BANGKO SENTRAL NG PILIPINAS

BSP Working Paper Series

Series No. 2022-01

January 2022

Balance Sheet Approach to Forecasting Currency in Circulation

Adrian Matthew G. Glova and
Roy R. Hernandez

Balance Sheet Approach to Forecasting Currency in Circulation

Adrian Matthew G. Glova and Roy R. Hernandez

Abstract

Currency in circulation (CIC) is an important variable in monetary policymaking as it affects overall liquidity in the economy and guides the currency issuance operations of central banks. Given the rich information that may be gleaned from CIC, it is in the best interest of monetary authorities, the BSP included, to continuously track and accurately forecast CIC.

This paper proposes an alternative way to model and forecast CIC based on the balance sheet of the central bank. In this framework, an expansion of the BSP's assets would be offset by an equivalent increase in the BSP's reserve money liability. For example, foreign exchange inflows, when exchanged into domestic currency, expand overall liquidity in the system. To the extent that expansion affects the inflation target, the excess liquidity is mopped-up through open market operations. The unsterilized portion of the expansion in domestic liquidity are either kept as deposits in banks or withdrawn as cash, thereby, increasing CIC.

The stylized assets and liabilities of the BSP are employed to forecast the levels of CIC using time series models. This approach is nascent and novel as it departs from the existing literature in currency demand forecasting, anchored on the demand-for-cash framework, which treats transaction motives, precautionary motives, and opportunity costs in holding cash as primary factors in predicting CIC.

Several models are estimated, with mean absolute percentage error (MAPE) ranging between one to two percent for in-sample fit. For out-of-sample forecast errors, the MAPE ranges between one to two percent up to twelve months ahead, suggesting promising predictive ability. Furthermore, forecast averaging methods such as the simple mean, mean square error weighting, and least squares weighting produce superior forecasts compared to the baseline models. These CIC models may complement the BSP toolkit in forecasting and analyzing CIC, which may help inform currency policy (and overall monetary policy) of the BSP.

JEL Classification: E41; E47; C22; E58

Keywords: Currency in circulation; central bank balance sheet; sterilization; Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX) Model; Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Model

Corresponding authors: Adrian Matthew G. Glova (agglova@up.edu.ph) and
Roy R. Hernandez (rhernandez@bsp.gov.ph)

Table of Contents

Balance Sheet Approach to Forecasting Currency in Circulation

Adrian Matthew G. Glova and Roy R. Hernandez[1]

1. Introduction

The Bangko Sentral ng Pilipinas (BSP) is the sole issuer of the domestic currency, pursuant to Republic Act (RA) No. 7653, as amended by RA No. 11211.[2] Thus, the BSP is mandated to provide the economy's currency requirements, while retiring unfit currency from circulation. The activities encompassing the cash cycle – from forecasting to retirement of currency – are some of the most notable and unique functions of the BSP.

At the operational level, the mandate requires forecasting currency in circulation (CIC). Given the rich information that may be gleaned from CIC, it is in the best interest of monetary authorities, the BSP included, to continuously track and accurately forecast CIC. This paper seeks to propose an alternative way to model and forecast CIC based on the balance sheet of the central bank. The expansion in BSP's assets would be offset by an equivalent increase in the BSP's reserve money liability. For example, foreign exchange inflows, when exchanged into domestic currency, expand overall liquidity in the system. To the extent that the expansion affects the inflation target, the excess liquidity is mopped-up through open market operations. The unsterilized portion of the expansion in domestic liquidity is kept as deposits in banks or withdrawn as cash, thereby, increasing CIC.

The assets and liabilities of the BSP are employed to forecast the levels of CIC using univariate time series models. This approach is nascent and novel as it departs from the existing literature in currency demand forecasting that is anchored on the demand-for-cash framework, with transaction motive, precautionary motive, and opportunity costs of holding cash as primary factors in predicting CIC.

1.1 Cash Cycle

The cash cycle starts with forecasting the annual currency requirements (both banknotes and coins) of the economy based on currency management indicators and prevailing macroeconomic conditions. Once approved, the forecasted currency requirements, broken down by denomination and by the monthly preferred schedule, would become the basis of currency production and deliveries.

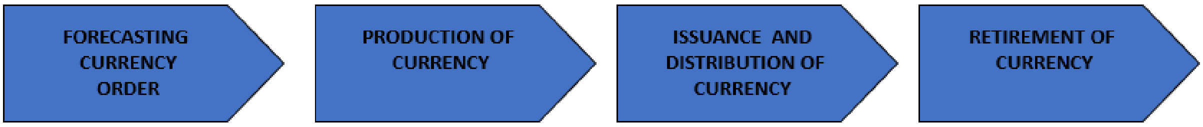
---

[1] Mr. Adrian Glova is Instructor IV at the UP School of Statistics, and formerly Acting Bank Officer IV at the Currency Policy and Integrity Department (CPID). Mr. Roy Hernandez is presently Bank Officer V at the CPID. The authors are grateful for the valuable inputs of CPID Director Eloisa Glindro and Monetary Board Member Felipe Medalla, especially for suggesting the framework of forecasting CIC from the central bank's balance sheet.

[2] Section 50 of the said law states: "The *Bangko Sentral* shall have the sole power and authority to issue currency, within the territory of the Philippines. No other person or entity, public or private, may put into circulation notes, coins or any other object or document which, in the opinion of the Monetary Board, might circulate as currency, nor reproduce or imitate the facsimiles of *Bangko Sentral* notes without prior authority from the *Bangko Sentral*."

Currency deliveries would then be used to service the currency requirements of the economy and, to some extent, fill up the buffer stock.[3] In particular, banknotes and coins are circulated in the economy through the BSP's transactions with banks. Likewise, banks are required to deposit to the BSP currency which are no longer fit for circulation. The BSP would then retire and replace the unfit currency with newer ones. Figure 1 shows the various stages in the cash cycle.

Figure 1: The Cash Cycle



1.2 Demand for Currency

The currency requirements of the economy can be better understood by examining the traditional demand-for-currency framework. This is motivated by the fundamental functions of currency in an economy, namely as: (a) unit of account; (b) store of value; and (c) medium of exchange. Given these functions, Shirai and Sugandi (2019) argued that the motivations for holding cash are driven primarily by the following factors:

- **Transaction motive** – cash is used as payment for goods and services such that the demand for cash is positively related to economic activity.
- **Opportunity cost** – cash holdings are weighed against financial returns arising from cash substitutes like demand deposits such that higher opportunity costs (e.g., higher retail deposit rates and/or higher inflation rates) lower the demand for cash.
- **Precautionary motive –** cash holdings ensure liquidity in times of crises such that demand for cash increases during uncertain times or when investors' risk appetite falls
- **Other motives –** demographic factors may affect cash holdings such that older populations, which are less familiar with digital payment methods, are more likely to hold and use cash.

The COVID-19 pandemic has changed currency holding patterns in the Philippines. The demand for cash for transaction purposes has declined amid softer economic activity due to disruptions and mobility restrictions related to the pandemic. At the same time, the pandemic accelerated the adoption of digital payments[4] for efficiency, convenience, and to some extent, hygiene concerns.[5]

[3] The buffer stock serves as a precaution for and insurance against unanticipated shocks in the supply of and demand for cash.

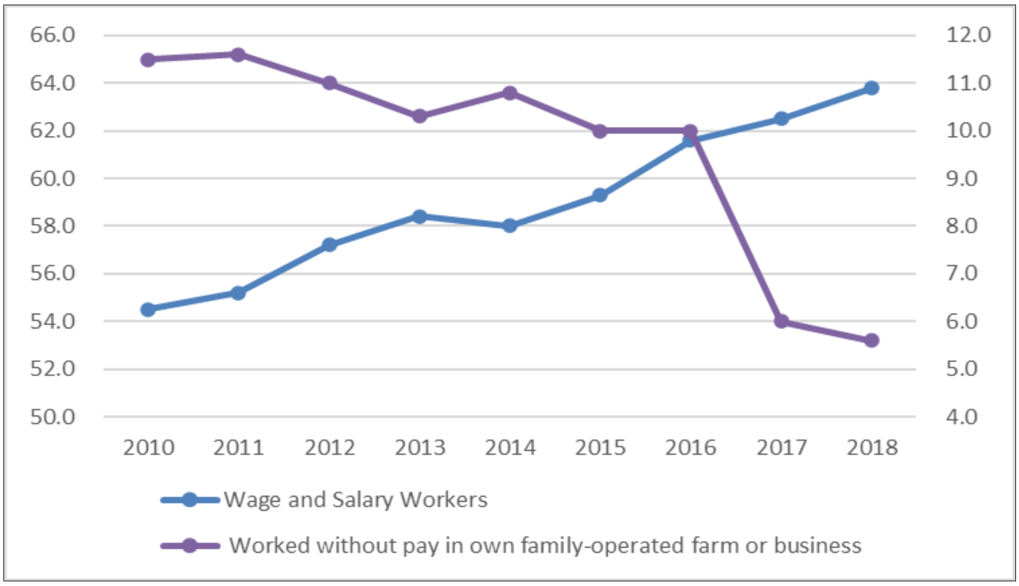
[4] In a speech before the Fintech Alliance Philippines on September 3, 2021, BSP Governor Benjamin E. Diokno bared that as of end-July 2021, InstaPay transaction volume and value rose by 64 percent and 103 percent, relative to the same period in 2020. PESONet transaction volume and value also grew by 190 percent and 50 percent as of end-July 2021. Source: https://www.bsp.gov.ph/SitePages/MediaAndResearch/MediaDisp.aspx?ItemId=5920. Last accessed on January 2, 2022.

[5] Whether concerns are warranted or not – as studies are still ongoing as to the possible spread of pathogens through cash handling – the perception of consumers alone may translate to reduced reliance on physical currency and increased usage of digital payment methods (Auer et al., 2020).

However, the decreased appetite for cash due to lower transaction motives was offset by heightened precautionary motives given uncertainties brought by the pandemic. This is evident in the net increase in the cash holdings of the public, as demand for store-of-value high denominations picked up. In fact, CIC[6] in the Philippines continued to grow despite the community quarantines and contraction in economic output.

The ratio of CIC to nominal GDP is an indicator of how much of the economy is financed through cash and it is the most common way to express the degree of cash usage in a country (Khiaonarong & Humphrey, 2019). The country's CIC-to-GDP ratio remains on an uptrend as demand for physical currency has been lifted by economic activity.[7] Consistent with the Lewis model of economic development, improving economic conditions lead to a shift from unpaid family laborers to the sector with formal wage structure, necessitating the need to pay these workers with cash (Figure 2).

Figure 2. Philippines: Salaried and Unpaid Family Workers Share to Total, in percent (2010-2019)

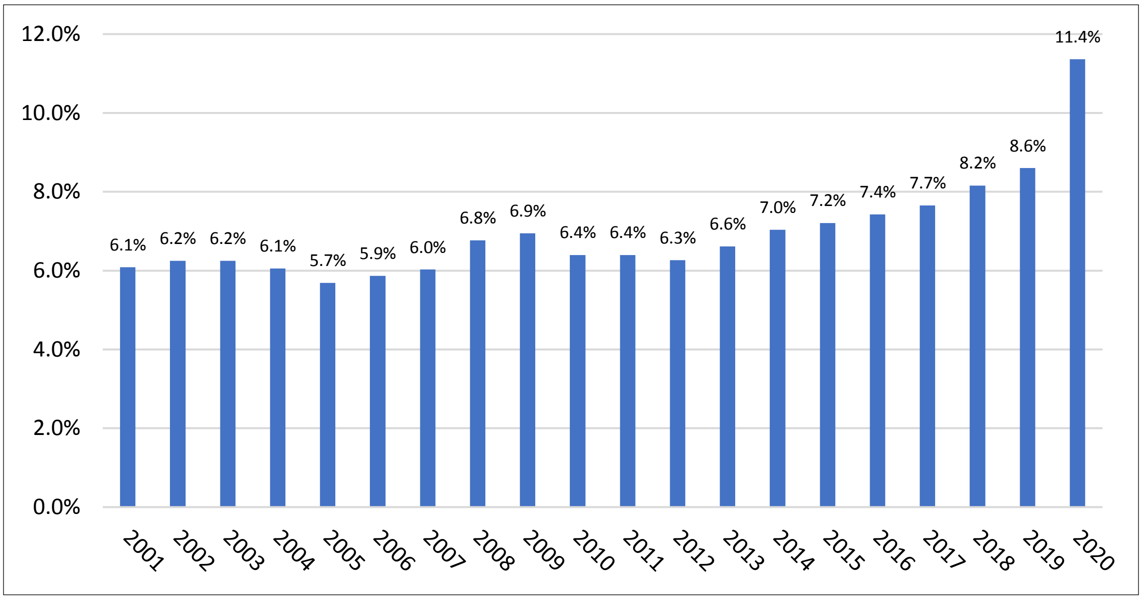


Source: PSA

Likewise, periods of crises have increased cash holdings due to heightened precautionary motive. This is clearly shown in the CIC-to-GDP ratio of the Philippines over the years, which has spiked in times of crises as with the Global Financial Crisis in 2008 and the COVID-19 pandemic in 2020 (Figure 3).

[6] CIC accounts for outstanding banknotes and coins in the economy, excluding balances held at the BSP's vaults.
[7] The discussions were lifted from Hernandez, Arellano, Vijuan (2021). An Empirical Analysis of the Philippine Demand for Cash. Unpublished Manuscript. Bangko Sentral ng Pilipinas.

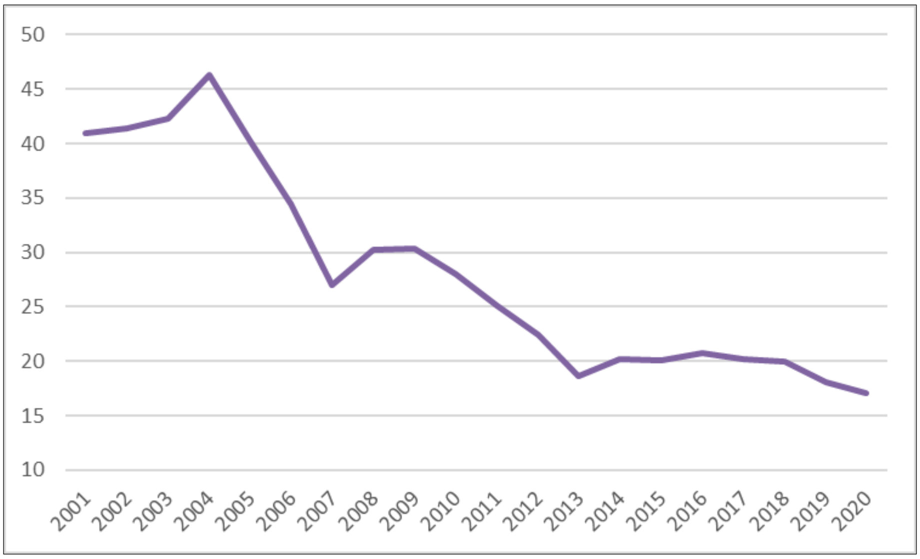
Figure 3. Philippines: CIC-to-GDP Ratio, in percent (2001-2020)



Source of basic data: PSA and BSP data

Increasing preference to hold the local currency relative to the US dollar also lifted the demand for cash. From a high of 46.3 percent in 2004, the ratio of foreign currency deposits to peso deposits is steadily declining, reaching a low of 17.1 percent in 2020 (Figure 4).

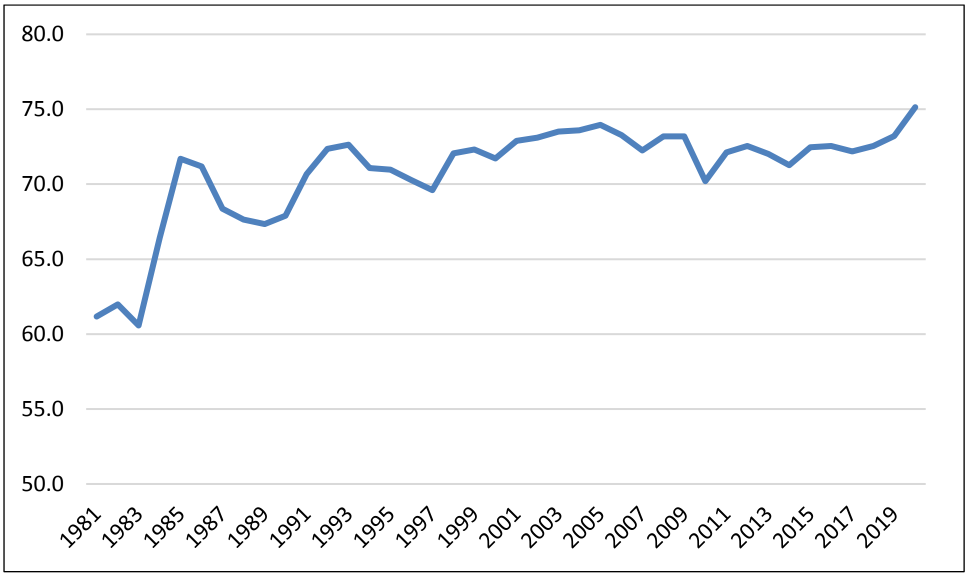
Figure 4. FCDU-to-Peso Deposits, in percent (2001-2020)



Source of basic data: BSP

Demand for cash was also lifted by consumption activities. Household consumption expenditures remained strong, accounting for three-fourths of GDP in 2020 (Figure 5).

Figure 5. Household Consumption to GDP, in percent (1981-2020)

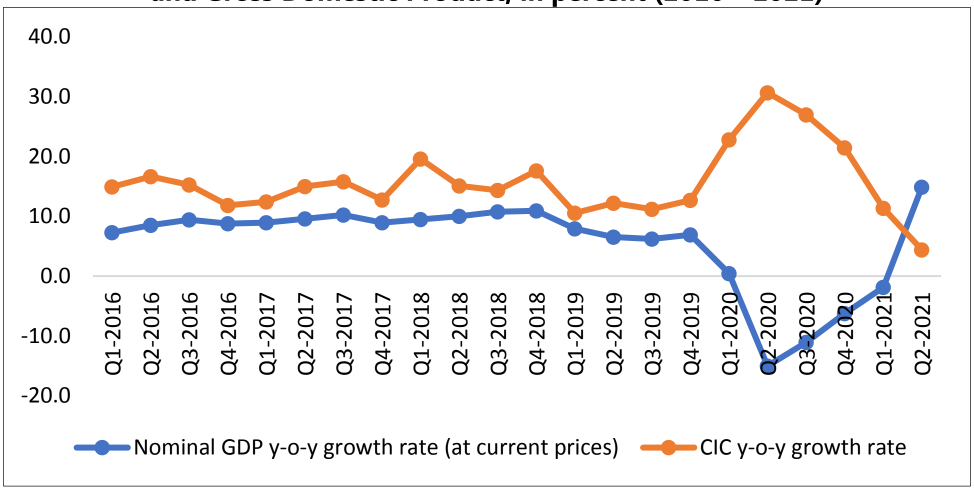


Source of basic data: BSP

Likewise, the opportunity cost of holding alternative financial instruments relative to cash is nil, given the low-interest rate environment, which makes keeping cash less costly and more attractive. The availability of wide array of financial instruments for use in transactional and store-of-value purposes likewise tempers the demand for cash.

Considered separately, Figure 6 shows the year-on-year growth rates of CIC and nominal gross domestic product (GDP). It can be observed that from 2016 to 2019, both were increasing as CIC kept pace with the expanding Philippine economy. However, CIC growth spiked in Q2 2020 even though the economy suffered from the mobility restrictions and uncertainties posed by the pandemic. This indicates that precautionary motives stimulated the demand for cash at the onset of the pandemic.

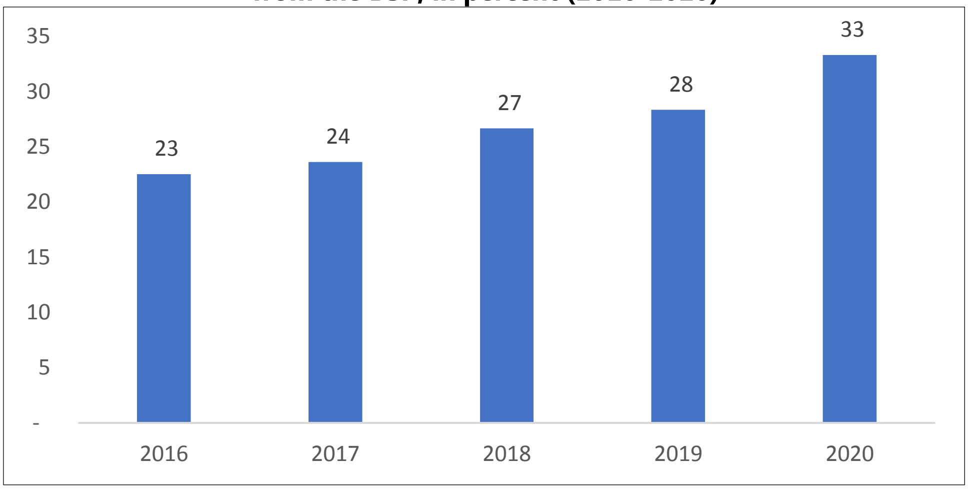
Figure 6: Annual Growth Rates of Currency in Circulation and Gross Domestic Product, in percent (2016 – 2021)



Source of basic data: PSA, BSP

In addition, the demand for the 1000-Piso, the highest banknote denomination – which functions more as a store of value – remained elevated despite weaker economic activity (Figure 7). This supports the claim that, in the time of the pandemic, heightened precautionary motive tends to offset the decline in the demand for cash due to lower transaction motives[8].

Figure 7
Share of 1000-Piso in Banks' Total Volume of Withdrawals from the BSP, in percent (2016-2020)



Source: BSP, Staff Calculations

Precautionary demand for physical currency has also been observed in crisis episodes as previously discussed. Like the COVID-19 pandemic shock, CIC recorded sharp annual increases during the 2008 Global Financial Crisis as cash was preferred during heightened uncertainties (Figure 8).

Figure 8
Share of 1000-Piso in Banks' Total Volume of Withdrawals from the BSP, in percent (2016-2020)

Source of basic data: BSP

[8] "Consumers holding banknotes as a store of value is another source of domestic demand for high-denomination banknotes... The store-of-value function performed by high-denomination banknotes appears to be particularly important during times of significant financial instability, such as the global financial crisis." (Flannigan and Parsons, 2018).

1.3 Estimating the Economy's Currency Requirements

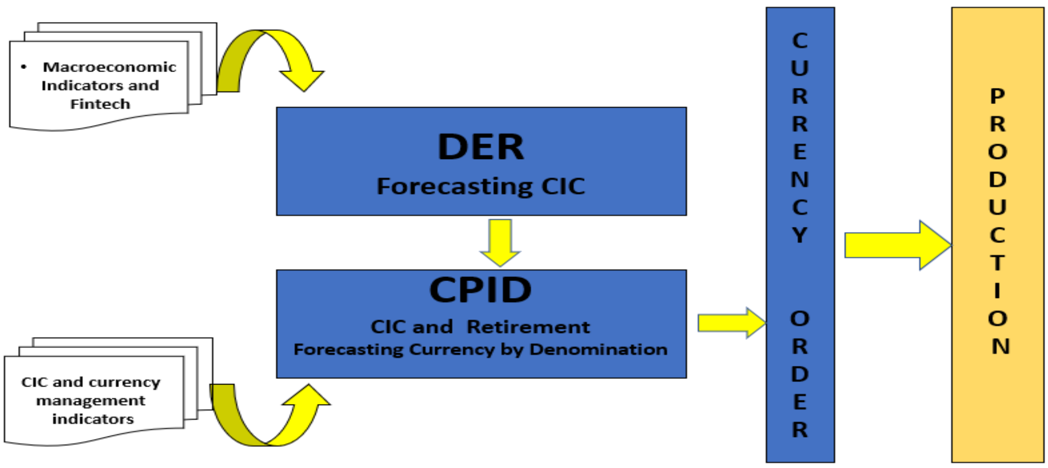
Before arriving at the estimated currency requirements of the economy (and by extension the BSP's currency order), CIC must first be forecasted based on macroeconomic variables that reflect or proxy the motives to hold cash. Real GDP accounts for the transaction motives in the demand for currency while inflation is one measure of the opportunity cost of holding cash.[9] CIC forecasts[10] using macroeconomic variables generate quarterly estimates consistent with the frequency of GDP data.

The flow equivalent of the aggregate CIC forecast and unfit currency for retirement are incorporated in the model for currency order. The fitness of the currency is also affected by economic conditions (i.e., heightened economic activity leads to higher turn-over and usage of currency, which may imply faster wear and tear), and the currency's natural attrition or lifespan. Statistical models such as Autoregressive Integrated Moving Average (ARIMA) and Co-integrating Regression Analysis (CiRA) are then employed to forecast the economy's currency requirements.[11]

The currency order forecasts would then be adjusted to account for the BSP's existing inventory and buffer stock requirement before arriving at the final currency order. Furthermore, the total currency order would be disaggregated by denomination. The denominational currency order will guide the production of currency. Figure 9 summarizes the demand-driven currency forecasting flowchart.

Figure 9

Currency Forecasting Flowchart



[9] Studies are underway to formally include digital transactions in forecasting CIC.
[10] CIC forecasts are generated by the Department of Economic Research (DER). The CPID then uses these CIC forecasts as inputs, along with internal data on currency management variables, to arrive at the currency order.
[11] CPID (2021). Evolution of Currency Forecasting at BSP. Unpublished manuscript.

2. Demand-side Forecasting of Currency in Circulation

Considering the prominent role of CIC in forecasting the economy's currency requirements, a reliable and timely forecast of CIC is necessary. Thus, it would be useful if several approaches in forecasting CIC are examined. The literature in forecasting CIC is based on univariate models that depend on the series' own history or time series models that consider macroeconomic variables that affect the demand for currency.

Seasonal Autoregressive Integrated Moving Average (SARIMA) models are commonly deployed to forecast CIC**.** These models rely on previous observations of CIC to forecast its future values. Such models have been deployed in Poland (Kozinski and Swist, 2014), Maldives (Shuaib and Nazeeh, 2019), and Qatar (Balli and Elsamadisy, 2011). The European Central Bank has also employed both exponential smoothing and ARIMA techniques (Strickland, 2015).

As for models that rely on macroeconomic variables, CIC forecasting is heavily based on the theory on the demand for currency. Demand for currency is taken to be a function of economic output, inflation and/or interest rates, and exogenous interventions to account for market shocks. These variables reflect the factors affecting the demand for currency, namely transaction motives, the opportunity cost of holding cash, and precautionary motives. ARIMA with exogenous variables (ARIMAX) and Vector Autoregressive (VAR) Models have also been deployed to model CIC following the theory on the demand for currency (Khatat, 2018).

The Bank of England utilized an error correction model to estimate a long run relationship between CIC and macroeconomic and currency management variables (Miller, 2017). Prayoga, Suhartono and Rahayu (2017) noted that CIC in Indonesia is influenced by Eid al-Fitr.[12] To account for this event, a linear model using ARIMAX was used to forecast CIC. However, non-linear factors may not be captured by the ARIMAX model. Thus, they proposed "a hybrid model of ARIMAX and artificial neural networks (ANN) that can handle both linear and nonlinear correlation."[13]

The Banca d'Italia used both ARIMA and breakpoint regression, as well as ARIMAX and VAR models. Based on its observation "pure ARIMA models outperform more complicated models in terms of forecast accuracy", as including macroeconomic variables did not translate to better predictive performance (Sasso, 2018). Khatat (2018) further argued that while forecasts from ARIMA tend to be superior compared to pure expert knowledge, "the combination of ARIMA forecasts with expert judgment is warranted, especially around the periods of significant and unexpected change in the CIC."

Most CIC models in the literature applied non-structural time series methods in the form of ARIMA or exponential smoothing. Meanwhile, other time-series models relied on macroeconomic and currency variables that reflect the motives to hold currency. However, there is scant literature on forecasting CIC outside the theory on the demand for currency.

[12] Eid al-Fitr is an Islamic religious holiday celebrated by Muslims to mark the end of Ramadan.

[13] Prayoga, Suhartono and Rahayu (2017). Forecasting currency circulation data of Bank Indonesia by using hybrid ARIMAX-ANN model. Retrieved from https://www.researchgate.net/publication/316916715_Forecasting_currency_circulation_data_of_Bank_Indonesia_by_using_hybrid_ARIMAX-ANN_model

There are hardly any studies assessing how central bank assets, especially foreign exchange purchases, may be converted into CIC.

3. An alternative approach in Forecasting Currency in Circulation

Another approach to estimate CIC is by looking at the demand for local currency emanating from foreign exchange (FX) inflows. This approach entails re-examination of the BSP's balance sheet, since whenever it purchases FX, it effectively sells the local currency, which, when left unsterilized, could end up as cash.

3.1 Stylized BSP Balance Sheet

The BSP's assets are composed of its net foreign assets (NFA),[14] which is dominated by the country's gross international reserves. Assets are also derived from the BSP's domestic claims (DC) in relation to its transactions with residents.[15]

NFA accounted for more than 90 percent of the BSP's assets until 2019. In 2020, claims on the central government rose as the BSP granted loans to the national government to help finance its COVID-19 response, reducing the share of NFA to total assets at 87 percent in 2020.

Over the years, the country has been a recipient of FX inflows on the back of strong macroeconomic fundamentals, remittances from overseas Filipinos, as well as FX inflows arising from exports.[16] Likewise, FX liquidity because of unconventional monetary policies in advanced economies found its way into emerging economies like the Philippines. The FX inflows led to an accumulation of international reserves on the part of the BSP, especially after the Global Financial Crisis, thereby, expanding its assets. [17] These developments are shown in Figure 10.

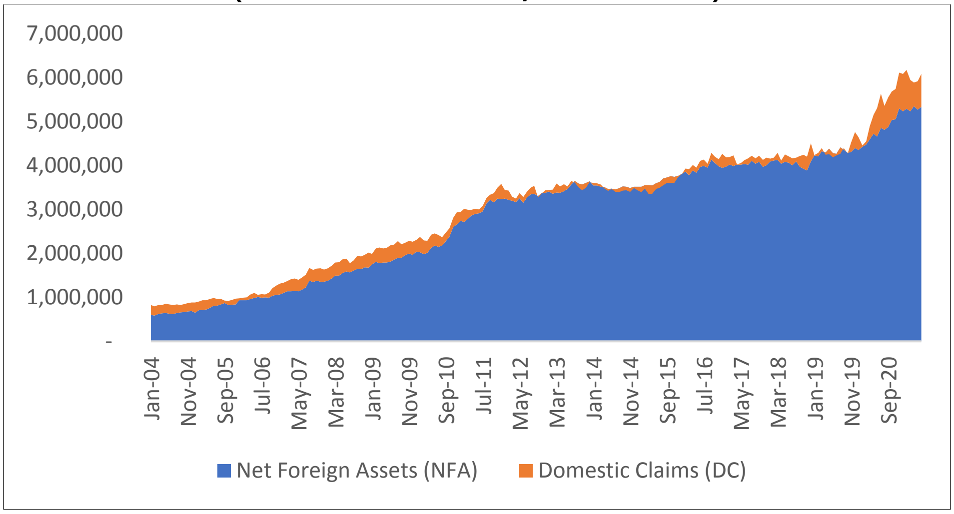
[14] These consist of a) Claims on Non-Residents comprising of the country's official reserve assets and other foreign assets; and b) Liabilities to Non-Residents consisting of gross foreign liabilities segregated into short-term and long-term maturities.

[15] These comprise a) Net Claims on Central Government which consist of securities other than shares and loans less deposit liabilities to CG; b) Claims on Other Depository Corporations such as deposits, securities other than shares, loans, and financial derivatives; and c) Claims on Other Sectors which comprise mainly of loans to other financial corporations, claims on state and local government, claims on public nonfinancial corporations and claims on private sector.

[16] Foreign investments including proceeds from Business Process Outsourcing and receipts from tourism activity were also sources of FX revenues.

[17] There are various motives for holding FX reserves, namely, transaction motive, precautionary motive, insurance motive, investment motive, endowment fund motive (Hernandez, 2010).

Figure 10: BSP Balance Sheet Assets
(Jan. 2004 – June. 2021, in Million PhP)



Source: BSP, Staff Calculations

Meanwhile, CIC is a liability of the BSP and forms part of the reserve money (RM).[18] Other liabilities of the BSP include those derived from the Reverse Repurchase Facility, Overnight Deposit Facility and Term Deposit Facility,[19] as well as Other Equity and Treasury-International Monetary Fund (IMF) accounts. Broadly, this class of liabilities can be classified as liabilities other than reserve money (LOTRM)[20].

In 2020, the share of LOTRM to total BSP liabilities jumped to 44 percent from the previous year's 32 percent.[21] This coincided with the BSP's expansionary monetary policy in an attempt to stimulate the economy amid the lingering COVID-19 shock, with cumulative reduction of 200 basis points since February 2020 (Figure 11).

[18] Aside from currency issued, there are other items in the reserve money including:

A. Liabilities to Other Depository Corporations (LODC) which comprise:
- Required reserves and clearing balances of Other Depository Corporation (ODCs) which refer to the BSP's regular peso demand deposit liabilities to commercial banks, specialized government banks, thrift banks, rural banks and nonbanks with quasi-banking functions and accrued interests.

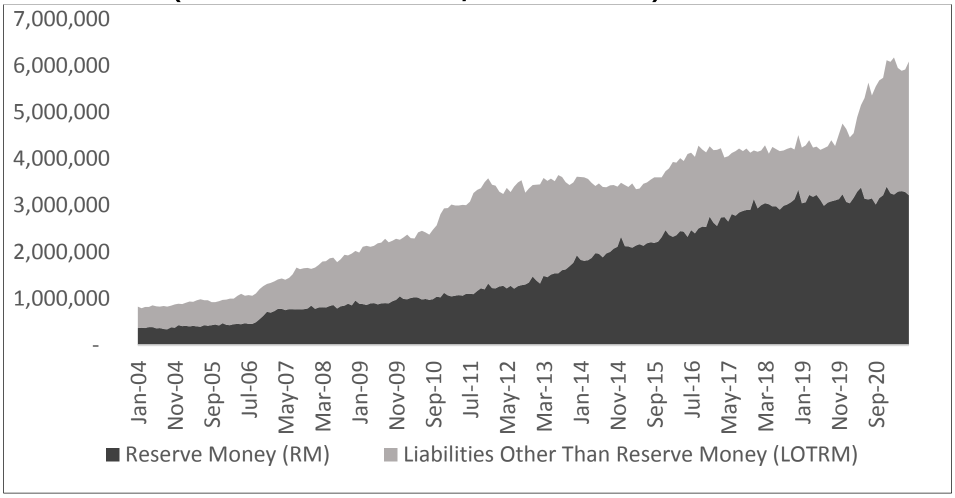
B. Liabilities to Other Sectors (LOS) consist of:
- Transferable deposits of other financial corporations (OFCs) included in broad money refer to the BSP's demand deposit reserve accounts of Common Trust Funds (CTF) and Trust and Other Fiduciary Accounts (TOFA) of OFCs and accrued interests.
- Reserve Deposit Account of OFCs which pertains to the funds placed with the BSP in lieu of government securities holdings to be bought directly from the BSP in compliance with the liquidity reserve requirement on CTF and TOFA accounts and accrued interests.

[19] This was introduced in June 2016 following the implementation of the Interest Rate Corridor (IRC) system.

[20] Liabilities Other Than Reserve Money include all other unclassified accounts such as deposits and securities other than shares, shares and other equity and other items (net).

[21] From 2017 to 2020, CIC accounted for a third of total liabilities of the BSP.

Figure 11: BSP Balance Sheet Liabilities (Jan. 2004 – June. 2021, in Million PhP)



Source: BSP, Staff Calculations

For purposes of this study, it is assumed that the BSP's capital and surplus accounts remain constant over time and are excluded from the analysis as they constitute a miniscule fraction of the BSP's assets. As of end-2020, the BSP's capitalization amounted to PhP50 billion, with accumulated capital reserves reaching PhP120.9 billion, equivalent to the 2.4 percent of the BSP's assets.

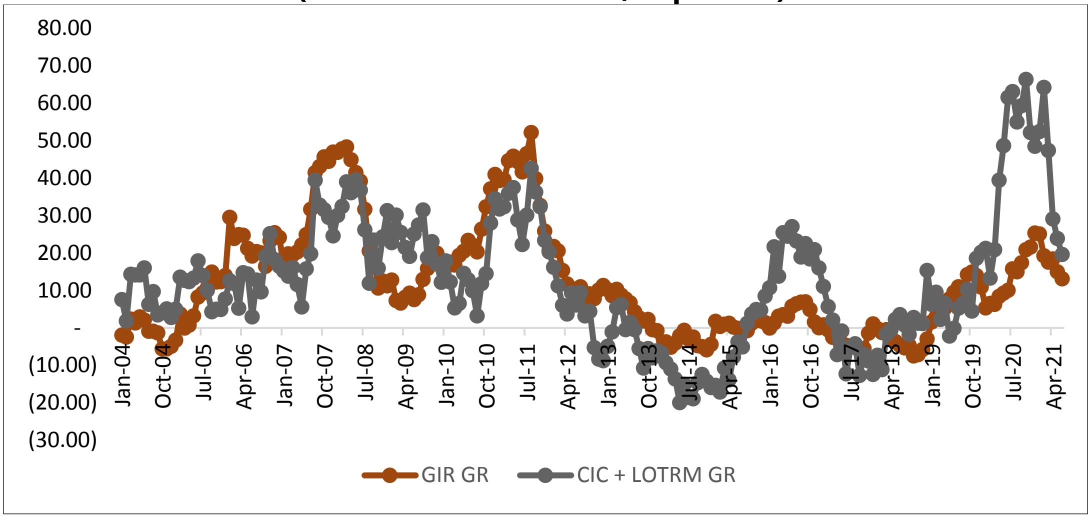
An increase in the BSP's assets through reserve accumulation leads to an equal increase in its liabilities. The increase in foreign reserve assets could be offset by an expansion of its liabilities through reserve money, which is potentially inflationary, if left unsterilized (Aizenman and Glick, 2008). Consistent with the inflation target, the increase in reserve money may be partially counteracted and mopped up by selling market instruments through open market operations where the BSP sells securities (buy local currency) with an agreement to buy (sell local currency) them back in the future, or by accessing the BSP's deposit facility.[22]

Sterilization activities through the Reverse Repurchase Facility, Overnight Deposit Facility and Term Deposit Facility increase the BSP's liabilities under LOTRM, effectively offsetting the accumulation of assets while moderating inflationary risks. Local currency converted through FX purchases that are not sterilized could be kept as deposits in banks or could be withdrawn as cash, thereby, increasing CIC.

Given that reserve accumulation entails BSP's sale of domestic currency to fund such FX purchases (and sterilizing the domestic liquidity injected through the BSP's open market operations and deposit facility), it is not surprising that the correlation between GIR on the asset side and CIC and LOTRM on the liability side is significantly high at 92.1 percent as they generally move in tandem as shown in Figure 12.

[22] Likewise, FX swaps and forward contracts may also be employed to manage liquidity. The costs associated in sterilization, as well in holding international reserves (such as negative carry) is not within the scope of the paper.

Figure 12: Growth Rate of GIR and CIC plus LOTRM
(Jan. 2004 to June 2021, in percent)



Source: BSP, Staff Calculations

Figure 12 also shows that the COVID-19 pandemic increased domestic liquidity relative to reserve accumulation. Though there was still a net increase in CIC due to heightened precautionary motive, the surge in domestic liquidity (i.e., CIC plus LOTRM) was significantly driven by increasing LOTRM.

The recent spike in CIC and LOTRM on the liabilities side was offset by the increase in domestic claims on the asset side as the BSP extended loans to the national government to help finance its pandemic response.[23]

4. Framework in Forecasting CIC: Balance Sheet Approach

The framework starts with the basic accounting identity that "assets are equal to liabilities and equity" is used as the foundation in conceptualizing the framework in forecasting CIC. For simplicity, the equity account is dropped from the identity since it represents a negligible proportion of total BSP assets.

$$Assets \equiv Liabilities + Equity$$

Expanding the BSP's assets and liabilities into their respective components,

$$NFA + DC = RM + LOTRM \tag{1}$$

[23] At the onset of the pandemic, the BSP provided support through a repurchase agreement with the National Government (NG) amounting to PhP300 billion in March 2020, repaid in September 2020. Thereafter, the BSP provided direct provisional advances of no more than 20 percent of the average annual income of the national government and payable within a maximum term of six months. In Bayanihan 2 Act, the BSP can extend additional advances to NG but the amount shall not exceed 10 percent of the average income of NG for the last three years, provided these funds are explicitly earmarked for the government's COVID-19 response programs. The additional amount can only be availed of until 2022 and must be repaid within one year upon availment.

Reserve money could be further broken down into its components

$$RM = CIC + LODC + LOS \tag{2}$$

From equations (2) and (3), the following relationship is obtained:

$$NFA + DC \ = CIC + LODC + LOS + LOTRM \tag{3}$$

Isolating CIC in equation (4) yields the following equation:

$$CIC = (NFA + DC) - (LODC + LOS + LOTRM) \tag{4}$$

The non-CIC liabilities (i.e., LODC, LOS, and LOTRM) of the BSP are then grouped under the variable "liabilities other than currency issued" (LOTCI). This leads to:

$$CIC = (Assets) - (Liabilities\ Other\ Than\ Currency\ Issued) \tag{5}$$

In this framework, CIC is positively related to total assets. To maintain equality between the left-hand and right-hand sides, an increase in assets would require an increase in CIC, holding LOTCI constant.

On the other hand, CIC is negatively related to LOTCI. Holding assets constant, an increase in LOTCI will lead to a decrease in CIC. This is intuitive such that an increase in LOTCI must be offset by a decrease in other components on the liability side (i.e., CIC) if we are to hold assets constant and still maintain equality between assets and liabilities.

From equation (5), we may take CIC as a function of lagged values of assets, lagged values of LOTCI, and lagged values of itself – to enhance predictive ability of the model – such that $CIC_t = f(\mathrm{Assets}_{\mathrm{t-x}}, \mathrm{LOTCI}_{\mathrm{t-x}}, CIC_{t-x})$. This may provide guidance in estimating stochastic models that forecast the future values of CIC. In particular, we take:

$$CIC_t = B_1 Assets_{t-x} + B_2 LOTCI_{t-x} + \ B_3 CIC_{t-x} + \epsilon \ \ where\ \epsilon \sim WN(0, \sigma^2) \tag{6}$$

5. Data Description

The models have a monthly frequency, in line with the frequency of reporting of the BSP's balance sheet. The entire dataset runs from January 2004 to June 2021 (210 observations). Furthermore, the dataset was divided into training and testing sets. The training set covers the period January 2004 to June 2020 (198 observations). Out-of-sample forecast errors were then computed for three months ahead (July 2020 to September 2020), six months ahead (July 2020 to December 2020), and twelve months ahead (July 2020 to June 2021).

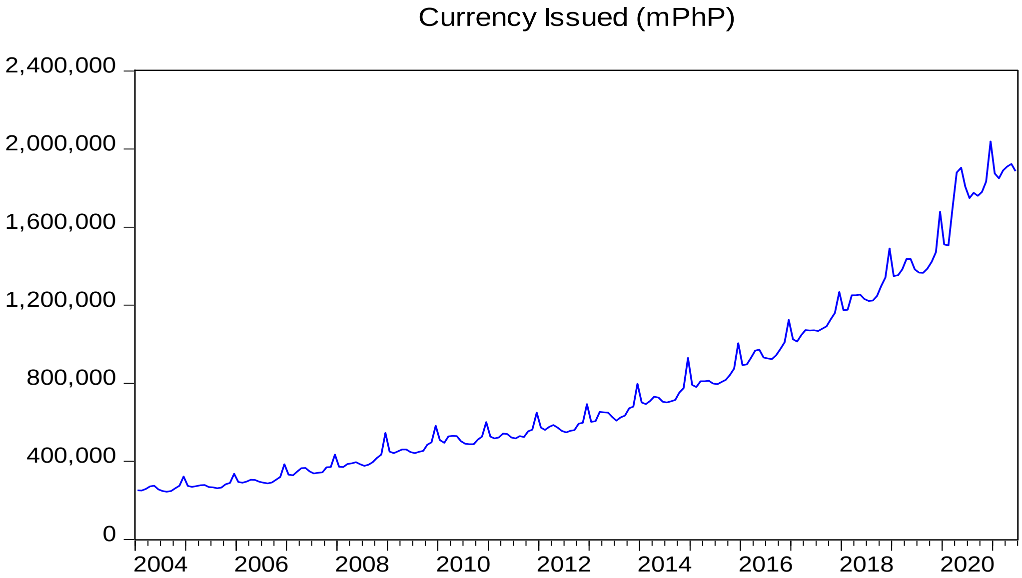
The following observations can be made for the dependent variable, CIC:

- CIC has been trending upwards since 2004 as can be seen in Figure 13, consistent with growing economy.
- Using TRAMO-SEATS decomposition, the seasonal factor was extracted for CIC (Figure 14). Peaks are observed every December. The holiday season translates to

strong economic activity, requiring a lot of currency to service transactions for goods and services; and

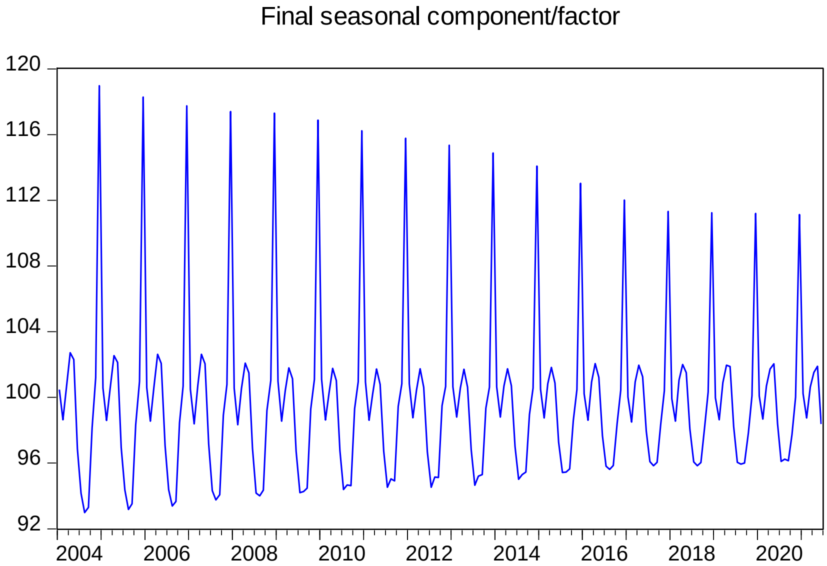
- Troughs may be observed every July or August. This has something to do with the ghost month where financial markets and investment spending are down.

Figure 13: Currency in Circulation
(Jan. 2004 to June 2021, in million PhP)



Source: BSP, Staff Calculations

Figure 14
Seasonal Factor of CIC
(Jan. 2004 to June 2021, in million PhP)



Source: BSP, Staff Calculations

6. Methodology

Using the balance-sheet approach to estimate CIC, three time series models are proposed: (i) an Autoregressive Distributed Lag (ARDL) Model, (ii) an Autoregressive Integrated Moving Average with Explanatory Variables (ARIMAX) Model, and (iii) an ARIMAX-Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Model.

There is insufficient evidence that CIC, lagged values of BSP assets, lagged values of LOTCI, and lagged values of CIC have a long-run relationship. This is shown in the Engle-Granger cointegration test results (Table 1 of the Annex). In the absence of a long-run relationship, all variables were log-transformed and differenced to achieve stationarity prior to modeling since all variables at their levels were integrated of order one or I(1).

Note that seasonality was accounted for by modelling the deseasonalized CIC data using TRAMO-SEATS decomposition. Nevertheless, the final forecasted values were transformed back to the nominal levels of CIC as this is the variable of interest for policymakers.

Lagged values of regressors were also included in the ARDL model to account for serial correlation as long-range temporal dependencies could still be observed (Tables 2.1 and 2.2 of the Annex). Moreover, White heteroskedasticity-consistent (HC) standard errors were obtained as the ARDL model residuals exhibited non-constant variance (Table 2.3 of the Annex). Not accounting for heteroskedasticity can lead to biased estimates of the standard errors, which may lead to unreliable hypothesis testing and incorrect confidence intervals.

6.1 Forecast Models

The baseline model is an ARDL model with lagged values of Assets, LOTCI and CIC. The variables have been log-transformed and first-differenced to achieve stationarity . White heteroskedasticity-consistent (HC) standard errors were obtained given evidence for non-constant variance. $\widetilde{CIC_t}$ refers to the seasonally adjusted CIC variable.

Model 1: ARDL Model for CIC

$$\Delta\log(\widetilde{CIC_t}) = B_1\Delta\log(Assets)_{t-12} + B_2\Delta\log(LOTCI)_{t-12} + B_3\Delta\log(CIC)_{t-18} + \epsilon_t, \quad (7)$$

$$\epsilon_t \sim WN(0, \sigma^2)$$

Moving on to the ARIMAX model, the error term was modeled as an MA(24) process to better account for serial correlation (Tables 3.1 and 3.2 of the Annex). Note, however, that this model still exhibited non-constant variance (Table 3.3 of the Annex), so White-HC standard errors were again obtained.

Model 2: ARIMAX Model for CIC

$$\Delta\log(\widetilde{CIC_t}) = B_1\Delta\log(Assets)_{t-12} + B_2\Delta\log(LOTCI)_{t-12} + B_3\Delta\log(CIC)_{t-24} + \epsilon_t, \quad (8)$$

$$\epsilon_t = \theta v_{t-24} + v_t,$$

$$v_t \sim WN(0, \sigma^2)$$

In the GARCH model, a variance equation was introduced to account for heteroskedasticity. This complements the mean equation from the ARIMAX model. The errors were assumed to be normally distributed. Model diagnostics for the GARCH model may be found in the Annex (Tables 4.1 and 4.2).

Model 3: GARCH Model for CIC

$$\Delta\log(\widetilde{CIC_t}) = B_1\Delta\log(Assets)_{t-12} + B_2\Delta\log(LOTCI)_{t-12} + B_3\Delta\log(CIC)_{t-24} + \epsilon_t, \quad (9)$$

$$\epsilon_t = \theta v_{t-24} + v_t,$$

$$v_t \sim N(0, \sigma_t^2)$$

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \gamma\sigma_{t-1}^2$$

6.2 Model Averaging

To complement the individual forecast models, three forecast averaging methods were explored to assess whether combining the models may lead to superior predictive ability. The first method is simple forecast averaging such that:

$$y_t = \frac{\sum_{i=1}^{N}\widehat{z_{i,t}}}{N} \quad (10)$$

In equation (10), y_t is the final CIC forecast at time t while $\widehat{z_{i,t}}$ represents the individual forecasts for CIC from the ARDL, ARIMAX, and GARCH models. Simple forecast averaging was done 3 months ahead, 6 months ahead, and 12 months ahead. Note that $N = 3$ since we have three individual forecast models.

Mean squared error (MSE) weighting was also utilized. MSE weights were obtained by comparing individual forecasts with actual values over some forecast period. As such, the MSE of the i-th model is represented as:

$$MSE_i = \frac{1}{n}\sum_{t=1}^{n}(z_{i,t} - \widehat{z_{i,t}})^2 \quad (11)$$

In particular, we take the entire twelve months (i.e., n = 12) of the forecast horizon to get the MSE weights. The specific formula for the weighting system is as follows:

$$w_i = \frac{1/MSE_i}{1/\sum_{j=1}^{N} MSE_j} \tag{12}$$

In equation (12), w_i represents the respective MSE weights. Once the weights were obtained, MSE-weighted forecasts were generated with the following equation:

$$y_t = \sum_{i=1}^{N} w_i(z_{i,t}) \tag{13}$$

Finally, least squares weighting was conducted where forecasts are regressed against actual values with the coefficients from the regression serving as the weights.

6.3 Limitations of the Models

One limitation of the proposed models is that forecasts with actual values can only be generated up to 12 months ahead. This is because there are regressors that are lagged 12 periods behind, particularly total assets of the BSP and LOTCI. If the forecast horizon will be expanded beyond 12 months, then future values of the individual regressors (i.e., LOTCI, Assets) would have to be forecasted or assumed. For instance, if a 13-month ahead forecast is to be generated, then LOTCI and assets would have to be forecasted one period ahead – through ARIMA, exponential smoothing, or similar regression techniques – before the proposed models can be used.

7. Results and Discussion

In the proposed models for deseasonalized CIC, lagged values of assets and lagged values of LOTCI are statistically significant as explanatory variables. Results are in line with expectations that assets are positively associated with CIC. As explained by the framework, a rise in assets should correspond to a rise in liabilities, one of which is CIC. Furthermore, the rise in BSP assets has been driven by reserve accumulation over the years. Some of the local currency converted through purchases of foreign reserve assets – which were not sterilized – end up as cash, thereby, increasing CIC.

On the other hand, LOTCI is negatively related to CIC as expected. Holding assets fixed, an increase in LOTCI should lead to a decrease in CIC to maintain parity between assets and liabilities. If assets are held constant and LOTCI are increased – converting some of the circulating cash into deposits or other forms of liabilities – then CIC is expected to decline.

Finally, CIC levels in prior periods are shown to be related to CIC in the present period. This is straightforward as the historical behavior of CIC may provide information on its future values.

Only the direction of the effect of the independent variables can be interpreted. This is because the left-hand and right-hand side variables were log-transformed and differenced to achieve stationarity prior to modelling. The consequence is that interpretations on the coefficient estimates are unwieldy.[24]

The model estimates are shown below, beginning with the ARDL model.

Table 2: ARDL Model Estimates

Variables		Coefficient	Standard Error (robust)	P-value
$DLOG(Assets_{t-12})$	B_1	0.360	0.108	0.001***
$DLOG(LOTCI_{t-12})$	B_2	- 0.256	0.097	0.009***
$DLOG(CIC_{t-18})$	B_3	0.025	0.018	0.173

***Significant at the 1 percent level

Results of the ARIMAX model again follow the signs expected from the framework. Assets are positively related to CIC and LOTCI is negatively related to CIC, *ceteris paribus*. Meanwhile, the coefficient of lagged values of CIC is now statistically significant in explaining the current period's CIC. The error term is modeled as an MA(24) to account for long-range temporal dependencies.

Table 3: ARIMAX Model Estimates

Variables		Coefficient	Standard Error (robust)	P-value
$DLOG(Assets_{t-12})$	B_1	1.082	0.457	0.019**
$DLOG(LOTCI_{t-12})$	B_2	-0.887	0.377	0.020**
$DLOG(CIC_{t-24})$	B_3	-0.214	0.068	0.076*
$MA(24)$	θ	0.831	0.041	0.000***

*Significant at the 10 percent level
**Significant at the 5 percent level
***Significant at the 1 percent level

The GARCH model results mirror that of the ARIMAX model, with an additional variance equation to account for heteroskedasticity. The variance of the error term is assumed to follow a GARCH(1,1) process to account for heteroskedasticity. The innovations are then assumed to be normally distributed. Modeling the variance is expected to lead to improvements in forecast performance, especially when volatility clustering may be observed.

[24] DLOG-transformed coefficient estimates can be interpreted as "month-on-month growth rates" similar to "investment returns" in financial markets. With both left-hand and right-hand side variables dlog-transformed, and the independent variables being lagged by 12 or 24 periods, the coefficient interpretations become less intuitive.

Table 4: GARCH Model Estimates

Variables	Coefficient		Standard Error	P-value
$DLOG(Assets_{t-12})$	B_1	0.513	0.197	0.009***
$DLOG(LOTCI_{t-12})$	B_2	-0.432	0.171	0.011**
$DLOG(CIC_{t-24})$	B_3	-0.102	0.046	0.027**
$MA(24)$	θ	0.777	0.032	0.000***
$ARCH(1)$	α	0.229	0.106	0.031**
$GARCH(1)$	γ	0.391	0.303	0.1967

**Significant at the 5 percent level
***Significant at the 1 percent level

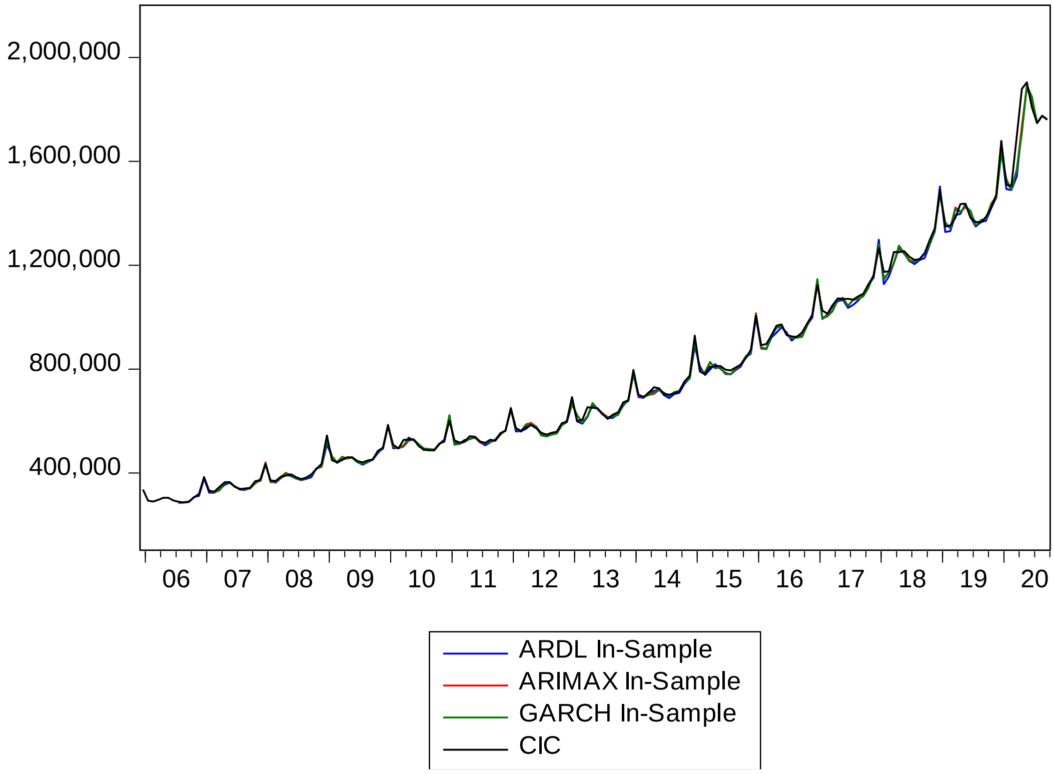
In terms of in-sample fit, the goodness-of-fit statistics points to the ARIMAX and GARCH models as the superior models (Table 5). Mean absolute percentage error (MAPE), root mean squared error (RMSE), and the Akaike Information Criterion (AIC) were computed to evaluate in-sample fit.

Table 5: In-Sample Forecast Performance of Estimated Models (Dec. 2004 to June 2020)

Model	MAPE (in percent)	RMSE	AIC
ARDL	1.38	21,186.02	-5.02
ARIMAX	1.21	19,285.13	-5.19
GARCH	1.25	20,817.62	-5.27

Figure 15 shows the in-sample fit of the three models, superimposed with actual CIC. The deviation of actual CIC from the estimated models are minimal, which is expected as the respective in-sample MAPE scores are close to 1 percent.

Figure 15: In-Sample Forecast (Jan. 2006 to June 2020, in million PhP)



Some models perform well in-sample but do poorly out-of-sample. This may be due to many factors such as model overfitting, structural change in the variable(s), and/or unanticipated shocks that are not captured by the training data. Therefore out-of-sample forecasts were calculated to gauge model accuracy for decision-making.

In this regard, the models show promise. Forecasts up to twelve months ahead were computed. This would allow the models to inform the periodic consolidated currency management report of the Currency Policy and Integrity Department (CPID), as well as guide the forecasting of the economy's currency requirements one year ahead.

Out-of-sample forecast performance suggests that all three models perform well even up to twelve months ahead with the models' MAPE ranging from 1.2 percent to 2.3 percent. In particular, the ARDL and GARCH models produced the most accurate out-of-sample forecasts (see Table 6).

Forecast averaging methods also consistently result in superior forecasts compared to the baseline models. The least squares-weighted forecasts yielded the best out-of-sample MAPE at 0.7 percent twelve months ahead. This is followed by the mean square error-weighted forecasts with out-of-sample MAPE of 1.5 percent twelve months ahead. Lastly, simple forecast averaging resulted in an out-of-sample MAPE of 1.7 percent twelve months ahead (see Table 7).

The nominal values of the model forecasts are summarized in Table 8. Also, the out-of-sample forecast errors of the estimated models may be visualized in Figures 16 and 17. Clearly, forecast averaging produces superior out-of-sample forecasts compared to the standalone forecasts of the estimated models. It can also be seen that even up to twelve months ahead, the out-of-sample forecasts are still quite accurate, especially with forecast averaging.

Table 6: Out-of-Sample MAPE of Estimated Models
(July 2020 to June 2021, in percent)

Date	ARDL MAPE	ARIMAX MAPE	GARCH MAPE
Jul-20	0.6%	1.0%	1.2%
Aug-20	1.4%	1.7%	1.5%
Sep-20	0.9%	0.4%	0.6%
Average MAPE (3 months ahead)	1.0%	1.0%	1.1%
Oct-20	1.1%	2.3%	2.1%
Nov-20	0.3%	0.7%	0.4%
Dec-20	1.4%	3.1%	2.0%
Average MAPE (6 months ahead)	0.9%	1.5%	1.3%
Jan-21	3.3%	4.7%	3.8%
Feb-21	0.1%	1.3%	0.9%
Mar-21	1.5%	2.2%	0.3%
Apr-21	1.1%	3.8%	2.5%
May-21	0.4%	0.7%	0.5%
Jun-21	2.1%	5.6%	4.3%
Average MAPE (12 months ahead)	1.2%	2.3%	1.7%

Table 7: Out-of-Sample MAPE of Estimated Models with Forecast Averaging (July 2020 to June 2021, in percent)

Date	Mean Forecast Average	MSE-weighted Forecast Average	LS-weighted Forecast Average
Jul-20	0.9%	0.8%	0.5%
Aug-20	1.5%	1.5%	1.2%
Sep-20	0.7%	0.8%	1.3%
Average MAPE (3 months ahead)	1.0%	1.0%	1.0%
Oct-20	1.8%	1.5%	0.4%
Nov-20	0.4%	0.4%	0.1%
Dec-20	2.2%	1.8%	0.0%
Average MAPE (6 months ahead)	1.2%	1.1%	0.6%
Jan-21	3.9%	3.6%	2.2%
Feb-21	0.7%	0.4%	1.1%
Mar-21	1.3%	1.3%	0.2%
Apr-21	2.5%	1.9%	0.9%
May-21	0.5%	0.4%	0.1%
Jun-21	4.0%	3.2%	0.3%
Average MAPE (12 months ahead)	1.7%	1.5%	0.7%

Table 8: CIC Out-of-Sample Forecasts of Estimated Models
(July 2020 to June 2021, in million PhP)

Date	Actual CIC	ARDL	ARIMAX	GARCH	Forecast Average (Mean)	Forecast Average (MSE Weights)	Forecast Average (LS Weights)
Jul-20	1,747,988	1,758,148	1,764,839	1,768,285	1,763,757	1,761,916	1,757,491
Aug-20	1,775,062	1,749,858	1,745,618	1,748,537	1,748,004	1,748,852	1,753,608
Sep-20	1,760,690	1,777,325	1,768,068	1,771,531	1,772,308	1,774,341	1,783,611
Oct-20	1,780,652	1,799,492	1,821,408	1,817,276	1,812,725	1,807,658	1,787,265
Nov-20	1,832,810	1,827,478	1,820,244	1,826,014	1,824,579	1,825,976	1,834,392
Dec-20	2,038,851	2,067,428	2,101,042	2,080,021	2,082,831	2,075,975	2,039,081
Jan-21	1,874,822	1,813,208	1,787,539	1,803,057	1,801,268	1,806,537	1,834,507
Feb-21	1,850,435	1,847,869	1,874,993	1,866,799	1,863,220	1,857,141	1,830,725
Mar-21	1,889,934	1,917,775	1,932,453	1,894,947	1,915,059	1,913,834	1,886,886
Apr-21	1,909,698	1,930,794	1,983,004	1,957,932	1,957,243	1,946,122	1,891,716
May-21	1,923,045	1,916,127	1,909,980	1,913,784	1,913,297	1,914,553	1,921,284
Jun-21	1,886,725	1,846,837	1,780,711	1,805,217	1,810,922	1,825,460	1,891,593

Figure 16: Out of Sample Forecasts of Estimated Models (July 2020 to June 2021, in million PhP)

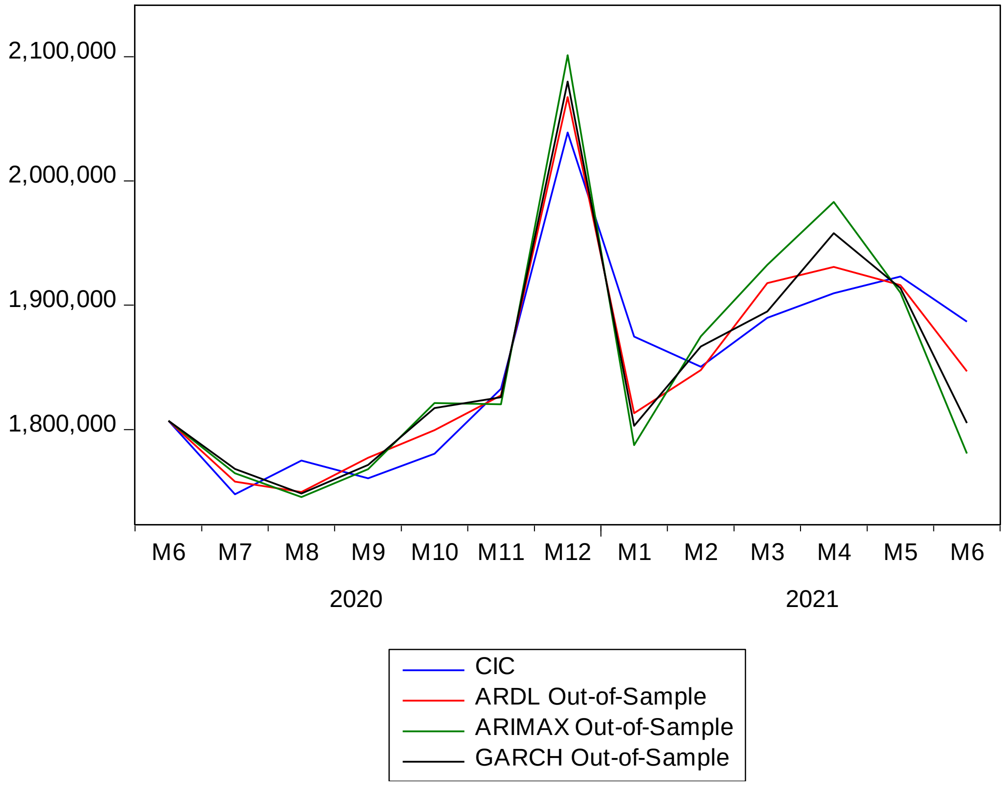
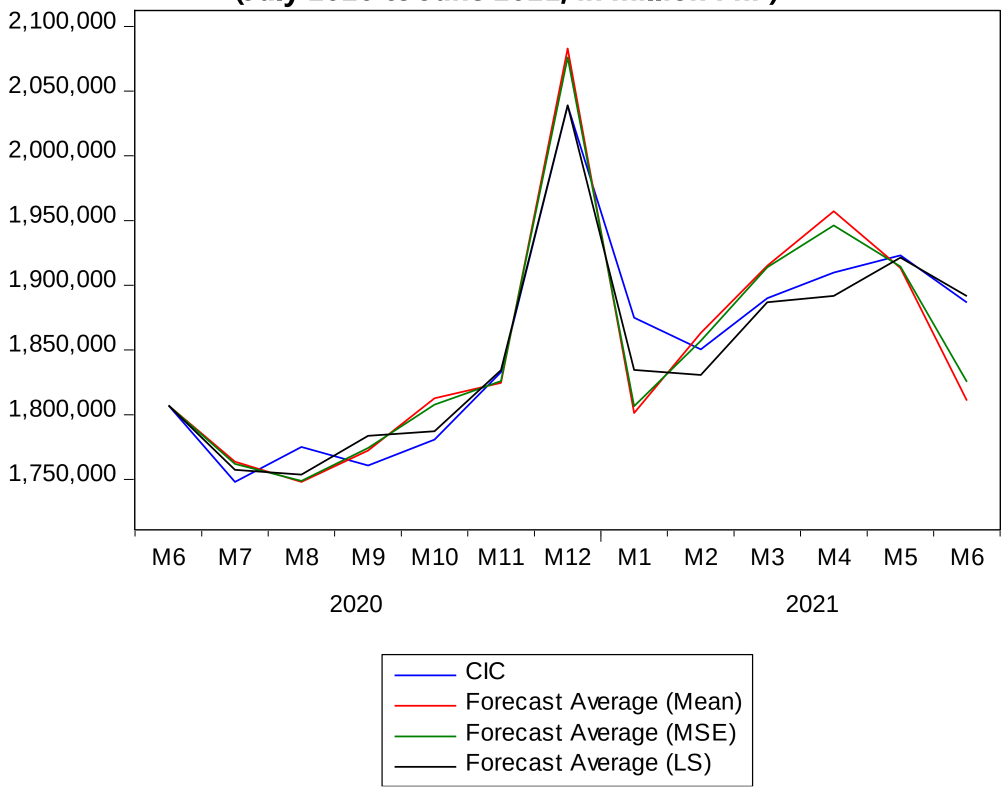


Figure 17: Out of Sample Forecasts of Estimated Models with Forecast Averaging (July 2020 to June 2021, in million PhP)



While the pandemic is still raging, currency policymakers should keep in mind the fluid nature of the motives to hold cash. On one hand, precautionary motive may gradually decline with vaccination momentum and easing of community quarantines. On the other hand, transaction motive may be gaining ground as economic activity starts to recover. Hence, it remains to be seen how the models will perform when CIC levels start reverting to their pre-pandemic behavior, if such will happen at all. Nevertheless, there is good reason to believe that the models will still produce fairly accurate forecasts, given the computed in-sample and out-of-sample performance statistics.

8. Concluding Remarks

The balance sheet approach in estimating CIC is especially useful in generating monthly forecasts as they do not rely on official GDP figures, which are released quarterly. While the balance sheet-based CIC models are not intended to replace existing demand-side CIC models that are grounded on the motives to hold cash[25], the proposed models in this paper may present viable alternatives in generating CIC forecasts. More reliable CIC forecasts would lead to a better matching of currency supply and currency demand.

[25] These "demand for cash" models are ultimately more interpretable as they are anchored on inflation, economic output, and dummy variables for economic shocks. Hence, even if the balance sheet approach offers more frequent and potentially more accurate forecasts, the demand-based models still offer rich economic information. It is not so intuitive to interpret changes in the central bank's balance sheet as compared to changes in macroeconomic conditions.

References

Aizenman, J. and Glick, R. (2008). Sterilization, Monetary Policy, and Global Financial Integration. Federal Reserve Bank of San Francisco Working Paper Series. Retrieved from https://www.frbsf.org/economic-research/files/wp08-15bk.pdf.

Auer, R., Cornelli, G. and Frost, J. (2020). COVID-19, cash, and the future of payments. BIS Bulletin No 3. Retrieved from https://www.bis.org/publ/bisbull03.pdf.

Balli, F. and Elsamadisy, E. (2011). Modelling the Currency in Circulation for the State of Qatar. MPRA Paper. Retrieved from https://mpra.ub.uni-muenchen.de/20159/.

Currency Policy and Integrity Department (2021). Evolution of the Currency Forecasting Model at the BSP. Unpublished manuscript.

Flannigan, G. and Parsons, S. (2018). High-denomination Banknotes in Circulation: A Cross-country Analysis. Reserve Bank of Australia. Retrieved from https://www.rba.gov.au/publications/bulletin/2018/mar/high-denomination-banknotes-in-circulation-a-cross-country-analysis.html.

Hernandez, R. (2010). Some Thoughts on Diversifying International Reserves. BSP Economic Newsletter. Retrieved from https://www.bsp.gov.ph/Media_And_Research/Publications/EN10-06.pdf.

Hernandez, R., Arellano J. and Vijuan, S. (2021). An Empirical Analysis of the Philippine Demand for Cash (Unpublished Manuscript). Bangko Sentral ng Pilipinas

Khatat, M. (2018). Monetary Policy and Models of Currency Demand. International Monetary Fund Working Paper Series. Retrieved from https://www.imf.org/en/Publications/WP/Issues/2018/02/16/Monetary-Policy-and-Models-of-Currency-Demand-45633.

Khiaonarong and Humphrey (2019). Cash Use across Countries and the Demand for Central Bank Digital Currency. IMF Working Paper. Retrieved from https://www.imf.org/en/Publications/WP/Issues/2019/03/01/Cash-Use-Across-Countries-and-the-Demand-for-Central-Bank-Digital-Currency-46617

Kozinski, W. and Swist, T. (2015). Short-term currency in circulation forecasting for monetary policy purposes: The case of Poland. Financial Internet Quarterly. Retrieved from https://www.econstor.eu/bitstream/10419/147121/1/842153985.pdf.

Miller, C. (2017). Addressing the Limitations of Forecasting Banknote Demand. Paper for International Cash Conference 2017 hosted by The Deutsche Bundesbank. Retrieved from https://www.bankofengland.co.uk/-/media/boe/files/paper/2017/addressing-the-limitations-of-forecasting-banknote-demand.

Prayoga, G., Suhartono, S. and Rahayu, S. (2017). Forecasting currency circulation data of Bank Indonesia by using hybrid ARIMAX-ANN model. Retrieved from https://www.researchgate.net/publication/316916715_Forecasting_currency_circulation_data_of_Bank_Indonesia_by_using_hybrid_ARIMAX-ANN_model.

Sasso, F. (2018). Forecasting Banknote Requirements in Banca d'Italia. XIV Meeting of Central Bank Treasurers, October 23-24, 2018, Lima.

Shirai, S. and Sugandi, E. (2019). What Explains the Growing Global Demand for Cash. Asian Development Bank Institute. Retrieved from https://www.adb.org/publications/what-explains-growing-global-demand-cash.

Shuaib, D. and Nazeeh, I. (2019). Forecasting Currency in Circulation for the Maldives. Maldives Monetary Authority. Retrieved from http://www.mma.gov.mv/documents/Research%20and%20Policy%20Notes/2019/Forecasting%20Currency%20in%20Circulation%20for%20the%20Maldives.pdf.

Strickland, N. (2015). Forecasting. Dela Rue Regional Conference, Maldives.

Annex

Table 1: Engle-Granger Cointegration Test Results

Cointegration Test - Engle-Granger
Date: 09/06/21 Time: 17:28
Equation: COINTEG
Specification: LOG(CIC) LOG (ASSETS (-12)) LOG (LOTCI (-12)) LOG (CIC (-24)) C
Cointegrating equation deterministic: C
Null hypothesis: Series are not cointegrated
Automatic lag specification (lag=0 based on Schwarz Info Criterion, maxlag=14)

	Value	Prob.*
Engle-Granger tau-statistic	-3.300135	0.2781
Engle-Granger z-statistic	-20.15591	0.2761

*MacKinnon (1996) p-values.

Table 2.1: ARDL Model Serial Correlation LM Test

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	3.558016	Prob. F (12,153)	0.0001
Obs*R-squared	36.65355	Prob. Chi-Square (12)	0.0003

Table 2.2: ARDL Model Ljung-Box Test

Date: 12/23/21 Time: 13:32
Sample: 2004M12 2020M06
Included observations: 168
Q-statistic probabilities adjusted for 3 dynamic regressors

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.012	-0.012	0.0241	0.877
		2	0.002	0.001	0.0246	0.988
		3	-0.036	-0.036	0.2449	0.970
		4	-0.063	-0.064	0.9389	0.919
		5	0.009	0.007	0.9527	0.966
		6	0.010	0.010	0.9719	0.987
		7	0.012	0.008	0.9970	0.995
		8	0.013	0.010	1.0285	0.998
		9	-0.022	-0.020	1.1172	0.999
		10	-0.079	-0.078	2.2450	0.994
		11	0.052	0.052	2.7302	0.994
		12	-0.111	-0.111	4.9675	0.959
		13	0.008	-0.003	4.9788	0.976
		14	0.103	0.100	6.9535	0.936
		15	-0.015	-0.015	6.9960	0.958
		16	0.043	0.031	7.3448	0.966
		17	-0.019	-0.007	7.4117	0.978
		18	0.037	0.050	7.6746	0.983
		19	0.043	0.042	8.0271	0.986
		20	-0.003	-0.002	8.0285	0.992
		21	0.064	0.069	8.8306	0.990
		22	0.017	0.005	8.8863	0.994
		23	-0.046	-0.026	9.2945	0.995
		24	-0.026	-0.021	9.4252	0.997
		25	0.058	0.056	10.095	0.996
		26	0.027	0.056	10.246	0.998
		27	-0.073	-0.093	11.314	0.996
		28	-0.057	-0.052	11.971	0.996
		29	-0.016	-0.005	12.027	0.998
		30	0.036	0.036	12.289	0.998
		31	-0.005	0.004	12.295	0.999
		32	0.079	0.055	13.596	0.998
		33	0.042	0.050	13.965	0.999
		34	-0.036	-0.031	14.240	0.999
		35	0.087	0.087	15.863	0.998
		36	-0.038	-0.036	16.174	0.998

*Probabilities may not be valid for this equation specification.

Table 2.3: ARDL Model ARCH Test

Heteroskedasticity Test: ARCH

F-statistic	3.298396	Prob. F (12,143)	0.0003
Obs*R-squared	33.81845	Prob. Chi-Square (12)	0.0007

Table 3.1: ARIMAX Model Serial Correlation LM Test

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.930197	Prob. F (12,146)	0.5187
Obs*R-squared	11.50595	Prob. Chi-Square (12)	0.4861

Table 3.2: ARIMAX Model Ljung-Box Test

Date: 12/23/21 Time: 13:36
Sample: 2004M12 2020M06
Included observations: 162
Q-statistic probabilities adjusted for 1 ARMA term and 3 dynamic regressors

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.022	0.022	0.0765	
		2	-0.062	-0.063	0.7199	0.396
		3	-0.045	-0.042	1.0537	0.590
		4	-0.059	-0.062	1.6447	0.649
		5	0.018	0.015	1.6967	0.791
		6	-0.068	-0.079	2.4753	0.780
		7	0.006	0.006	2.4810	0.871
		8	-0.041	-0.054	2.7686	0.906
		9	-0.038	-0.040	3.0183	0.933
		10	-0.081	-0.097	4.1613	0.900
		11	0.027	0.024	4.2896	0.933
		12	-0.139	-0.174	7.7160	0.738
		13	-0.033	-0.036	7.9100	0.792
		14	0.056	0.015	8.4668	0.812
		15	-0.002	-0.025	8.4673	0.864
		16	0.121	0.087	11.124	0.744
		17	0.003	0.002	11.126	0.802
		18	-0.000	-0.016	11.126	0.850
		19	-0.002	-0.003	11.127	0.889
		20	0.021	0.021	11.206	0.917
		21	0.137	0.128	14.767	0.790
		22	-0.010	-0.023	14.787	0.833
		23	-0.060	-0.034	15.482	0.841
		24	-0.262	-0.275	28.716	0.190
		25	0.043	0.061	29.067	0.218
		26	0.070	0.057	30.016	0.224
		27	-0.078	-0.096	31.220	0.220
		28	0.003	0.012	31.222	0.262
		29	-0.028	-0.018	31.379	0.301
		30	0.061	0.029	32.128	0.314
		31	-0.005	0.011	32.133	0.361
		32	0.044	0.026	32.522	0.392
		33	0.016	0.022	32.578	0.438
		34	-0.013	-0.046	32.615	0.486
		35	0.110	0.137	35.135	0.414
		36	0.078	-0.004	36.426	0.402

*Probabilities may not be valid for this equation specification.

Table 3.3: ARIMAX Model ARCH Test

Heteroskedasticity Test: ARCH

F-statistic	3.667109	Prob. F (12,137)	0.0001
Obs*R-squared	36.46742	Prob. Chi-Square (12)	0.0003

Table 4.1: GARCH Model Ljung-Box Test

Date: 12/23/21 Time: 13:38
Sample: 2004M12 2020M06
Included observations: 162
Q-statistic probabilities adjusted for 1 ARMA term and 3 dynamic regressors

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.068	-0.068	0.7574	
		2	-0.037	-0.042	0.9907	0.320
		3	-0.028	-0.034	1.1214	0.571
		4	-0.050	-0.057	1.5469	0.671
		5	0.034	0.024	1.7385	0.784
		6	-0.030	-0.032	1.8962	0.863
		7	0.037	0.032	2.1323	0.907
		8	-0.048	-0.048	2.5376	0.924
		9	-0.050	-0.054	2.9762	0.936
		10	-0.101	-0.117	4.7689	0.854
		11	-0.006	-0.026	4.7754	0.906
		12	-0.085	-0.113	6.0604	0.869
		13	-0.018	-0.046	6.1189	0.910
		14	0.060	0.030	6.7750	0.913
		15	0.025	0.027	6.8919	0.939
		16	0.152	0.149	11.070	0.748
		17	-0.020	0.015	11.146	0.800
		18	-0.030	-0.025	11.308	0.840
		19	-0.020	-0.028	11.378	0.878
		20	0.024	0.010	11.488	0.906
		21	0.151	0.128	15.769	0.731
		22	-0.032	-0.023	15.963	0.772
		23	-0.016	-0.014	16.010	0.815
		24	-0.294	-0.295	32.627	0.088
		25	0.015	-0.009	32.669	0.111
		26	0.085	0.100	34.073	0.106
		27	-0.107	-0.096	36.308	0.086
		28	0.006	-0.022	36.315	0.109
		29	-0.022	-0.012	36.409	0.132
		30	0.043	0.035	36.775	0.152
		31	-0.017	0.012	36.833	0.182
		32	0.044	0.016	37.229	0.204
		33	0.040	0.031	37.550	0.230
		34	-0.033	-0.080	37.779	0.260
		35	0.106	0.106	40.121	0.217
		36	-0.013	-0.069	40.154	0.252

*Probabilities may not be valid for this equation specification.

Table 4.2: GARCH Model ARCH Test

Heteroskedasticity Test: ARCH

F-statistic	1.478400	Prob. F (12,137)	0.1394
Obs*R-squared	17.19727	Prob. Chi-Square (12)	0.1423

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
2022-01	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
2020-04	Zernan C. Talabong	Do Prudential Regulations Affect Bank Lending Rates? Insights from Philippine Banks Using an Accounting-Based Approach	June 2020

No	Author	Title	Date
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
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

No	Author	Title	Date
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