BANGKO SENTRAL NG PILIPINAS

BSP Working Paper Series

Series No. 2022-02

February 2022

Nowcasting Inflation: A State-Space Approach using High-Frequency Data

Joan Christine S. Allon,
Dennis M. Bautista and
Jasmin E. Dacio

Nowcasting Inflation: A State-Space Approach using High-Frequency Data

Joan Christine S. Allon, Dennis M. Bautista and Jasmin E. Dacio

Abstract

The forward-looking nature of monetary policy formulation under an inflation targeting (IT) regime requires the accurate and timely assessment of key macroeconomic variables, such as inflation. This study develops nowcasting models for headline and core inflation in the Philippines, in the form of time-varying regressions using state-space representation. To exploit the information content of more available high-frequency price and financial data, the state-space models are analyzed using the Kalman filter, which updates estimates upon the availability of new information. Based on one-month-ahead forecasts, the forecasting performance of the state-space models has been found to be at par with that of existing linear inflation forecasting models at the BSP. In addition, the paper serves as an initial exercise for modeling structural changes in inflation.

JEL classification: C32, E37, C53

Keywords: State-space modelling, nowcasting, inflation, time-varying regression

Corresponding Authors Joan Christine S. Allon (AllonJS@bsp.gov.ph)
Dennis M. Bautista (DMBautista@bsp.gov.ph)
Jasmin E. Dacio (JDacio@bsp.gov.ph)

Table of Contents

Nowcasting Inflation: A State-Space Approach using High-Frequency Data

Joan Christine S. Allon, Dennis M. Bautista and Jasmin E. Dacio[1]

1. Introduction

Central banks under inflation targeting (IT) regime are mandated to undertake policy actions intended to address current and emerging threats to price stability.[2] More often than not, however, monetary authorities form policy decisions based on a partial view of economic and financial conditions. Given the inherent lags in the dynamics of the economy, pre-emptive policy action is anchored on the ability of a central bank to gauge the present and future states of the economy in a precise and timely manner.

The forward-looking nature of monetary policy formulation under the IT regime requires the forecasting of key macroeconomic variables that monetary policy intends to influence over the policy horizon. With the adoption of the IT framework in 2002,[3] the Bangko Sentral ng Pilipinas (BSP) has continuously developed and refined its suite of economic models for forecasting, policy analysis, and simulation exercises. This paper aims to incorporate state-space nowcasting in the BSP's Forecasting and Policy Analysis System to complement its existing inflation forecasting models such as the Single Equation Model, Multi-Equation Model, as well as the Policy Analysis Model for the Philippines (PAMPh), consistent with the BSP's "thick" economic modelling philosophy.

With roots in meteorology,[4] nowcasting is defined as the prediction of the present or the very near future (Banbura et al. 2010). Nowcasting exploits the information content of higher-frequency indicators to forecast more accurately the lower-frequency variable for the current period. Giannone et al. (2008) formalize the process in time series models and show evidence of increased precision in current-quarter US GDP forecast as new monthly data becomes available. The finding also applies in the case of Euro area GDP as described in Angelini et al. (2008) and Bańbura and Rünstler (2011).

Literature on nowcasting has primarily focused on GDP growth, typically using monthly measures of economic activity to produce estimates for current quarter growth. However, recent economic writings show a growing interest in nowcasting higher-frequency indicators, such as inflation. Knotek and Zaman (2017) proposes a parsimonious model for nowcasting

[1] The authors are Mr. Dennis M. Bautista, and Ms. Jasmin E. Dacio, Deputy Directors at the Department of Economic Research (DER), and Ms. Joan Christine S. Allon, Bank Officer IV at the DER. The authors are thankful to Dr. Suleyman Ozmucur of the University of Pennsylvania for sharing his insights and providing useful comments in improving the model. The usual disclaimer applies. Views, errors and omissions are sole responsibilities of the authors, and not those of the institution represented.

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

[3] Republic Act No. 7653 or the New Central Bank Act of 1993 (as amended by RA No. 11211) states that price stability is the primary mandate of the BSP. Prior to the adoption of IT, the BSP used the monetary targeting approach to monetary policy.

[4] The term "nowcasting" was coined in 1980s by British weather forecaster Keith Browning, as "the description of the current state of the weather in detail and the prediction of changes that can be expected on a timescale of a few hours." Retrieved from https://public.wmo.int/en/resources/bulletin/nowcasting-guidelines-%E2%80%93-summary.

US price indices using high-frequency food and energy prices. Allon (2015) likewise describes a disaggregated nowcasting model for Philippine inflation that uses a seasonal ARIMA process with high-frequency food and energy data added as exogenous variables.

As an innovation to existing models at the BSP, this paper uses the state-space representation of a least squares regression model to estimate time-varying coefficients. In one of its simplest applications, Issler and Notini (2016) used the state-space representation as an interpolation method that enables the estimation of nowcasts for monthly Brazilian GDP. Similarly, Franco and Mapa (2014) employ mixed frequency modelling using state-space models with time-varying parameters to address the frequency mismatch between GDP growth and potentially important macroeconomic determinants. Also addressing frequency mismatch, Schorfheide and Song (2015) develop a mixed-frequency vector autoregression (VAR) using a state-space approach for forecasting a number of economic indicators in the US, including real GDP growth, unemployment, inflation and interest rates. Finally, Rusnak (2016) and Sanyal and Das (2018) employ the dynamic factor modelling framework written in state-space form to nowcast the quarterly GDP growth of the Czech Republic and India, respectively.

Another advantage of the state-space representation is that it can be analyzed using the powerful recursive algorithm known as the Kalman (Bucy) filter, which 'updates' model parameters based on the availability of new information. The possible non-linearity in the relationship between inflation and other economic variables suggests specifying an appropriate model with time-varying coefficients. This can be easily adopted in a state-space form which can simultaneously model observed economic variables and unobserved time-varying coefficients, by exploiting the ability of the Kalman filter to draw information from the latest additional data points to update coefficients over time. Modugno (2013) provides an illustrative example of inflation nowcasting using the Kalman filter in a state-space representation, and finds that exploiting weekly and daily data improves forecast accuracy. Yemittan and Shittu (2015) apply the same methodology for Nigerian inflation and find that regime switches in the inflation series could cause a shift from a linear space to a non-linear one, which can be better estimated using the Kalman filter.

Literature on nowcasting Philippine inflation is quite limited, while practically non-existent for inflation nowcasting using state-space modeling. Allon (2015) provides a methodology for forecasting headline and core inflation by aggregating the forecasts of the individual components of the Philippine consumer price index (CPI) derived from a seasonal ARIMA process, using high-frequency domestic rice and oil price data as exogenous variables. Mapa (2018) develops a nowcasting model for inflation using mixed-frequency data and state-space modeling. The said model uses weekly data on agricultural commodity prices reported by the Philippine Statistics Authority (PSA), together with daily data on Dubai crude prices and exchange rates.

The model described in this paper builds on the strategies of Allon (2015) and Mapa (2018) with an aim to develop nowcasting models for headline and core inflation that exploit the availability of higher-frequency indicators and the time-varying parameters of state-space modelling. To distinguish from the state-space model developed by Mapa (2018), this study provides month-to-date updates to the monthly series of price variables instead of using weekly price data. The variables considered as well as the specification of the state-space model have also been altered to incorporate both constant and time-varying coefficients, as well as both random or autoregressive specifications for time-varying coefficients. This paper also develops a state-space nowcasting model for core inflation using demand-based indicators to reflect underlying drivers of inflation, rather than supply-side volatilities.

This paper is organized as follows: (a) Section II explains the econometric framework including discussions on the data and methodology; (b) Section III discusses the estimations of the model as well as the resulting forecast accuracy; and (c) Section IV provides recommendations for further study.

2. Econometric Framework

2.1 Data and publication schedules

Official Philippine data on the consumer price index (CPI) and inflation are compiled and estimated by the Philippine Statistical Authority (PSA) and are published monthly in the PSA's Summary Inflation Report Consumer Price Index (hereon referred to as SIR).[5] In 2018, the PSA rebased the CPI and recalculated the index to update the composition of the CPI basket, changing the base year from 2006 to 2012 (PSA, 2018). There are two popular aggregate measures of inflation in the Philippines namely, headline and core. Headline inflation refers to the annual percentage change in the average price of the CPI basket as a whole. Meanwhile, core inflation is officially calculated as the annual percentage change in the price of the non-volatile components of the CPI. The core measure excludes a fixed set of volatile CPI items and as such, takes into account about 77 percent of the total CPI basket. Although headline inflation is the more widely used measure, core inflation as an indicator of the underlying price movement, informs monetary authorities whether current movements in consumer prices represent short-lived shocks or are part of a more permanent trend that could otherwise require monetary policy actions.

In nowcasting headline inflation, explanatory variables were selected to represent potential shocks to major categories of the CPI which are published at a higher frequency than inflation itself (see Table 1). The month-on-month (m-o-m) change in the prices of these selected variables appeared to be more volatile than the overall m-o-m headline inflation, with standard deviations ranging from less than half a percentage point (ppt) in the case of beef inflation to almost 10 ppts in the case of ampalaya (see Figure 1). Unlike smoothing models whose estimates tend to lean towards some historical average, the use of such price data and the application of the Kalman filter could better capture turning points or one-off deviations from normal price movements.

For instance, rice is a historically volatile component of the CPI, comprising 9.6 percent of the index. As a proxy for shocks to rice inflation, the model contains a variable derived from the average price per kilo of regular-milled rice that is published weekly by the PSA. Other food variables include ampalaya prices as a proxy for shocks to vegetable inflation (2.6 percent

[5] Philippine Statistical Authority (n.d.). Summary Inflation Report Consumer Price Index. Retrieved from https://psa.gov.ph/price-indices/cpi-ir

of the CPI basket), bangus prices as a proxy for shocks to fish (5.7 percent), and beef prices as a proxy for shocks to meat (6.2 percent). Incidentally, the variables on the prices of rice, ampalaya, kerosene and liquefied petroleum gas (LPG) are already being used to forecast the inflation of their respective commodity groups (Rice CPI, Vegetables CPI, Transport CPI and Gas CPI, respectively) in the BSP's Disaggregated SARIMAX Model,[6] suggesting high levels of correlation with actual inflation. The nationwide average prices per kilo of the selected food items are published in the PSA's Weekly Price Situationer of Selected Agricultural Commodities (hereon referred to as WPS)[7] and Updates on Palay, Rice and Corn Prices (hereon referred to as PRC).[8]

Volatility in the price of crude oil in the global market is also a known source of shock to domestic inflation. To proxy for global oil price shocks, the monthly average per liter prices of kerosene and LPG were included in the model. In total, the exogenous variables included in the state-space inflation nowcasting model represent about 33 percent of the 2012-based CPI basket.

Core inflation is a smoother series compared to headline inflation since it excludes volatile components of the CPI that are assumed to represent transitory shocks. Rather than proxies for shocks, the selected explanatory variables for the nowcasting core inflation are demand-based indicators that reflect the fundamentals of the economy (see Table 1). Most determinants cited in literature are low-frequency real sector indicators (e.g., unemployment, GDP growth) based on the established relationship between inflation and aggregate demand (Ghrissi et al., 2015). The money demand channel as an intermediary between inflation and aggregate demand then could serve as a reference for the selection of alternative high-frequency variables that may also be correlated with core inflation (Akinci, 2012). In this study, explanatory variables for the state-space core inflation nowcast include financial market indicators such as the weighted average Treasury bill rate (all maturities) in the secondary market and the composite index of the Philippine Stock Exchange (PSE). The net domestic credit sourced from the Depository Corporation Survey (DCS) of the BSP was also included as a measure of credit activity in the economy. Finally, the value of production index (VAPI) and the capacity utilization rate (CAPUT) from the PSA's Monthly Integrated Survey of Selected Industries (MISSI) were included to reflect the level of country's economic activity.

[6] The Disaggregated SARIMAX and state-space models are used to nowcast the month-ahead inflation rate in line with the "thick" modelling approach of the BSP, which enables the institution to maintain a suite-of-models for forecasting and policy simulation. This approach offers BSP flexibility to address different policy issues and forecasting requirements of monetary policy analysis. This view also recognizes the natural limitations of models to (i) forecast accurately the exact path of the variables over the forecast horizon; and (ii) adequately address or cover all policy issues in the economy. For more information on Disaggregated SARIMAX, a link to the published newsletter is included in the references section.

[7] Philippine Statistical Authority (n.d.). Price Situationer Selected Agricultural Commodities. Retrieved from http://www. psa.gov.ph/content/price-situationer-selected-agricultural-commodities-0

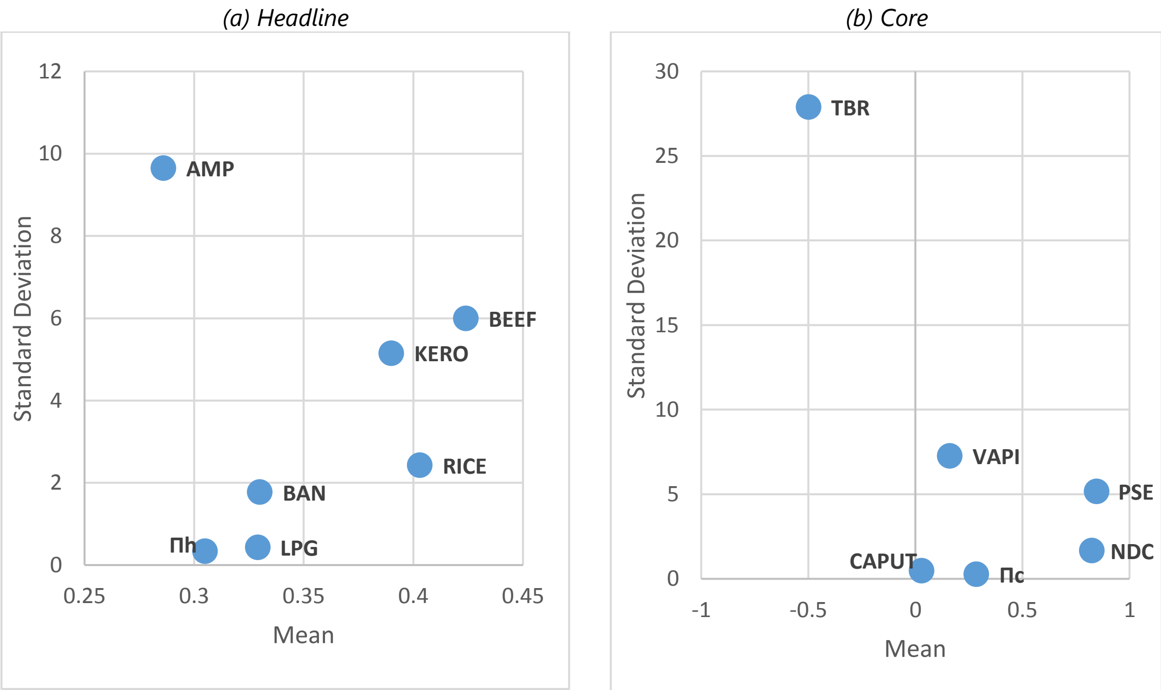
[8] Philippine Statistical Authority (n.d.). Updates Palay Rice and Corn Prices. Retrieved from http://www.psa.gov.ph/ content/updates-palay-rice-and-corn-prices-0

Table 1. List of Variables

Data	Source	Frequency	Publication Lag
	Headline Inflation		
CPI (Π_H)	PSA SIR	Monthly	1 month
Rice (RICE)[1]	PSA PRC	Weekly	1 to 2 weeks
Ampalaya (AMP)[1]	PSA WPS	Weekly	1 to 2 weeks
Bangus (BAN)[1]	PSA WPS	Weekly	1 to 2 weeks
Beef (BEEF)[1]	PSA WPS	Weekly	1 to 2 weeks
Kerosene (KERO)[2]	DOE	Weekly	1 week
Liquefied petroleum gas (LPG)[2]	DOE	Weekly	1 week
	Core Inflation		
Core CPI (Π_C)	PSA SIR	Monthly	1 month
Treasury bill rate (TBR)[3]	Bloomberg	Daily	None
PSEi composite index (PSE)	Bloomberg	Daily	None
Net Domestic Credit (NDC)	BSP DCS	Monthly	2 months
Value of production index (VAPI)	PSA MISSI	Monthly	2 months
Capacity utilization (CAPUT)	PSA MISSI	Monthly	2 months

[1] Nationwide average price per kilo
[2] Nationwide average price per liter
[3] Weighted average

Figure 1. Descriptive Statistics*



*month-on-month percentage change for the period January 2005 to August 2019

2.2 State-Space and the Kalman filter

State-space modeling is an established framework primarily used to estimate the unobserved components of a system. Rummel (2015a) indicates that a wide range of dynamic time series models in economics and finance can be written and estimated as special cases of a state-space form. This likewise applies to the time-varying regression model used in this paper.

The state-space form has two main benefits. First, unobserved variables can be incorporated into and estimated along with the observable variables in the model. State equations formulate the dynamics of the unobserved variables while the signal equations relate the observed variables to the unobserved state vector. Second, the Kalman filter is a built-in specification in state-space modeling. In particular, the Kalman filter is a recursive algorithm for sequentially updating the one-step-ahead estimate of the state mean and variance with every input of new information (Rummel, 2015b).

The general form of a linear state-space model can be written as a system of two equations namely, the signal equation and the state equation. For a time-varying regression model, the **signal** equation (also known as the **measurement** or **observation** equation) is given by:

$$y_t = \alpha_t + H_t x_t + A_t Z_t + \varepsilon_t$$

where y_t is an (n × 1) vector of observable dependent variables, α_t is an (n × 1) vector of constants, H_t is an (n × m) matrix of observable independent variables, x_t is an (m × 1) vector of unobservable coefficients, Z_t is an (n × k) matrix of exogenous variables, A_t is a (k × n) matrix of parameters, and ε_t is an observational error with E(ε_t) = 0 and var(ε_t) = R_t, where R_t is a known (n × n) matrix.

The coefficients of the explanatory variables, x_t, are unobserved state variables which are generated by a first-order Markov process[9] defined by the **state** (or **transition**) equation:

$$x_t = \mu_t + F_t x_{t-1} + S_t v_t$$

where μ_t is an (m × 1) vector of constants, F_t is an (m × m) matrix of parameters, S_t is an (m × g) matrix and v_t is a (g × 1) vector of serially uncorrelated disturbances with E(v_t) = 0 and var(v_t) = Q_t, where Q_t is a known (g × g) matrix.

For this paper, the nowcasting model for headline inflation consists of one state equation with month-on-month headline inflation as the observed dependent variable. Predictor variables include a persistence measure or the one-month lag of month-on-month headline inflation, contemporaneous rice, ampalaya, beef and LPG prices, the one-month lag of kerosene prices, and the three-month lag of bangus prices.

[9] A first-order Markov process describes a stochastic variable wherein information that could influence the future evolution of the series is fully captured by the present state only and, as such, is independent of any and all past states.

In the nowcasting model for core inflation, month-on-month core inflation is the observed dependent variable of the state equation. The predictor variables include a constant, a persistence measure, the two-month lag of the T-bill rate, contemporaneous net domestic credit growth, the three-month lag of the composite PSE index, the four-month lag of VAPI, and the twelve-month lag of the capacity utilization rate.

The Kalman filter as described in Kalman (1960, 1963) and Kalman and Bucy (1961) is an algorithm for generating minimum mean square error forecasts in state-space modelling. In particular, the Kalman filter updates the information content of the state vector x_t as soon as new observations in the signal vector y_t become available. The filter estimates the changes in the unobserved variables over time and, as such, plays a central role in the estimation of time-varying parameter models. If Gaussian errors are assumed, the filter allows the computation of the log-likelihood function of the state-space model, as well as the estimation of model parameters by maximum-likelihood methods (Rummel, 2015b). According to Yemittan and Shittu (2015), estimating the states through Kalman filter involves three steps, namely: initialization, prediction, and updating.

- Initialization

  $x_{0\backslash 0}$, $P_{0\backslash 0}$

- Prediction

  $$\hat{x}_{t\backslash t-1}=\hat{x}_{t-1\backslash t-1} \tag{1}$$
  $$P_{t\backslash t-1}=\{(x_{t-1\backslash t-1}-\hat{x}_{t-1\backslash t-1})(x_{t-1\backslash t-1}-\hat{x}_{t-1\backslash t-1})'\} \tag{2}$$

- Updating

  $$K_t=(H_t P_{t\backslash t-1})(\ H_t P_{t\backslash t-1} H_t{}'+R_t)^{-1} \tag{3}$$
  $$\hat{x}_{t\backslash t}=\hat{x}_{t\backslash t-1}+K_t\ (y_t-H\hat{x}_{t\backslash t-1}) \tag{4}$$
  $$P_{t\backslash t}=P_{t\backslash t-1}-K_t H_{t+1} P_{t\backslash t-1} \tag{5}$$

In the first step, $x_{0\backslash 0}$ is the initial state vector and $P_{0\backslash 0}$ is the initial covariance matrix, wherein $P_{0\backslash 0}$ depicts the noise of $x_{0\backslash 0}$. If there are no prior assumptions, the vector $x_{0\backslash 0}$ is assumed to be zero and the diagonal elements of matrix $P_{0\backslash 0}$ are assumed to be large numbers. In the following equations, subscripts, t\t refer to the current time period, t−1\t−1 to the previous time period, and t\t−1 to the intermediate steps taken in the transition equations.

In the prediction stage, $\hat{x}_{t\backslash t-1}$ is the intermediate state and $P_{t\backslash t-1}$ is the intermediate state variance matrix (i.e. error due to intermediate process). As such, Equations (1) and (2) are transition equations which estimate the expected values of the state and state variance, generating the update derived from the new observation.

Lastly, Equations (3), (4) and (5) comprise the set of update equations, where y_t is the observed variable, H_t is the measurement matrix (i.e. mapping the relationship between the observed variable and the state variable), K_t is the Kalman gain, and R_t is the measurement variance matrix (i.e. error due to measurement). K_t in Equation (3) or the Kalman gain refers to the weight given to new information. A high K_t, due to uncertainty in the intermediate state (i.e. model noise), indicates that the new observation is highly informative and, thus, must be given more weight. Meanwhile, a low K_t due to a high R_t suggests that the model is less uncertain and places less weight on new information. The terms adjusted by K_t in Equations (4) and (5) are prediction errors, which contain information that is new relative to the intermediate state. Equation (4) updates the intermediate state based on the Kalman gain and the prediction error. Similarly, Equation (5) updates the covariance matrix for the state vector.

3. Results and Evaluation

3.1 Model Estimation

The nowcasting models aim to produce one-month ahead forecasts for year-on-year headline and core inflation through a state-space specification that predicts month-on-month changes in the price aggregates.[10] The analysis in this paper uses monthly or month-to-date averages covering the period January 2005 to August 2019, which enter the models as logged month-on-month differences.[11] The variables were found to be stationary at this transformation based on the results of the Augmented Dickey-Fuller (ADF) and Phillips-Perron tests (see Table 2). The estimation of time-varying parameters in this paper was computed and programmed based on Rummel (2015b) using Eviews10 software. The estimates and corresponding statistics were taken from the August 2019 run of the nowcasting models.

Table 2. Tests for Stationarity

Data	ADF[1]	Philips-Perron[2]	Data	ADF[1]	Philips-Perron[2]
Headline Inflation			*Core Inflation*		
$\Pi_{H, t-1}$	-8.36 (0.00)	-8.47 (0.00)	$\Pi_{C, t-1}$	-10.25 (0.00)	-10.29 (0.00)
RICE	-7.94 (0.00)	-6.26 (0.00)	TBR_{t-2}	-11.20 (0.00)	-15.01 (0.00)
AMP	-13.30 (0.00)	-55.07 (0.00)	PSE_{t-3}	-12.25 (0.00)	-12.35 (0.00)
BAN_{t-3}	-10.05 (0.00)	-10.00 (0.00)	NDC_{t-2}	-11.99 (0.00)	-13.90 (0.00)
BEEF	-10.60 (0.00)	-11.08 (0.00)	$VAPI_{t-4}$	-4.81 (0.00)	-25.47 (0.00)
$KERO_{t-1}$	-10.12 (0.00)	-10.14 (0.00)	$CAPUT_{t-12}$	-8.89 (0.00)	-17.90 (0.00)
LPG	-10.33 (0.00)	-10.77 (0.00)			

[1] Augmented-Dickey Fuller, H_0: Series has unit root.
[2] H_0: Series has a unit root.

[10] Month-on-month as opposed to year-on-year transformation was chosen since it contains greater information (e.g. greater variations, seasonal changes).

[11] The variables were not standardized ($x_{it} = \frac{\pi_{it}-\bar{\pi}_i}{s_i}$) to avoid the mean revisions associated with the normalization formula.

Table 3. Parameter Estimates

Variable	State-space		Linear		Variable	State-space		Linear	
	Headline Inflation					*Core Inflation*			
$\Pi_{H, t-1}$	0.303	*	0.465	*	α	0.001	*	0.002	*
RICE	0.060	***	0.050	*	$\Pi_{C, t-1}$	0.223	*	0.254	*
AMP	0.011	*	0.011	*	TBR_{t-2}	-0.003	*	-0.003	*
BAN_{t-3}	0.030	**	0.031	*	PSE_{t-3}	-0.008	*	-0.008	**
BEEF	0.222	*	0.206	*	NDC_{t-2}	0.025	**	0.024	**
$KERO_{t-1}$	0.008	***	0.007	***	$VAPI_{t-4}$	0.010	**	0.010	*
LPG	0.008	*	0.008	**	$CAPUT_{t-6}$	0.056	*	0.056	

*/**/*** denote significance at 1%, 5% and 10%, respectively

As shown in Table 3, coefficients and state variables are generally found to be statistically significant at the 10-percent level. Both headline and core inflation exhibit strong persistence, while the results for other coefficients are consistent with economic theory.[12] Larger m-o-m increases in the prices of the key CPI items would naturally imply higher inflation rate. Meanwhile, higher interest rates and stock exchange index are associated with lower core inflation as these variables represent the cost of and alternatives to holding money, respectively.

Interestingly, it is noted that coefficients under the two specifications are not significantly different when the coefficient estimates in the state-space models and similarly-specified linear regression model are compared. This could suggest the absence of significant structural changes in the relationships between inflation and selected explanatory variables over time.

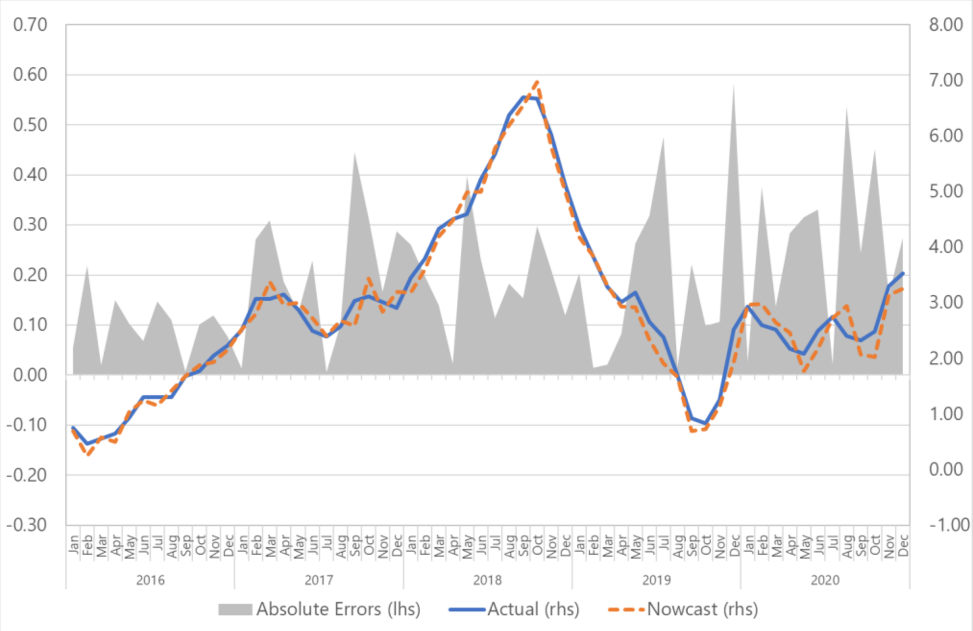
The model specification was repeatedly altered by (1) removing variables from the set of chosen variables, (2) adding other theoretically relevant variables and (3) using different lags to check for robustness. The final specifications shown above for headline and core state-space models contain variables that remained stable through various iterations. Across the evaluation period, the final specifications are also found to be consistent in terms of convergence and forecast performance.

3.2 Forecast Evaluation

In order to examine the real-time operation of the model, forecasting accuracy was assessed by simulating forecasting exercises using an expanding rolling window. Available data from January 2005 up to the second week of July 2019 were used to estimate the state-space model and forecast headline and core inflation outcomes for July 2019. For the following month, the window is moved by one period and available data from January 2005 up to the second week of August 2019 were then used to forecast August 2019 inflation.

[12] This is consistent with the stock exchange index being negatively related to inflation in the short-run, while being positively related in the long-run (Eldomiaty et al., 2020 and Al-Khazali, 2004).

Figure 2. Forecast Performance for Headline Inflation



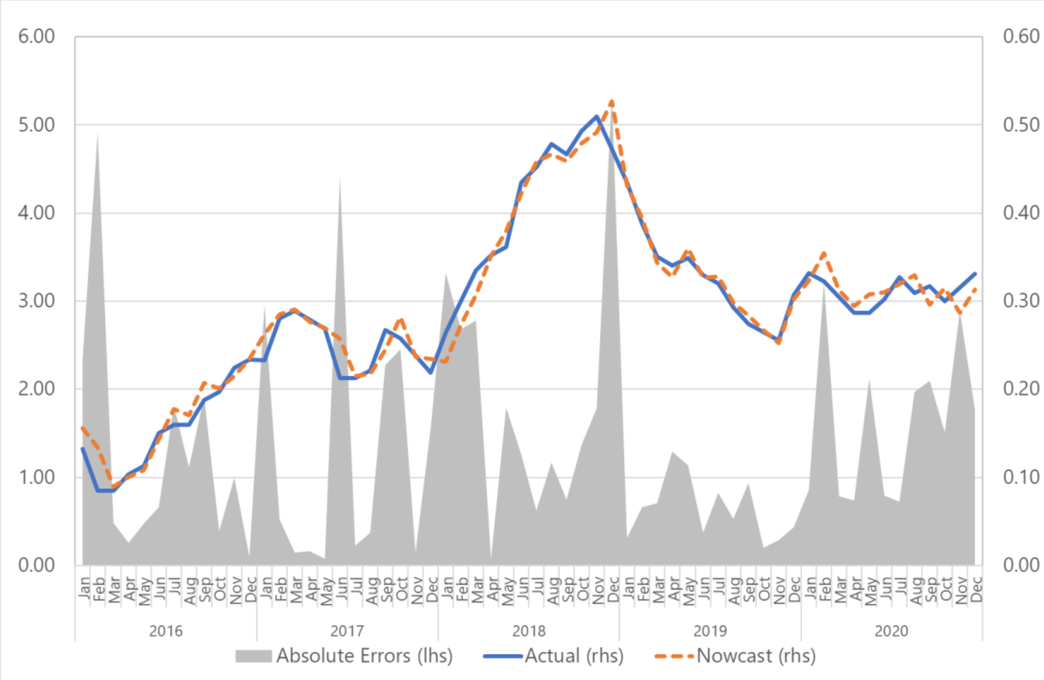
Forecast evaluation covers the one-step ahead forecasts from January 2016 to December 2020. Figures 1 and 2 suggest that both state-space models exhibit fairly high forecasting accuracy with both models able to consistently track actual headline and core inflation. On average, the absolute error[13] between actual and forecasted headline inflation is 0.19 percentage point (ppt), with the highest absolute error recorded in December 2019 at 0.58 ppt. For core inflation, the average absolute error is 0.13 ppt with the maximum recorded at 0.54 ppt in December 2018 (see Figure 3).

The state-space nowcast models also appear to outperform the AR(1) models for year-on-year inflation with average absolute errors of 0.34 ppt for headline and 0.21 ppt for core. The nowcasts from the headline state-space model was found to slightly underperform the one-step ahead out-of-sample forecasts from the Disaggregated SARIMAX model with headline inflation forecast accuracy at around 0.16 ppt. Meanwhile, nowcasts from the core state-space model was found to be at par with forecasts from the Disaggregated SARIMAX model with core inflation forecast accuracy at around 0.13 ppt. These findings have been confirmed using a simplified version of the Diebold-Mariano test.[14]

[13] The absolute error is defined as the absolute value of the difference between actual and forecasted value.

[14] The Diebold-Mariano test examines whether two competing forecasts have equal predictive accuracy. In its simple form, the test is calculated by regressing the difference of the loss functions (squared or absolute error) on a constant using Newey-West standard errors. The assessment uses a 5-percent level of significance (EViews (1 April 2011), Diebold-Mariano Test, accessed thru http://forums.eviews.com/ viewtopic.php?t=3954)

Figure 3. Forecast Performance for Core Inflation



3.3 Time-Varying Coefficients

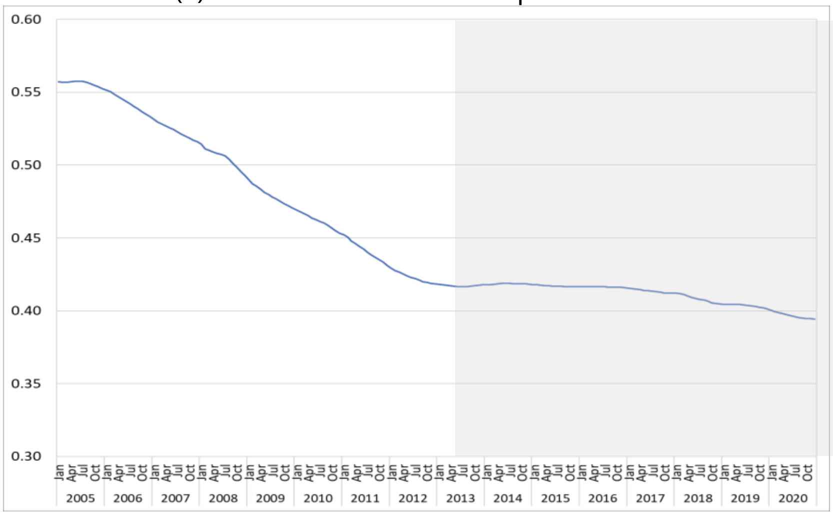
Aside from supplementing the BSP's "thick" economic forecasting philosophy, another advantage of the state-space method is that the model can capture non-linearities and even generate time-varying coefficients. This means that the coefficients that are usually constant in linear models, can vary and update itself given new observations that provide additional information about the relationship between inflation and its predictors. Despite the possible absence of significant structural changes, this section explores the historical movements of the coefficients of select variables in the headline inflation model, namely inflation persistence and rice prices, and attempts to interpret or align the movements with actual events.

For the purpose of this paper, inflation persistence is defined as the long-lasting effect of shocks to inflation[15] or how well immediate past values predict current value. In the state-space model, the first lag of month-on-month inflation represents the persistence of inflation. As shown in Figure 4, the time-varying coefficient of this variable shows a steady decline until it reaches a stable level around 2013. This decline is consistent with textbook theories of price dynamics with forward-looking expectations.[16]

[15] https://www.kansascityfed.org/research/economic-bulletin/why-has-inflation-persistence-declined-2018/
[16] https://www.frbsf.org/economic-research/publications/economic-letter/2006/october/inflation-persistence-in-an-era-of-well-anchored-inflation-expectations/

Figure 4. Time-Varying Coefficient of Inflation Persistence

(a) Coefficient of inflation persistence



(b) Monthly Headline Inflation

A common explanation for the decline in persistence is the more aggressive response of monetary policy to inflation effects. This fundamental shift to a more systematic stabilization of inflation around a constant long-run "target" as well as increased public credibility of the central bank could have resulted in better-anchored inflation expectations and, thus, lower persistence. Other likely causes include the generally lower trend of the inflation rate and the lower magnitude of "permanent inflation shocks." Looking at Table 4, inflation rates after 2012 are, on average, lower by almost 2 ppts and are less volatile than in past years.[14,15]

Table 4. Statistics on Headline Inflation

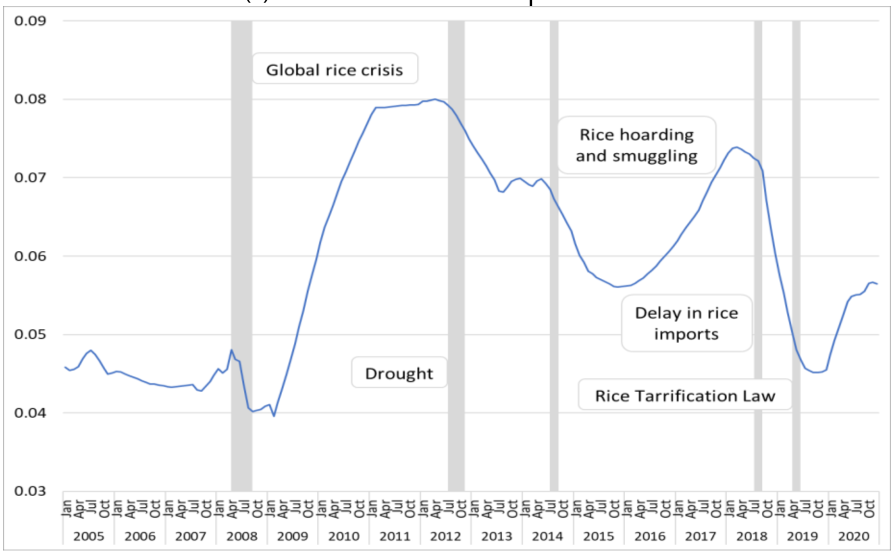
Dates	Mean	Standard Deviation
2006-2012	4.6	2.0
2013-2020	2.7	1.5

In the case of rice prices, the time-varying coefficient does appear to move along with actual events that significantly influence rice prices. Figure 5 shows that the coefficient tends to rise in times of stability and fall following global or local events that warrant price volatility. For example, global rice prices surged in 2008 which prompted the National Food Authority

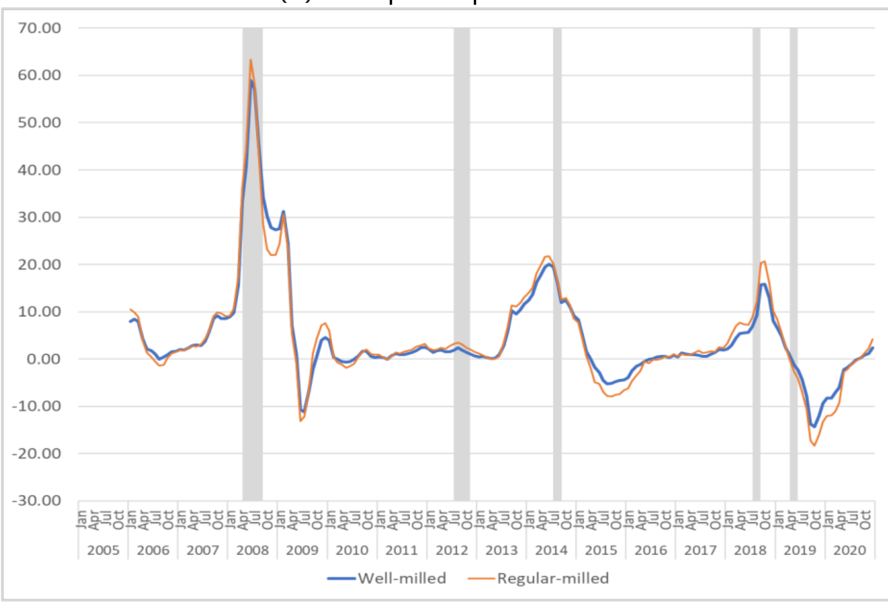
(NFA) to import the country's largest volume to date.[17] After which, the coefficient gradually increased amid the normalization of prices and stability in succeeding years. Incidents of rice hoarding and smuggling caused another surge in rice prices in late 2013, which peaked in 2014. During that time, rice hoarding reached 2.3 million metric tons from 2011-2014 and prompted the government to enact RA 10845 or the Anti-Agricultural Smuggling Act of 2016.[18] A decline in the coefficient was once again observed in the second half of 2018 possibly owing to the surge in rice prices amid the delay in rice imports. After which, the rice tariffication law was enacted in Q2 2019 which stabilized rice prices and may have led to the succeeding rise in the coefficient.[19]

Figure 5. Time-Varying Coefficient of Rice Prices

(a) Coefficient of rice prices



(b) Rice prices per kilo



17 https://www.bworldonline.com/taking-a-longer-look-back-on-rice-imports-palay-and-rice-prices/
18 https://www.rappler.com/newsbreak/211310-things-to-know-rice-prices-philippines/
19 https://asiafoundation.org/2021/04/14/fighting-the-good-fight-the-case-of-the-philippine-rice-sector/

3. Conclusion and Recommendation

Drawing from available literature, the proposed state-space models for nowcasting exploit the availability of higher-frequency indicators, in the form of weekly updated agricultural commodities and petroleum price data for headline inflation, as well as financial data and demand-based indicators for core inflation. The models also use time-varying regressions via the Kalman filter under a state-space representation.

In contrast to smoothing models, the nowcasting model for headline inflation leveraged on the use of proxies for known sources of shocks, in order to better capture turning points or one-off deviations from normal price movements. Meanwhile, the selection of demand-based indicators for core inflation is consistent with the view that core inflation reflects long-term trends in economic fundamentals, rather than transitory price changes. Chosen explanatory variables were shown to have significant and theoretically-consistent relationships with their respective inflation measures.

The use of the Kalman filter in this paper is evidence of the ease with which non-linearity can be introduced in state-space modeling. The forecast performance of the state-space models has been found to be fairly similar to existing linear forecasting models of the BSP. While this suggests that there have been no significant shifts in the relationships between inflation and selected explanatory variables, the proposed state-space methodology provides BSP the ability to address and sufficiently consider possible non-linearities that could emerge over time. The state-space model is also a good addition to the BSP's suite of forecasting models in line with the BSP's "thick" economic forecasting philosophy. Forecasting can leverage on the ability of the Kalman filter to update estimates as new information is made available. Also, the study remains useful as an initial exercise for modeling structural changes in inflation that could appear in the event of policy regime shifts (e.g. new administration), structural reforms (e.g. rice tariffication), revisions in composition or computation of data (e.g. PSA's chain method for CPI), and other such developments.

Further studies slated for the BSP's inflation nowcasting models include mixed-frequency state-space modeling, specifically, the integration of weekly price series instead of month-to-date updates to monthly price series. The addition of other high-frequency variables and the effective extrapolation of the same could also improve the range (e.g. two- to six-month ahead) and accuracy of the existing nowcasting model. Likewise, more research can be pursued on re-specifying the signal and state equations of the model to incorporate known idiosyncrasies of the time-varying coefficients (e.g. coefficient covariance, time-varying error terms).

References

Akinci, O. (2012). Modeling the demand for currency issued in Turkey. *Central Bank Review*, 3(1), 1 25.

Al-Khazali, O. M., and C.S. Pyun (2004). Stock prices and inflation: new evidence from the Pacific-Basin countries. *Review of Quantitative Finance and Accounting*, 22(2), 123-140.

Allon, J. S. (2015). Forecasting Inflation: A Disaggregated Approach Using ARIMA Models. *BSP Newsletter, 15(2).* Retrieved from http://www.bsp.gov.ph/downloads/EcoNews/EN15-02.pdf.

Angelini, E., Banbura, M., and G. Rünstler (2008). Estimating and forecasting the euro area monthly national accounts from a dynamic factor model. *ECB Working Paper No. 953.* Retrieved from https://www.econstor.eu/bitstream/10419/153387/1/ecbwp0953.pdf.

Banbura, M., Giannone, D., and L. Reichlin (2010). Nowcasting. *ECB Working Paper No. 1275.* Retrieved from https://www.econstor.eu/bitstream/10419/153709/1/ecbwp1275.pdf.

Bańbura, M., and G. Rünstler (2011). A look into the factor model black box: publication lags and the role of hard and soft data in forecasting GDP. *International Journal of Forecasting, 27(2)*, 333-346.

Bangko Sentral ng Pilipinas (2019). Core Inflation and the Estimation of Core Inflation. Retrieved from http://www.bsp.gov.ph/downloads/Publications/FAQs/inflation.pdf.

Diebold, F. X., and R.S. Mariano (2002). Comparing predictive accuracy. *Journal of Business and Economic Statistics*, 20(1), 134-144.

Eldomiaty, T., Y. Saeed, R. Hammam, and S. Aboul Soud (2020). The associations between stock prices, inflation rates, interest rates are still persistent. Empirical evidence from stock duration model. *Journal of Economics, Finance and Administrative Science*, 25(49), 149-162.

Franco, R. J. G., and D. S. Mapa (2014). The Dynamics of Inflation and GDP Growth: A Mixed Frequency Model Approach.

Ghrissi, M., M. Smida, and R. Farhani (2014). Indicators of core inflation: Case of Tunisia. HAL.

Giannone, D., L. Reichlin, and D. Small (2008). Nowcasting: The real-time informational content of macroeconomic data. *Journal of Monetary Economics, 55(4)*, 665-676.

Issler, J. V., and H. H. Notini (2016). Estimating Brazilian monthly GDP: A state-space approach. *Revista Brasileira de Economia*, 70(1), 41-59.

Knotek, E. S., and S. Zaman (2017). Nowcasting US headline and core inflation. *Journal of Money, Credit and Banking*, 49(5), 931-968.

Mapa, D.S. (2018). *Nowcasting Inflation Rate in the Philippines using Mixed-Frequency Models* [Powerpoint slides]. Presented in BSP-UP Professorial Chair Lecture Series, 21 – 22 November 2018.

Modugno, M. (2013). Now-casting inflation using high frequency data. *International Journal of Forecasting*, *29*(4), 664-675.

Philippine Statistical Authority (2012). Consumer Price Index Primer. Retrieved from https://psa.gov.ph/sites/default/files/Primer%20on%20Consumer%20Price%20Index2_1_0.pdf

Philippine Statistical Authority (2018). Technical Notes in the Rebasing of Consumer Price Index to Base Year 2012 and Adopting the Chain Method in the 2012-based CPI. Retrieved from https://psa.gov.ph/sites/default/files/Primer%20on%20Consumer%20Price%20Index2_1_0.pdf

Rummel, O. (2015a). *The common components of CPI: an alternative measure of underlying inflation* [Powerpoint slides]. Presented in 2nd SEACEN Intermediate Course on Econometric Modelling and Forecasting, 27 September – 2 October 2015.

Rummel, O. (2015b) Dynamic factor models, the state-space approach and EViews. Unpublished manuscript, Centre for Central Banking Studies, Bank of England.

Rusnák, M. (2016). Nowcasting Czech GDP in real time. *Economic Modelling*, 54, 26-39.

Sanyal, A., and A. Das (2018). Nowcasting sales growth of manufacturing companies in India. *Applied Economics*, 50(5), 510-526.

Schorfheide, F., and D. Song (2015). Real-time forecasting with a mixed-frequency VAR. *Journal of Business and Economic Statistics*, 33(3), 366-380.

Yemitan, R. A., and O. I. Shittu. (2015). Forecasting Inflation in Nigeria by state-space modeling. *International Journal of Scientific and Engineering Research, 6*, 778-786.

BANGKO SENTRAL NG PILIPINAS
BSP Working Paper Series

Scope: The Bangko Sentral ng Pilipinas (BSP) Working Paper Series constitutes studies relevant to central banking, which are conducted by BSP researchers and occasionally, in collaboration with external contributors. The topics may include monetary policy framework and operations, bank supervision, financial markets, macro-financial risks, payments and settlements system, digitalization, big data management and analytics for central banks, central bank communication, central bank governance and legal frameworks, among others.

Peer-reviewed: The BSP working papers are reviewed by the Editorial Committee, led by the Deputy Governor of the Monetary and Economics Sector. Completed working papers are published for the purpose of soliciting comments and discussion for further refinements. The views and opinions expressed are those of the author(s) and do not necessarily reflect those of the BSP.

Submissions: Authors may submit their manuscripts to the following addresses below:
- BSP.Working.Paper@bsp.gov.ph with the subject line that reads BSP Working Paper Series
- The Managing Editor, BSP Working Paper Series, Center for Monetary and Financial Policy, Room 402, 4/F, 5-Storey Building, BSP Main Complex, Malate, Manila

Editorial Guidelines:
- The title page of the manuscript must include the following: title, author's name, abstract describing the main arguments and conclusions of the article, affiliation, corresponding author, 3 - 5 keywords, JEL classification
- Manuscripts must be written in English and in MS Word format, text-aligned with 1.5 line spacing, 1" margins, font Segoe UI, font size 11.
- All graphs, tables, and footnotes must be in font Segoe UI, font size 9.
- Tables must contain only essential data and hence, must be kept to a minimum. Each figure and table must be given an Arabic numeral, followed by a heading.
- All diagrams, charts, and graphs must be referred to as figures and consecutively numbered.
- All figures and tables must be cited in the text.
- Headings and sub-headings must be clearly marked.
- References must be consistent with in-text citations.
- Manuscripts must adopt the Harvard referencing system or APA referencing system.

Authors must include in their submission all graphs and tables in Excel format. They must also ensure that their manuscripts are consistently referenced and free from typographical and presentation errors. The Editorial Committee and the Editorial Staff will not undertake any retyping of manuscripts before publication.

List of BSP Working Paper Series

- Available at
https://www.bsp.gov.ph/Pages/MediaAndResearch/PublicationsAndReports/BSPWorkingPaperSeries.aspx

No	Author	Title	Date
2022-02	Joan Christine S. Allon, Dennis M. Bautista and Jasmin E. Dacio	Nowcasting Inflation: A State-Space Approach using High-Frequency Data	February 2022
2022-01	Adrian Matthew G. Glova and Roy R. Hernandez	Balance Sheet Approach to Forecasting Currency in Circulation	January 2022
2021-03	Jean Christine A. Armas	Spillover risks from emerging economies' loss of confidence: Insights from the G-Cubed model simulations	December 2021
2021-02	Bernadette Marie M. Bondoc and Christofer A. Martin	Market Herding and Market Stress in the EMEAP Economies	June 2021
2021-01	Reynalyn G. Punzalan and Roberto Leon-Gonzalez	Microeconomic and Macroeconomic Determinants of Non-performing Loans: The Case of Philippine Commercial and Savings Banks	May 2021
2020-12	Sarah Jane Alarcon, Paul Reimon Alhambra, Rosemarie Amodia and Dennis Bautista	Policy Analysis Model for the Philippines	December 2020
2020-11	Jean Christine A. Armas	Is bank lending channel of monetary policy evident in the Philippines? A dynamic panel data approach	December 2020
2020-10	Vidal Marvin C. Gabriel, Dennis M. Bautista, and Cherrie R. Mapa	Forecasting regional inflation in the Philippines using machine learning techniques: A new approach	October 2020
2020-09	Nickson J. Cabote and Justin Ray Angelo J. Fernandez	Distributional Impact of Monetary Policy: Evidence from The Philippines	October 2020
2020-08	Eloisa T. Glindro, Jean Christine A. Armas, V. Bruce J. Tolentino, and Lorna Dela Cruz-Sombe	Heterogenous Impact of Monetary Policy on the Philippine Rural Banking System	September 2020
2020-07	Jean Christine A. Armas and Pamela Kaye A. Tuazon	Revealing investors' sentiment amid COVID-19: the Big Data evidence based on internet searches	September 2020
2020-06	V. Bruce J. Tolentino and Beulah Maria de la Pena	Deregulation and Tariffication At Last: The Saga of Rice Sector Reform in the Philippines	July 2020
2020-05	Eloisa T. Glindro, Hazel C. Parcon-Santos, Faith Christian Q. Cacnio, and Marites B. Oliva	Shifting macroeconomic landscape and the limits of the BSP's pandemic response	June 2020

No	Author	Title	Date
2020-04	Zernan C. Talabong	Do Prudential Regulations Affect Bank Lending Rates? Insights from Philippine Banks Using an Accounting-Based Approach	June 2020
2020-03	Veronica B. Bayangos, Rafael Augusto D. Cachuela and Fatima Lourdes E. Del Prado	Impact of Extreme Weather Episodes on the Philippine Banking Sector: Evidence Using Branch-Level Supervisory Data	June 2020
2020-02	Joselito R. Basilio and Faith Christian Q. Cacnio	Relative price changes, asymmetric adjustments and aggregate inflation: Evidence from the Philippines	June 2020
2020-01	Eloisa T. Glindro, Hazel C. Parcon-Santos, Faith Christian Q. Cacnio, Marites B. Oliva, and Laura L. Ignacio.	COVID-19 Exit Strategies: How Do We Proceed?	May 2020
2019-04	Charday V. Batac, Eduard Joseph D. Robleza I, Jan Christopher G. Ocampo, and Cherrie F. Ramos	BSPeak: A Text Analysis of BSP's Communications	November 2019
2019-03	Ramon Moreno, Hazel Parcon-Santos, and John Michael Rennie Hallig	A Preliminary Assessment of Drivers of Philippine FX Market Liquidity	October 2019
2019-02	Veronica B. Bayangos and Jeremy L. De Jesus	Have Domestic Prudential Policies Been Effective: Insights from Bank-Level Property Loan Data	March 2019
2019-01	Cherry Wyle G. Layaoen and Vernalin Grace F. Domantay	Do Capital Regulations Influence Banks' Holding of "Excess Capital"	March 2019
2018-01	Hazel C. Parcon-Santos	Foreign Exchange Interventions, Capital Outflows, and Financial Vulnerabilities in Selected Asian Emerging Economies	November 2018
2018-01	Roberto S. Mariano, Suleyman Ozmucur, Veronica B. Bayangos, Faith Christian Q. Cacnio, and Marites B. Oliva	Review of the Potential Output and Output Gap Estimation Models of the Bangko Sentral ng Pilipinas	October 2018
2017-01	Veronica B. Bayangos	Capital Flow Measures and Domestic Macro Prudential Policy in Asian Emerging Economies: Have These Been Effective?	June 2017
2016-02	Eufrocinio M. Bernabe, Jr., Hazel C. Parcon-Santos and John Michael Rennie G. Hallig	Spillovers in ASEAN-5 Equity Markets	July 2016

No	Author	Title	Date
2016-01	Veronica B. Bayangos, Lilia V. Elloso, John Michael Rennie G. Hallig, Jodeth Niña R. Yeung and April Michelle D. Salamatin	The Impact of Foreign Exchange Liberalization Reforms on the Philippine Economy: An Initial Assessment	March 2016
2015-01	Laura L. Ignacio, Hazel C. Parcon-Santos, Teresita B. Deveza, Maria Fatima C. Paule-de Leon, and Jean Christine A. Armas	Reformulating Effective Exchange Rates: Does the Exchange Rate Matter For Trade?	June 2015
2013-01	Francisco G. Dakila, Jr., Veronica B. Bayangos and Laura L. Ignacio	Identifying Sectoral Vulnerabilities and Strengths for the Philippines: A Financial Social Accounting Matrix Approach	July 2013
2012-02	Hazel C. Parcon-Santos and Eufrocinio M. Bernabe, Jr.	The Macroeconomic Effects of Basel III Implementation in the Philippines: A Preliminary Assessment	October 2012
2012-01	Veronica B. Bayangos	Going With Remittances: the Case of the Philippines	July 2012
2010-02	Eloisa T. Glindro and Vic K. Delloro	Identifying and measuring Asset Price Bubbles in the Philippines	June 2010
2010-01	Veronica B. Bayangos and Irene T. Estigoy	A Geometric Price Index for the Philippines: A Preliminary Assessment	March 2010
2009-01	Paul D. McNelis, Eloisa T. Glindro, Ferdinand S. Co, and Francisco G. Dakila, Jr.	Macroeconomic Model for Policy Analysis and Insight (a Dynamic Stochastic General Equilibrium Model for the BSP)	December 2009
2008-02	Agnes M. Yap and Cristeta B. Bagsic	Adjustments in the Face of Peso Volatility: Perspective from the Past and Policy Directions	September 2008
2008-01	Haydee L. Ramon	Forecasting the Volatility of Philippine Inflation Using GARCH Models	September 2008
2007-02	Francisco G. Dakila, Jr. and Racquel A. Claveria	Identifying the Determinants of Overseas Filipinos' Remittances: Which Exchange Rate Measure is Most Relevant?	January 2008
2007-01	Paul D. McNelis and Cristeta B. Bagsic	Output Gap Estimation for Inflation Forecasting: The Case of the Philippines	August 2007
2006-02	Cristela Goce-Dakila and Francisco G. Dakila, Jr.	Modeling the Impact of Overseas Filipino Workers Remittances on the Philippine Economy: An Inter-Regional and Economy-Wide Approach	September 2006
2006-01	Cristeta B. Bagsic and Eloisa T. Glindro	Bangko Sentral ng Pilipinas Modernization: A Policy Perpective PDF	August 2006

BSP International Research Conference Volume

Available at
https://www.bsp.gov.ph/Pages/MediaAndResearch/PublicationsAndReports/BSPInternationalResearchConferenceVolume.aspx

- BSP International Research Conference on " Expanding the Boundaries of Central Banking In an Environment of Globalized Finance", 24-25 September 2018
- BSP International Research Conference on "Revisiting Macro-Financial Linkages: Looking Back and Looking Ahead", 20-21 September 2016
- BSP International Research Conference on "The Evolving Role and Limits of Monetary Policy: New Perspectives for Emerging Market Economies", 28-29 October 2014
- BSP International Research Conference on "Contemporary Challenges to Monetary Policy", 28-29 February 2012
- 2010 Central Bank Macroeconomic Modeling Workshop, 19-20 October 2010
- BSP International Research Conference on Remittances, 30-31 March 2009
- Joint BSP-BIS High-Level Conference on Transparency and Communication in Monetary Policy, 01 February 2008