complementary univariate model such as the one described in this paper. The forecasting model in focus is a semi-structural and seasonal Autoregressive, Integrated, Moving Average (SARIMAX) process which forecasts the Consumer Price Index (CPI) and the inflation rate one- to three-months ahead by aggregating the forecasts of the individual components of the CPI. This paper adopts the standard methodologies in the SARIMAX inflation forecasting literature described in Pufnik and Kunovac (2006), Alnaa and Ahiakpor (2011), and Doguwa and Alade (2012).

This article presents the basic facts about the SARIMAX model and the processes involved in its formulation. It then tackles the Philippine CPI, the level of disaggregation and the choice of exogenous variables. The method of evaluation as well as some findings on the accuracy of the model are discussed in the last section.

Method

In supplementing the existing structural models used by the BSP, the model in focus is based on the procedure in Box et al. (1994) for fitting a seasonal ARIMA model (Figure 1). The method involves a univariate and purely statistical process which forecasts future values derived exclusively from past behavior. Despite the method's black box reputation and the exclusion of potentially important information, a certain type of analysis is possible so that simple models such as this, typically provide good results in the primary task of forecasting (Pufnik and Kunovac, 2006).

Before estimating an ARIMA model, the series under study must satisfy the following assumptions: (i) the error distribution is normal, (ii) the mean and variance are constant (stationarity); and (iii) the relationship between the seasonal and non-seasonal components is multiplicative (Doguwa and Alade, 2012). A basic ARIMA model features three components whose orders are determined

[1] Ms. Allon is a Research Analyst II at the Department of Economic Research.

[2] Republic Act No. 7653 or the New Central Bank Act of 1993 states that price stability is the main mandate of the BSP. Prior to the adoption of the IT, the BSP used the monetary targeting approach to monetary policy.

[3] Bangko Sentral ng Pilipinas, Primer on Inflation Targeting, June 2015, available online at http://www.bsp.gov.ph

over an iterative process, and expressed through the ARIMA (p, d, q) notation, where p and q stand for the order of the autoregressive (AR) process and of the moving average (MA) process, respectively, while d represents the order of integration.[4]

Figure 1. The ARIMA Process[5]

Preliminary	• Test the order of integration • Perform formal unit root test (Augmented Dickey-Fuller) to confirm stationarity
Identification	• Check the spikes of the sample autocorrelation function (SACF) for the corresponding MA terms • Check the spikes of the partial autocorrelation function (PACF) for the corresponding AR terms
Estimation	• Estimate parameters using standard regression analysis
Verification	• Verify whether error terms are "white noise processes" • Conduct residual diagnostics
Selection	• Choose the most appropriate model using various criteria • Perform equation diagnostics and evaluate forecast accuracy

To satisfy the assumption of stationarity, a unit root test (Dickey and Fuller, 1981) is usually conducted to determine the order of integration. For most modeled series, first-order integration is enough to achieve stationarity. Some series, on the other hand, fare better with the application of another 12-period differencing. There is a chance of overdifferencing in this respect but many studies empirically show that this does not affect the forecasts to a significant extent (see for example Gustavsson and Nordstrom, 2001).

The SACF and PACF are often used to determine the AR and MA orders of the stationary series. Particularly, the orders of the AR and MA processes are determined by the number of significant spikes in the corresponding autocorrelation functions (Akhter, 2013). To account for the seasonal components of a series, ARIMA extends from just (p, d, q) to (p, d, q) × (P, D, Q), where P, Q and D are the orders of the seasonal AR, MA and integration components, respectively. Finally, a SARIMAX process is a step further from the SARIMA process because it takes cognizance of exogenous inputs that could potentially explain the behavior of the dependent variables.

The form of the ARIMA model and the orders of its components are determined through an iterative process—that is, testing various combinations of orders and forms and selecting the best model based on statistical criteria. In the spirit of Fritzer et al. (2002), a preliminary selection of models is made based on satisfactory residual diagnostics.[6] However, unlike Fritzer et al. (2002), the models that have passed the above criteria undergo further testing through simultaneous minimization of the Schwarz' Bayesian Criterion (SBC),[7] optimization of model diagnostics[8] and most importantly, minimization of forecast errors.

Once a model for each CPI component is chosen, a dynamic[9] forecasting procedure is applied to the models for each to produce forecasts over the short-term horizon —one-, two- and three-months ahead. The resulting forecasts of each of the component models are then aggregated to form the headline CPI using their corresponding weights.

Data

The CPI, which is the basic data used in this paper, is *"an indicator of the change in the average retail prices of a fixed basket of goods and services commonly purchased by households relative to a base year."* The index, which is compiled and published by the Philippine Statistics Authority (PSA) on a monthly basis, has five levels of disaggregation

[4] For reference, AR and MA processes are defined as $x_t = c + \emptyset_1 x_{t-1} + \varepsilon_t$ and $x_t = c + \emptyset_1 \varepsilon_{t-1} + \varepsilon_t$, respectively. (Box and Jenkins, 1994)
[5] Author's elaboration of the Box et. al. (1994) Modelling Approach
[6] Residuals must be white noise processes (correlograms show coefficients of SACFs and PACFs below critical values), non-heteroskedastic (non-significant ARCH LM test) and normally distributed (non-significant Jarque-Bera).
[7] The index is defined as $SBC=-2Lm + m\ln n$ where n is the sample size, Lm is the maximized log-likelihood of the model and m is the number of parameters. This is the strictest type of information criterion as it imposes a penalty for increasing the number of parameters.
[8] This refers to a model that satisfies the invertibility condition, and has the highest adjusted R-squared, and the lowest standard error of equation.
[9] This involves using model-generated forecasts (e.g. forecast for January 2014) as observation inputs for forecasting further ahead in time (e.g. that for February 2014).

with roughly 650 items at the fifth or most detailed level (PSA, 2012).

Depending on the choice of method and level, the use of disaggregated data allows for the computation of different measures of inflation (i.e. core, food, non-food, utilities, etc.), and offers a more detailed insight into the sources of future inflationary or deflationary pressures. For the sake of simplicity, the choice of detail applied in this paper is mostly at the two-digit level of disaggregation in the PSA code on CPI items. This level has eleven components (refer to Table 1, items in **bold text**), and has the broadest clusters after the *All Items* (0) grouping. Three of the eleven components, however, are disaggregated further to break down their significant sizes and to single out important and specific sub-components for further analysis. The components (i) *Food and Non-Alcoholic Beverage*, (ii) *Alcoholic Beverages and Tobacco*, and (iii) *Housing, Water, Electricity, Gas, and Other Fuels* are broken down to focus on identified items of interest, namely *Rice*, *Gas*, and *Electricity*. As noted by Pufnik and Kunovac (2006), the level of disaggregation appropriate for modeling can be any level as long as the components are homogenous. Given this, the total number of components to be modeled and forecasted comes up to 26 individual series (Table 1).

Aside from the basic CPI data, two variables exogenous to the CPI system are used in the estimation of two component models. Firstly, the Rice CPI model uses the average nationwide prices of well-milled and regular-milled rice sourced from the PSA. Secondly, the Transport CPI model uses weighted domestic oil price data as one of its parameters. The said data on oil prices is a consolidation of the local prices of premium plus gasoline, regular gasoline, kerosene, diesel and LPG, which are all sourced from the Department of Energy. These exogenous inputs are found to at least halve the forecast errors of their respective components.[10]

In summary, the overall forecasting model aggregates 26 forecasts estimated through 26 individual component models which comprise 8 ARIMA, 16 SARIMA and 2 SARIMAX processes (Table 2). Together, these models account for 100 percent of the CPI.

Table 1. List of Endogenous and Exogenous Variables

PSA Code	Components	Weight
0	*All Items*	*100.00*
01	***Food and Non-Alcoholic Beverage***	***38.98***
01.1.11	Rice	8.93
01.1.12-18	Other Bread and Cereals	3.52
01.1.2	Meat	6.97
01.1.3	Fish	5.83
01.1.4	Milk, Cheese and Eggs	3.29
01.1.5	Oil and Fat	0.72
01.1.6	Fruits	1.71
01.1.7	Vegetables	3.19
01.1.8	Sugar	1.05
01.1.9	Other Foods	1.09
01.2	Non-Alcoholic Beverages	2.69
02	***Alcoholic Beverages and Tobacco***	***2.00***
02.1	Alcoholic Beverages	1.01
02.2	Tobacco	0.99
03	**Clothing and Footwear**	**2.95**
04	***Housing, Water, Electricity, Gas, and Other Fuels***	***22.47***
04.1 & 3	Rent and Housing Maintenance and Repair	14.35
04.4	Water Supply	1.05
04.5.1	Electricity	4.51
04.5.2	Gas	1.48
04.5.4	Solid Fuels	1.07
05	**Furnishings & Household Equipment**	**3.22**
06	**Health**	**2.99**
07	**Transport**	**7.81**
08	**Communication**	**2.26**
09	**Recreation**	**1.93**
10	**Education**	**3.36**
11	**Restaurant and Miscellaneous Goods**	**12.03**
--	Average Nationwide Rice Prices	--
--	Weighted Domestic Oil Prices	--

Note: Italicized items were not estimated directly, but can be estimated based on the forecasts of its subcomponents.

Forecast Evaluation

The sample period which runs from January 2005 to November 2014, covers 119 monthly observations for each of the 26 component series. The estimation of parameters uses data from January 2005 to December 2013, and leaves the rest for the evaluation of out-of-sample characteristics. Without the 11 months in the extreme right of the sample period, the segment for parameter estimation drops to a length of 108 observations.

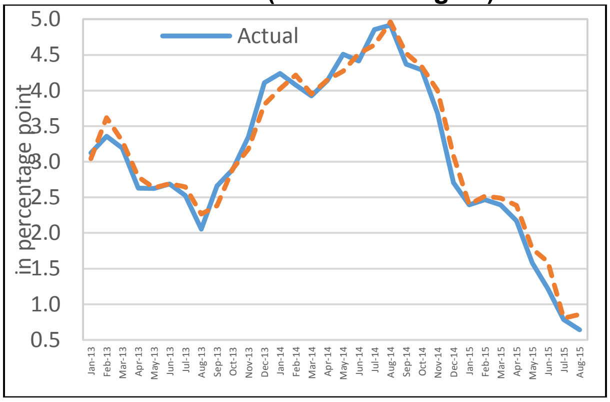
Each CPI component then generates a series for the time horizons **one-period ahead**, **two-periods ahead** and **three-periods ahead** with each series containing 11 observations (out-of-sample data from January 2014 to November 2014). The quality of the obtained forecasts is

[10] Doguwa and Alade (2012)

then tested against two standard measures:[11] the Mean Absolute Error (MAE) which measures errors in CPI points and the Mean Absolute Percentage Error (MAPE) which measures error as the sample period's average inflation by adjusting the MAE using the average CPI of the sample. In both cases, the general rule is that the smaller the value of the function the better the forecast.

Within the out-of-sample period, the one-period ahead forecasts of headline inflation generally followed the path of actual data (Figure 2). This partially confirms that, contrary to initial belief, the combination of forecasts from different models can actually improve the aggregate figure as particular biases or shortcomings in one model are offset by biases going the other way in another model (Timmerman, 2006).

Figure 2. Actual and One-Month Ahead Forecast of Headline Inflation (Jan'13 to Aug'15)



The estimates of the model, however, less frequently catch up with a consistently upward/downward trend in the data. In periods of rising inflation such as that from September 2013 to August 2014, the forecasts are mostly underestimated. On the same note, a period of continued disinflation, such as the one observed within the September 2014 to August 2015 period, exhibits an overestimation in the model's forecasts.

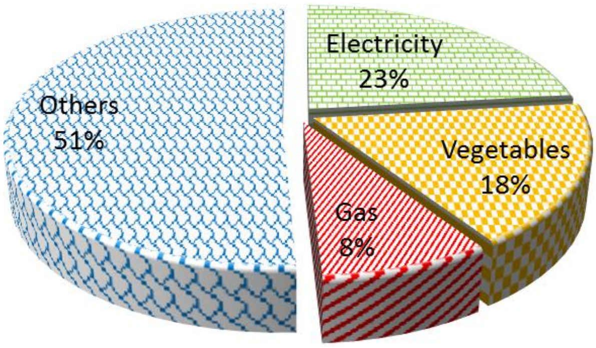
Such model performance —which is common to any smoothing model (e.g. moving averages)— results from forecasts that tend to lag behind in following deviations from trends or responding to turning points. The forecast estimates for any given period lean towards some historical average that is more or less influenced heavily by long-term trends rather than one-off deviations from averages.

Table 2. Specifications and MAPE Statistics of the Models

Components	Model	MAPE
Alcoholic Beverages	ARIMA(1,1,0)	0.207
Clothing and Footwear	$SARIMA(0,1,12)x(0,1,0)^{12}$	0.282
Communication	$SARIMA(12,1,3)x(0,1,0)^{12}$	0.061
Education	$SARIMA(12,1,5)x(0,1,7)^{12}$	0.086
Electricity	**ARIMA(0,1,2)**	**1.395**
Fish	ARIMA(12,1,6)	0.391
Fruit	SARIMA(6,1,1)x(8,0,0)	1.075
Furnishings	$SARIMA(12,1,21)x(3,1,6)^{12}$	0.312
Gas	**$SARIMA(8,1,12)x(0,1,0)^{12}$**	**7.617**
Health	$SARIMA(1,1,12)x(0,1,0)^{12}$	0.193
Meat	SARIMA(5,1,12)x(8,0,7)	1.075
Milk, Cheese and Eggs	$SARIMA(11,1,2)x(12,1,0)^{12}$	1.031
Non-alcoholic Beverages	ARIMA(2,1,0)	0.118
Oil and Fat	ARIMA(2,1,8)	1.655
Other Bread and Cereals	$SARIMA(1,1,0)x(12,1,0)^{12}$	0.182
Other Foods	ARIMA(1,1,0)	2.632
Recreation	SARIMA(3,1,0)x(17,0,0)	0.075
Rent and Housing	$SARIMA(17,1,12)x(0,1,0)^{12}$	0.134
Restaurant	$SARIMA(0,1,12)x(0,1,0)^{12}$	0.472
Rice	SARIMAX(1,1,0)x(6,0,0)	0.873
Solid Fuels	$SARIMA(12,1,0)x(0,1,0)^{12}$	0.520
Sugar	ARIMA(1,1,11)	1.181
Tobacco	ARIMA(1,1,0)	0.244
Transport	$SARIMAX(2,1,12)x(0,1,4)^{12}$	0.427
Vegetables	**SARIMA(4,1,1)x(6,0,6)**	**2.524**
Water	$SARIMA(12,1,11)x(0,1,0)^{12}$	0.282

As an example, the forecast variance during the November 2014 (start of forecast exercise) to August 2015 disinflation period, were mostly higher for CPI items that are commonly subject to supply shock adjustments, e.g. electricity, vegetables and gas. These items had the highest MAPEs (refer to Table 2 items in **bold**

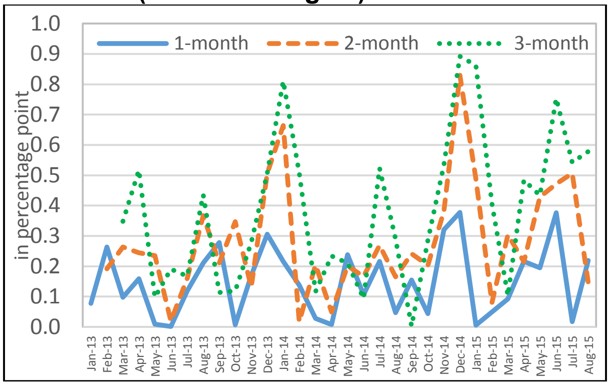
Figure 3. Composition of Average Weighted Forecast Variance



[11] The functions are computed as follows: $MAE = \frac{\sum_{j=1}^{n}|\hat{y}_j - y_j|}{n}$ & $MAPE = \left(\frac{MAE}{(\sum_{j=1}^{n} y_j)/n}\right) * 100$ where $\hat{y}_j$ represents the CPI forecasts for month j, y_j the actual CPI in month j and n the number of observations.

text) and composed 49.0 percent of the weighted average forecast variance (Figure 3). Thus, volatility as a result of supply shocks also account for the inaccuracy of the forecasts.

Figure 4. Absolute Errors of One-, Two- and Three-Month Ahead Headline Inflation Forecasts (Jan'13 to Aug'15)



Overall, the difference between the forecast numbers and official data has been relatively marginal (Figure 4). The absolute error between one-month ahead forecasts and official data averages around 0.149 inflation point, peaking at 0.377 inflation point in December 2014. Since the model has yet to take into account the influencing factors that are yet to happen, it is expected that the error of the forecasts would only increase for the two- and three-months ahead forecasts— and more so, the farther ahead the forecast is from the latest actual value. The evaluation of the sample also indicates that the last few months of the year seem to be the most difficult to predict given their consistent and relatively large absolute errors.

The forecasting exercise described in this paper is a case in point for disaggregation. As mentioned above, econometric models generally benefit from the use of disaggregated data as more information are fed into and considered in the model. The disaggregation also allows for the identification of trends or patterns that may not be readily observable from aggregate data. This helps in identifying and quantifying shocks for policy analyses and scenario building as the sources of shocks are better modeled and identified by using narrower items or sectors.[12]

For a practical purpose, the one- to two-months ahead forecasts from this model can be used as initial estimates to inform or initialize a structural model (such as the BSP's Multi-Equation Model) which is used for forecasting or for policy analysis. Such complimentary role helps facilitate forecasting activities.

Indeed, the model has room for improvement, especially in closing the gap between one-month ahead forecasts and those of longer periods. The addition of other high frequency exogenous variables, the effective extrapolation of the same, as well as the application of other tests and methods of estimation could enhance the accuracy and reliability of the discussed model. Further study on this model and the formulation of new methods are paramount to the advancement of BSP's forecasting capability and to the setting of appropriate monetary policy in line with the BSP's commitment to promote and maintain price stability.

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[12] Such recognition of the importance of disaggregated data in understanding the dynamics of macro-level or aggregate relationships was emphasized in the 2015 Sveriges Riksbank Nobel Prize in Economics.

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