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Forecasting currency in circulation with the central bank balance sheet

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Currency in circulation (CIC) is an important variable in monetary policy as it affects liquidity and guides the currency issuance operations of central banks. This paper proposes a novel approach to forecast CIC using central bank balance sheet variables, namely assets and liabilities other than currency issued. The balance sheet approach is able to generate monthly CIC forecasts as opposed to demand-for-currency models anchored on quarterly Gross Domestic Product (GDP). This allows for more responsive currency policy, particularly during crisis periods when precautionary motives intensify—reflected in a decoupling of GDP and CIC—or when spikes in currency demand arise due to heightened transaction motives.

Dynamic time series regression models are estimated to operationalize the balance sheet approach and are compared to baseline predictive methods such as Error-Trend-Seasonality (ETS) models, Autoregressive Integrated Moving Average (ARIMA), and seasonal naïve methods. Results show that including balance sheet variables significantly improves the predictive ability of CIC models in terms of mean absolute percentage error (MAPE) and root mean squared scaled error (RMSSE). These findings hold across multiple training and test sets through time series cross-validation, suggesting stability of forecast accuracy results.

JEL classification: E41, E47, C22
Keywords: currency in circulation, central bank balance sheet, time series analysis

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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. Thus, the BSP is mandated to provide the Philippine economy's currency requirements, while retiring unfit currency from circulation. The activities encompassing the cash cycle—from forecasting demand to retiring unfit currency—are some of the most notable and unique functions of a central bank. To successfully fulfill this mandate, central banks ought to accurately forecast the total amount of currency circulating in the economy.

This paper proposes an alternative way to model and forecast currency in circulation (CIC) based on the balance sheet of a central bank. An expansion in a central bank's assets would be offset by an equivalent increase in its 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 liquidity is kept as deposits in banks or withdrawn as cash, thereby increasing CIC.

To demonstrate this modeling approach, assets and liabilities other than currency issued (LOTCI) of the BSP are used to predict CIC. This methodology departs from the usual demand-for-cash framework, which treats transaction motives, precautionary motives, and opportunity costs in holding cash as determinants of CIC. One advantage of this novel approach is that monthly CIC forecasts may be generated as it utilizes central bank balance sheet data, which are available monthly. This is in contrast with demand-for-cash models which rely on Gross Domestic Product (GDP), limiting forecasts to quarterly intervals.[1]

From a policy perspective, adopting a higher-frequency model can more effectively inform a central bank's liquidity provisioning activities, particularly the issuance of notes and minting of coins, which are highly sensitive to economic shocks and shifts in consumer behavior. This approach is especially valuable during crises when GDP and CIC can become decoupled (e.g., GDP falls while CIC rises) due to heightened precautionary motives. High-frequency CIC can thus serve as a useful indicator of consumer confidence and purchasing behavior during periods of economic stress.

In the broader context of monetary policy, CIC forms the foundation of the money supply and plays a key role in central bank decisions to inject or withdraw liquidity from the economy, whether through repurchase agreements, foreign exchange swaps, or other liquidity management tools. Additionally, CIC influences the transmission of monetary policy, as changes in the policy rate affect how economic agents spend, borrow, and save through the banking system.

[1] The potential use of mixed-frequency CIC models to combine quarterly and monthly demand-for-cash variables, as well as balance sheet variables, is discussed in Section 8.

An increase in CIC may signal growing informality in economic activity, which can weaken the effectiveness of monetary policy as consumers and firms either bypass or lack access to the banking system [Ospina 2023]. This dynamic is particularly relevant in developing countries like the Philippines, where a large share of transactions is still carried out in cash. All told, the proposed models may complement the BSP toolkit in forecasting and managing CIC, better informing its currency policy and overall monetary policy.

2. Demand-for-currency and alternative approaches to CIC estimation

The currency requirements of the economy can be better understood with the 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 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, typically proxied by GDP;
- **Opportunity cost** – cash holdings are weighed against financial returns arising from cash substitutes like demand deposits. Larger opportunity costs (e.g. higher retail deposit rates or higher inflation rates) lower the demand for cash;
- **Precautionary motive** – cash ensures liquidity in times of crises so demand for cash increases during times of uncertainty or when investor risk appetite falls;
- **Other motives** – demographic factors may affect cash holdings as aging populations may prefer to hold cash.

Given this framework, CIC is often forecasted based on macroeconomic variables that capture demand-side factors. GDP accounts for the transaction motives, while inflation and interest rates proxy the opportunity costs to hold cash. Exogenous interventions are also introduced to consider market shocks over time. Autoregressive Integrated Moving Average Models with Exogenous Variables (ARIMAX) and Vector Autoregressive (VAR) Models are commonly deployed to model CIC following the theory of demand-for-currency [Khatat 2018].

Most central banks generate quarterly CIC forecasts consistent with the frequency of GDP measurement. ARIMAX and cointegrating regression models have also been deployed to predict the levels of CIC, and potentially model long-run relationships among variables. For instance, the Bank of England utilizes an error correction model to estimate the relationship between CIC and macroeconomic and currency management variables including nominal consumption, interest rates, exchange rates, the unemployment rate, the number of bank branches and post offices, and the number of regular payments made in cash per person per year, among other factors [Miller 2017]. This model performs well in longer forecast horizons but leads to larger forecast errors in the short run relative to a simple autoregressive model. This may be due to omitted variable bias or incorrect specification of the econometric model. The authors note that inaccuracies may arise as the input variables to the error correction model are extrapolated to arrive at the final CIC forecast.

Prayoga, Suhartono, and Rahayu [2017] note that CIC in Indonesia is influenced by Eid al-Fitr.[2] To account for this factor, an ARIMAX model was used to forecast CIC. They also estimated a hybrid model of ARIMAX and artificial neural networks (ANN) to model potential non-linearities in the data. By leveraging ANN, the hybrid model was more effective at capturing non-linear patterns over time. Nonetheless, both models were sensitive to outliers, highlighting the potential value of intervention analysis. This sensitivity may also point to overfitting, as the authors observed substantially stronger predictive performance on in-sample data compared to out-of-sample data.

The literature in forecasting CIC also includes univariate models that purely depend on the series' own history. Seasonal Autoregressive Integrated Moving Average (SARIMA) models are commonly deployed to forecast CIC and account for recurrent patterns in the data. Such models have been used in Poland [Kozinski and Swist 2014], the Maldives [Shuaib and Nazeeh 2019], and Qatar [Balli and Elsamadisy 2011]. The European Central Bank has also employed exponential smoothing and ARIMA techniques [Strickland 2015]. These models often perform well in the short term, as they rely on recent historical patterns. However, the lack of structure[3] can result in larger forecast errors in the long run (Balli and Elsamadisy [2011]; Shuaib and Nazeeh [2019]). Moreover, ARIMA models may struggle to capture non-linear dynamics, as they are not designed to model such patterns in time series data.

The *Banca d'Italia* uses a suite of models such as ARIMA, breakpoint regression, 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, combining ARIMA forecasts with expert judgment may significantly improve forecasts to account for unexpected and significant changes.

Khatat [2018] emphasized that "the fundamental longer-run determinants of the demand for cash are distinct from its short-run determinants." In the short run, potentially at a daily frequency, CIC is primarily influenced by factors such

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

[3] In this sense, structural models refer to time series models that rely on economic theory as opposed to pure time series models that only account for a series' historical behavior.

as the number of weekdays, payroll schedules, holidays, and other calendar effects. In contrast, long-run CIC dynamics are shaped by broader demand-for-money factors, including economic growth, inflation, interest and exchange rates, payment system usage, and the occurrence of economic shocks. As such, different forecasting models may be appropriate depending on the time horizon considered.

In the case of the Philippines, the BSP relies on the demand-for-currency framework to estimate the economy's currency requirements. The BSP, through its Department of Economic Research, first predicts CIC based on macroeconomic variables that reflect the motives to hold cash. In particular, GDP accounts for the transaction motives, while inflation is its measure of the opportunity cost to hold cash. CIC forecasts using macroeconomic variables generate quarterly estimates consistent with the frequency of GDP data reporting.

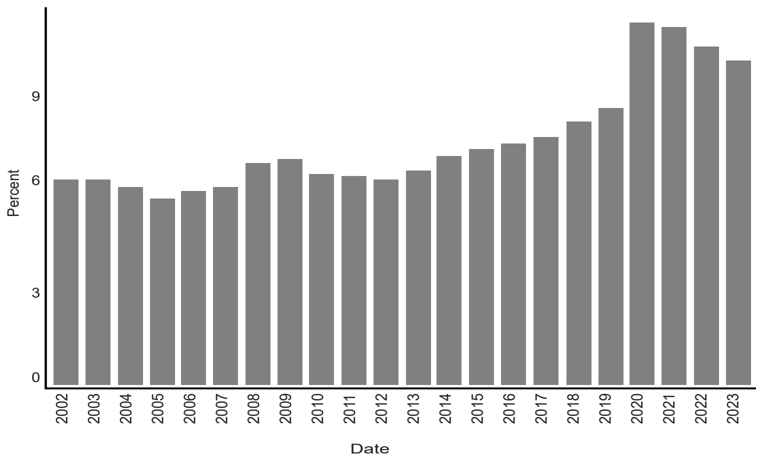
At this stage, the BSP estimates the volume of unfit currency to be retired in order to determine its currency order. Statistical models such as ARIMA and Co-integrating Regression Analysis (CiRA) are utilized. The initial currency order is then adjusted based on the BSP's current inventory and buffer stock requirements to arrive at the final order. This is subsequently broken down by denomination, forming the denominational currency order that ultimately guides the BSP's currency production.

This process highlights how more timely and accurate forecasting of CIC can lead to a better alignment between the BSP's currency order and the economy's actual currency needs. A key limitation of the demand-for-currency framework, however, is that the relationship between GDP and CIC can shift significantly during periods of uncertainty or economic shocks. In stable times, rising GDP requires a concomitant increase in CIC to support the expanding volume and value of transactions. Yet, in times of crisis or heightened volatility, GDP may decline while CIC rises, driven by precautionary motives.

The saying "cash is king" proved especially true during the COVID-19 pandemic, when the CIC-to-GDP ratio surged to 11.4 percent, an increase of 2.8 percentage points year-on-year (Figure 1). In periods of heightened uncertainty, such as this, traditional demand-for-currency models may produce larger-than-usual forecast errors. It is also worth noting that the CIC-to-GDP ratio was calculated by comparing year-end CIC levels to annual nominal GDP.

During times of crisis, higher-frequency CIC forecasts may be necessary to monitor liquidity conditions and assess consumer confidence. Alongside other monthly macroeconomic indicators like inflation, interest rates, and unemployment, CIC can be tracked and forecasted by economic agencies to gauge the pace and extent of economic recovery. These circumstances call for alternative models that do not depend on quarterly GDP.

FIGURE 1. CIC-to-Nominal GDP ratio (2002 to 2023, in percent)



Source: BSP, PSA, Authors' calculations.

In general, CIC models in the literature employ non-structural or "pure" time series forecasting techniques such as ARIMA and exponential smoothing. Time series regression models, on the other hand, incorporate macroeconomic and currency variables that reflect the underlying motives for holding cash, grounded on the demand-for-cash framework. However, there is limited research that models CIC beyond this traditional approach. This paper offers a novel perspective by proposing a method that forecasts CIC through the lens of the money creation process, as reflected in a central bank's balance sheet.

3. Examining the central bank's balance sheet

Another approach to predict CIC is by looking at the demand for local currency emanating from foreign exchange inflows. This entails the examination of the BSP's balance sheet, since whenever it purchases foreign exchange, it effectively sells the local currency, which when left unsterilized could end up as cash circulating in the economy. Examining the BSP's balance sheet, its assets are primarily composed of net foreign assets (NFA),[4] 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.[5] As of the end of August 2024, NFA and DC comprised 91.6 and 8.4 percent, respectively, of the BSP's total assets.

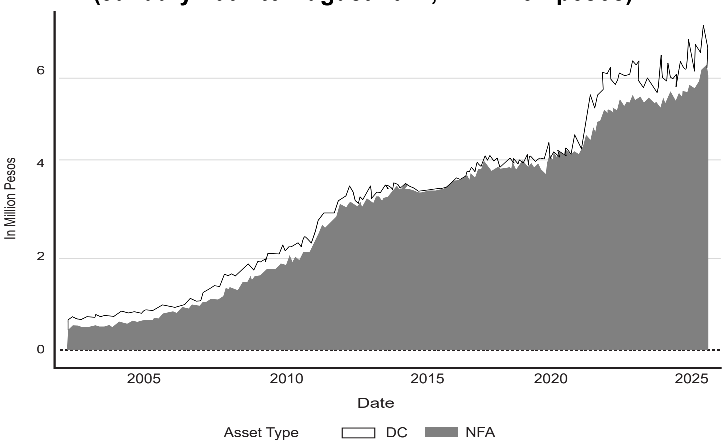
[4] These consist of a) Claims on Non-Residents that comprise the country's official reserve assets and other foreign assets; and b) Liabilities to Non-Residents consisting of gross foreign liabilities segregated into short-term and long-term maturities.

[5] 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.

Over the years, the country has received substantial foreign exchange inflows, on the back of strong macroeconomic fundamentals, overseas remittances, and export earnings, contributing to the increase in the BSP's net foreign assets (NFA). Additional liquidity also flowed into emerging economies like the Philippines as a result of unconventional monetary policies adopted by advanced economies following the 2008 Global Financial Crisis. These inflows led to a buildup of international reserves and a further expansion of the BSP's assets. These trends are illustrated in Figure 2.

On the other hand, claims on the central government briefly rose in the time of the pandemic as the BSP granted loans to the national government to help finance its COVID-19 response. This explains the rapid increase in DC in 2020 and 2021. In particular, DC reached ₱360.3 billion at end-2019 (7.6 percent of total assets) and then more than doubled to ₱813.2 billion in December 2020 (13.3 percent of total assets), before settling at ₱783.6 billion in December 2021 (12.3 percent).

FIGURE 2. BSP balance sheet assets (January 2002 to August 2024, in million pesos)



Source: BSP Central Bank Survey (SRF-based), Authors' calculations

Looking at the other side of the balance sheet, CIC is a liability of the BSP and forms part of the reserve money (RM).[6] Other liabilities of the BSP include those

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

A. Liabilities to Other Depository Corporations (LODC) which comprise:

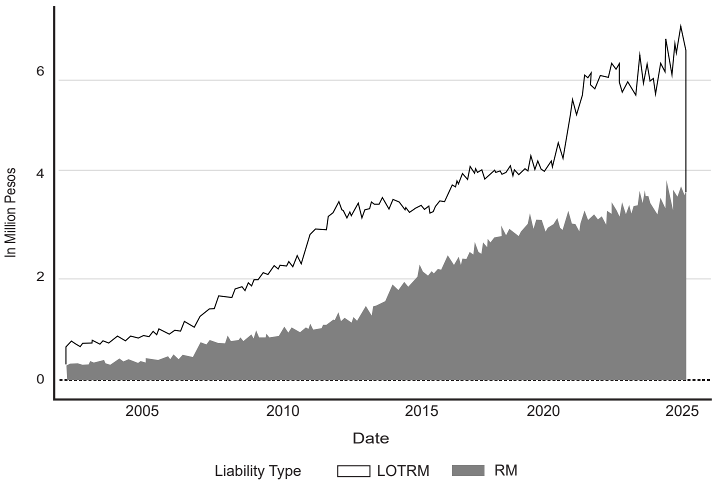
- Required reserves and clearing balances of Other Depository Corporation (ODCs) which refer to the BSP's regular peso demand deposit liabilities to commercial banks, specialized government banks, thrift banks, rural banks and nonbanks with quasi-banking functions and accrued interests.

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.

derived from the Reverse Repurchase Facility, Overnight Deposit Facility, and Term Deposit Facility,[7] as well as Other Equity and Treasury-International Monetary Fund (IMF) accounts. These types of liabilities can be classified as liabilities other than reserve money (LOTRM).[8] In December 2020, the share of LOTRM to total BSP liabilities rose sharply to 44.4 percent, up from 32.0 percent a year earlier. This shift is aligned with the BSP's expansionary monetary policy aimed at supporting the economy during the pandemic. From 2015 to 2019, the LOTRM-to-liabilities ratio averaged 33.2 percent, compared to an average of 42.2 percent between January 2020 and August 2024. These developments are illustrated in Figure 3.

FIGURE 3. BSP balance sheet liabilities (January 2002 to August 2024, in million pesos)



Source: BSP Central Bank Survey (SRF-based), Authors' calculations

An increase in the BSP's assets from reserve accumulation is mirrored by a corresponding rise in its liabilities, in line with the accounting identity. If unsterilized, this rise, often through reserve money, can be inflationary [Aizenman and Glick 2008]. To manage this, the BSP conducts open market operations and offers deposit facilities to absorb excess liquidity. These tools help align reserve money growth with the inflation target by selling securities (absorbing local currency) and later repurchasing them, or by attracting placements in its deposit facility.[9] In short, the BSP uses open market operations and its deposit facility to sterilize excess liquidity arising from reserve accumulation.

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

[8] 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).

[9] Likewise, foreign exchange 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.

Sterilization activities through the Reverse Repurchase Facility, Overnight Deposit Facility, and Term Deposit Facility increase the BSP's liabilities under LOTRM, offsetting the accumulation of assets while moderating inflationary risks. Local currency converted through foreign exchange purchases that are not sterilized could be kept as deposits in banks or could be withdrawn as cash, thereby increasing CIC. Some of the unsterilized assets may also make their way into non-CIC reserve money, such as Liabilities to Other Sectors or Liabilities to Other Depository Corporations (see footnote 6 for more information).

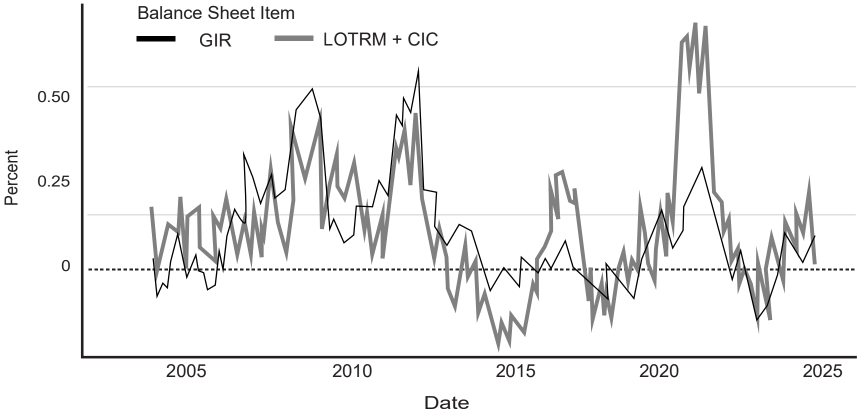
Figure 4 illustrates how CIC is created in a central bank's balance sheet: an expansion in assets through reserve accumulation (e.g., from remittances or export receipts) leads to a corresponding rise in liabilities. This increase is typically reflected in LOTRM through sterilization activities. Unsterilized assets, meanwhile, may appear on the liability side as CIC or other forms of reserve money.

FIGURE 4. CIC creation in the central bank balance sheet

Assets	Liabilities
Net Foreign Assets: +100	CIC: +10 Non-CIC Reserve Money (RM): +10 Liabilities Other than RM: +80

Given the flow of funds from asset accumulation via foreign exchange inflows, and their corresponding liabilities in the form of CIC and LOTRM through sterilization activities, it's not surprising that the correlation between Gross International Reserves (GIR) and CIC and LOTRM is extremely high at 91.6 percent. In terms of growth rates over time, these variables tend to move together as illustrated in Figure 5.

FIGURE 5. Growth rate of GIR and CIC plus LOTRM (January 2003 to August 2024, in percent)



Source: BSP Central Bank Survey (SRF-based), Authors' calculations.

Figure 5 also shows that the pandemic significantly increased domestic liquidity relative to reserve accumulation. While there was a net increase in CIC due to heightened precautionary motives, the surge in domestic liquidity was significantly driven by increasing LOTRM. The 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.[10]

It's worth noting that this study assumes that the BSP's capital and surplus accounts remain constant over time and are excluded from the analysis as they constitute a small fraction of the BSP's assets. As of July 2024, the BSP's capitalization amounted to PhP60.0 billion. Meanwhile, its accumulated surplus/ reserves reached ₱170.9 billion, equivalent to 2.5 percent of the BSP's total assets in the same period.

4. Framework in forecasting CIC: balance sheet approach

The framework starts with the basic accounting identity that assets are equal to liabilities and equity. For simplicity, the equity account is dropped from the identity as it represents a negligible proportion of total BSP assets. Expanding the BSP's assets and liabilities into their respective components, the identity is taken to be:

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

Reserve money could be further broken down into its components, namely: CIC, Liabilities Other than Currency Issued, and Liabilities to Other Sectors:

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

Combining equations (1) and (2), the following identity is obtained:

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

Next, isolating CIC in the previous equation yields the following expansion:

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

The non-CIC liabilities are then grouped under the variable "liabilities other

[10] At the onset of the pandemic, the BSP provided support through a repurchase agreement with the National Government (NG) amounting to ₱300 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.

than currency issued" (LOTCI), while the NFA and DC are taken together as "assets":

$$CIC \equiv (Assets) - (Liabilities\ Other\ Than\ Currency\ Issued) \qquad (5)$$

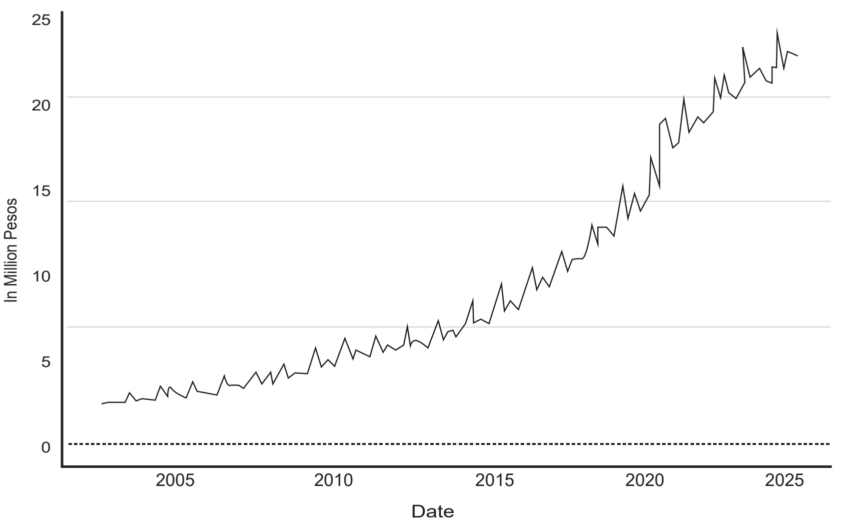
In this framework, CIC is positively related to total assets. To maintain the identity, an increase in assets would require an equal increase in CIC, holding LOTCI constant. On the other hand, CIC is negatively related to LOTCI. An increase in LOTCI should lead to a decrease in CIC, holding assets fixed. This is intuitive as an increase in LOTCI must be offset by a decrease in other components on the liability side to maintain the accounting identity that assets and liabilities are equal.

From Equation (5), we may construct a time series regression model based on historical values of assets and LOTCI to eventually forecast CIC. Likewise, temporal patterns of the stationary series may be modeled as an ARMA process to capture recurrent seasonal dynamics.

5. Data description

The central bank balance sheet data are available monthly, in line with the frequency of reporting of the BSP's balance sheet. The compiled dataset runs from January 2002 to August 2024 for a total of 272 observations. Exploratory analysis reveals some information for the target variable CIC. First, CIC has been trending upwards since 2002 as can be seen in Figure 6, consistent with the growth of the Philippine economy.

FIGURE 6. Currency in circulation (January 2002 to August 2024, in million pesos)



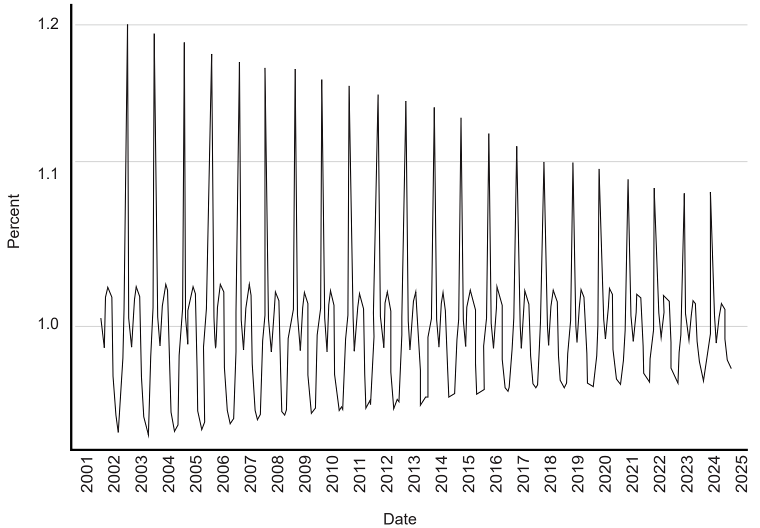
Source: BSP Central Bank Survey (SRF-based), Authors' calculations.

The seasonal index for CIC (Figure 7) reveals consistent peaks every December, reflecting heightened economic activity during the holiday season and the corresponding increase in demand for currency to support transactions. In contrast, troughs are typically observed around July or August, coinciding with the "ghost month," a period marked by subdued financial market activity and lower investment spending. The degree of seasonality appears to be moderating over time, which may point to a gradual smoothing of currency demand. This trend warrants further investigation and could be linked to the growing adoption of digital payments and electronic money platforms.

The *seasonal* package in R was used to perform seasonal decomposition, with the time series frequency set to 12 to reflect monthly data. It employs automated procedures to determine whether transformations (e.g., levels or logs) are needed, detect outliers, and identify trading day and Easter effects. The package also compares competing ARIMA models for signal extraction and selects the best X-13 ARIMA-SEATS specification based on the Akaike Information Criterion (AIC).

For CIC in the Philippines, the automated procedure indicated a preference for log transformation, implying multiplicative seasonal effects, consistent with the pattern observed in Figure 6. A seasonal ARIMA $(0,1,1) \times (0,1,1)_{12}$ model was selected to capture CIC's seasonal behavior, which included significant Easter effects, additive outliers (notably in December 2008, December 2014, and March 2020), and a mean-level shift in March 2020. These disruptions align with the impact of the COVID-19 pandemic and, to a lesser extent, the 2008 Global Financial Crisis on the long-standing seasonal patterns of CIC.

FIGURE 7. Seasonal index of CIC
(January 2002 to August 2024, in million pesos)



Source: Authors' calculations.

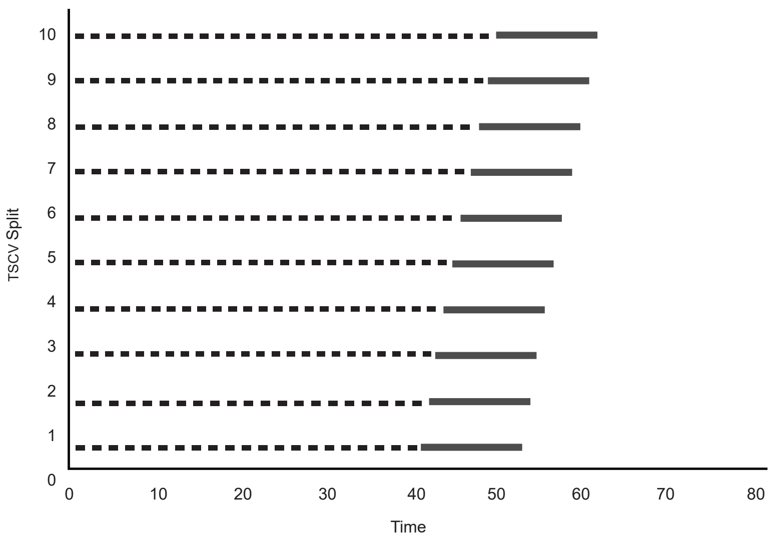
6. Methodology

To achieve stationarity, the first 13 observations were removed after applying both regular and seasonal differencing. The remaining data were then organized into ten sequential training and test sets using the time series cross-validation (TSCV) approach commonly used in machine learning. The first training set includes 239 observations from January 2003 to November 2022, while the corresponding test set covers December 2022 to November 2023. To enable TSCV and ensure sufficient data for estimating seasonal patterns, a sample size of over 200 observations was used. Hence, two decades of data were compiled.

The training and test sets follow a rolling forecast origin, where each training set advances by one period to reflect the monthly release of new data. The final training set spans January 2003 to August 2023, with its corresponding test set covering September 2023 to August 2024. This rolling approach allows the model to be refitted with additional information before generating forecasts. Each test set contains 12 observations, aligning with the practice of forecasting currency-in-circulation (CIC) one year ahead, an approach commonly used by the BSP for planning its currency orders.

TSCV is used to evaluate the forecasting performance of models on "unseen data" and is repeated ten times to ensure consistency in results. A model might perform well on a single test set by chance but fail to generalize across others due to issues like overfitting, shifts in the time series (e.g. changes in the mean level, trend direction or strength, seasonality), or the presence of outliers. Using 10 test sets helps mitigate these risks and provides a more reliable assessment of the model's predictive accuracy. Time series cross-validation can be visualized in Figure 8.

FIGURE 8. Time series cross-validation visualization



Source: Authors' calculations.

As new data becomes available, the training set is extended by one period, allowing the model to be re-estimated with updated information for more accurate predictions. The following 12 observations serve as the test set, reflecting a one-year-ahead forecast horizon in line with the BSP's currency forecasting practices. Rather than focusing solely on the twelfth-step forecast, all 12 predictions in each test set are evaluated to detect any potential decline in predictive performance. The final split represents the most up-to-date model, as it draws on the complete dataset available.

Using the balance-sheet approach in estimating CIC, two time series regression models were estimated: (i) a contemporaneous regression model with ARMA errors, and (ii) a distributed lag model[11] with ARMA errors. Modeling the errors with an ARMA structure would account for serial correlation since the data exhibit patterns over time.

For the ARMA-based models, the variables were transformed to achieve stationarity prior to modeling. In particular, a combination of logarithmic transformation, regular differencing, and seasonal differencing were applied to each variable. In backshift notation, for every variable Y_t, we obtain its weakly stationary form $\tilde{Y}_t = (1 - B)(1 - B^{12})\ lnY_t$. Henceforth, the tilde notation for each variable is used to denote the transformed stationary series. The Augmented Dickey-Fuller (ADF) test and inspection of the autocorrelation function (ACF) plots served as the criteria for stationarity. Model diagnostics are shown in the Appendix.

The proposed models that incorporate balance sheet variables are compared to baseline models, namely Error-Trend-Seasonality (ETS) models and a "pure ARIMA" model. ETS and ARIMA were taken to be baseline models as they rely solely on historical patterns, which according to the literature are preferred in short-term forecasting of CIC. Said models don't assume any theoretical framework in projecting the amount of currency circulating in the economy, hence, do not include any independent variables in the forecasting model.

A demand-for-cash model is not estimated as the BSP relies on GDP in predicting CIC, thereby generating quarterly forecasts. The literature is also unanimous in utilizing GDP as the proxy for the transaction motives to hold cash, ruling out other proxies for transaction motives. The prospect of merging monthly balance-sheet variables with other quarterly and monthly demand-for-cash variables via mixed-frequency models remains an open area of study. Some recommendations and future directions are discussed in Section 8.

6.1. Baseline models

The ETS model is specified below where Y_t is the level of the variable at time t, ℓ_t is the level of the series, b_t is the trend of the series, s_t is the seasonality of the

[11] This is a time series regression model where the covariates are lagged. This model is only used for prediction, while an ARDL model may traditionally be used for policy analysis to capture short and long-term dynamics via cointegration testing (i.e. ARDL bounds testing).

series, and $\hat{Y}_{t+h|t}$ is the point forecast for some horizon h conditional on information at time t [Hyndman and Athanosopolous 2021]. Note that a multiplicative error, additive damped trend, and multiplicative seasonality specification (M-Ad-M) was selected for ETS based on minimization of the corrected Akaike Information Criterion (AICc) in the training sets. The *forecast* package in R was utilized to estimate the ETS models.

In brief, an ETS model is a state-space specification of classical exponential smoothing. The advantage of ETS over classical exponential smoothing is its ability to arrive at forecast distributions aside from point forecasts. It estimates the individual time series components (i.e. level, trend, and seasonality) before aggregating them to form the time series. As for predictions h-steps ahead, the level of the series and the accumulated trend are added together before being multiplied with the estimated seasonal component. A damped trend was selected by the procedure, suggesting a gradual tapering off of the trend over time. The model is summarized below:

$$Y_t = (\ell_{t-1} + \phi b_{t-1})\, s_{t-m}\, (1 + \epsilon_t)$$

$$\ell_t = (\ell_{t-1} + \phi b_{t-1})(1 + \alpha\epsilon_t)$$

$$b_t = \phi b_{t-1} + \beta(\ell_{t-1} + \phi b_{t-1})\, \epsilon_t$$

$$s_t = s_{t-m}\,(1 + \gamma\epsilon_t) \tag{6}$$

and the predictions are taken to be:

$$\hat{Y}_{t+h|t} = (\,\ell_t + \sum_{j=1}^{h} \phi^j\, b_t)\, s_{t+h-m[h/m]}$$

where $\epsilon_t = \dfrac{Y_t - \hat{Y}_{t|t-1}}{\hat{Y}_{t|t-1}} \sim N(0, \sigma^2)$ are independent relative errors;

ϕ is the damping parameter to account for changes in the trend;

ℓ_t is the level of the series;

b_t is the slope (or trend) over time;

s_t is the seasonal component;

α, β, and γ are smoothing parameters;

m denotes the number of seasons in a year; and

$[h/m]$ is the is the ceiling function denoting the number of complete seasons spanned by the horizon h.

For the ARIMA-based models, the Box-Jenkins modeling approach was utilized. All variables were taken to be stationary prior to modeling following a logarithmic transformation, along with a seasonal and regular difference to handle regular and seasonal unit roots. Identification of candidate ARIMA models were based on the sample ACF and PACF plots of the residuals. Parameter estimation was conducted through the *forecast* package in R, which uses Maximum Likelihood Estimation (MLE) with Gaussian errors. With sufficiently large sample sizes, the Gaussian maximum likelihood estimator for causal and invertible ARMA models is consistent and asymptotically normal [Yao and Brockwell 2006].

Once autocorrelations were accounted for with the inclusion of ARMA terms, as validated by the ACF and PACF plots, a formal Ljung-Box test was conducted to confirm that residuals were white noise. Finally, model diagnostics, goodness-of-fit statistics and forecast evaluation metrics were inspected to compare the proposed models with the baseline models.

The baseline ARIMA model has a $(0,1,1) \times (1,1,0)_{12}$ specification. Note again that for every variable Y_t , we take its covariance stationary form $\tilde{Y}_t = (1\text{-}B)(1\text{-}B^{12}) lnY_t$. Equation 7 shows the full model in standard multiplicative SARIMA notation.[12] As with ETS, the forecast package in R was used to estimate the time series regression models with SARMA errors. A SAR(1) and MA(1) model[13] parsimoniously capture autocorrelations in the data:

$$\widetilde{CIC}_t = \alpha^{(1)} + u_t^{(1)} \tag{7}$$

$$(1 - \phi_t^{(1)} B^{12})\, u_t^{(b)} = (1 + \theta^{(1)} B)\, \varepsilon_t^{(1)}$$

$$\text{where } \varepsilon_t^{(1)} \sim WN(0, \sigma_{(1)}^2)$$

Errors are modeled as a SARMA process to account for temporal dependencies. Seasonality comes into play as the log-transformed CIC is differenced twice, one regular difference and another seasonal difference, while a SAR(1) term is added to capture seasonal patterns. This baseline model relies purely on the historical behavior of the series to forecast future values of CIC.

For diagnostics, variable stationarity was assessed using the Augmented Dickey-Fuller (ADF) test. Residual checks were also conducted to assess autocorrelation and conditional heteroskedasticity, including the Ljung-Box test, inspection of the ACF and PACF plots, and the ARCH test. These diagnostics help ensure the reliability of parameter estimates in line with the Box-Jenkins modeling framework. A complete set of model diagnostics, covering stationarity, serial correlation, and AR/MA root stability, is provided in the Appendix.

---

[12] Superscript (1) and subscript (1) denote the parameters for the baseline model.

[13] If the input data are seasonal with period 12 (i.e. monthly data), this is technically equivalent to an ARMA(12,1) process where the autoregressive parameters are fixed to zero for the first 11 lags.

6.2. Proposed models

ARIMA Model 1 is taken to be a time series model with contemporaneous regressors following an ARIMA $(0,1,1) \times (1,1,0)_{12}$ specification:[14]

$$
\begin{gathered}
CIC_t = \alpha^{(1)} + \beta_t^{(2)} \widetilde{Assets}_t + \beta_2^{(2)} \widetilde{LOTCI}_t + u_t^{(2)} \\
(1 - \phi_t^{(2)} B^{12})\, u_t^{(2)} = (1 + \theta^{(2)} B)\, \varepsilon_t^{(2)} \qquad (8) \\
\text{where } \varepsilon_t^{(2)} \sim WN(0, \sigma_{(2)}^2)
\end{gathered}
$$

The errors are modeled as a SARMA process to account for autocorrelation. Said model includes the stationary-transformed central bank assets and LOTCI as independent variables. To arrive at estimates out-of-sample (test set), the transformed regressors were also forecasted with ARIMA so that CIC forecasts 12 months ahead may be generated.[15] This is crucial as for some forecast horizon h, the values of regressors must be available. One potential advantage of this model is that it uses contemporaneous regressors in fitting the model instead of lagged predictors. The more recent information may more accurately capture seasonal dynamics and autocorrelations. The downside is that the regressors also need to be forecasted, potentially compounding forecast errors in predicting CIC out-of-sample. The models for the regressors are as follows:

$$
\begin{gathered}
\widetilde{Assets}_t = \alpha^{(a)} + u_t^{(a)} \\
(1 - \phi_t^{(a)} B^{12})\, u_t^{(a)} = (1 + \theta^{(a)} B)\, \varepsilon_t^{(a)} \qquad (9) \\
\text{where } \varepsilon_t^{(a)} \sim WN(0, \sigma_{(a)}^2)
\end{gathered}
$$

$$
\begin{gathered}
\widetilde{LOTCI}_t = \alpha^{(b)} + u_t^{(b)} \\
(1 - \phi_t^{(b)} B^{12})\, u_t^{(b)} = (1 + \theta^{(b)} B)\, \varepsilon_t^{(b)} \qquad (10) \\
\text{where } \varepsilon_t^{(b)} \sim WN(0, \sigma_{(b)}^2)
\end{gathered}
$$

The second model adopts a different approach in specifying the exogenous regressors. Lagged values of assets and LOTCI were taken to be the predictors of CIC. In this specification, it is not necessary to add multiple lags to the exogenous regressors since the errors already admit a SAR(1) and MA(1) term to adequately account for serial correlation. The full specification of this dynamic regression model is as follows:

[14] Superscript (2) and subscript (2) denote the parameters for the first proposed model. The same goes for (3) for the second proposed model.

[15] Superscript (a) and subscript (a) denote the parameters in predicting the Assets regressor. The same goes for (b) in relation to predicting the LOTCI covariate.

$$\widetilde{CIC}_t = \alpha^{(3)} + \beta_t^{(3)} \widetilde{Assets}_{t-12} + \beta_2^{(3)} L\widetilde{OTCI}_{t-12} + u_t^{(3)}$$

$$(1 - \phi_1^{(3)} B^{12})\, u_t^{(3)} = (1 + \theta^{(3)} B)\, \varepsilon_t^{(3)} \tag{11}$$

$$\text{where } \varepsilon_t^{(3)} \sim WN(0, \sigma^2_{(3)})$$

In summary, the ARIMA-based models address autocorrelation by specifying the error term using a SARMA structure. These models also incorporate historical information through exogenous regressors, either in contemporaneous or lagged form. The SARMA specification was supported by residual ACF and PACF plots and was chosen to ensure robustness across different scenarios and test sets, avoiding overfitting associated with more complex models that may yield poor forecasts.

As Nau [2020] notes, including multiple AR and MA terms in the same model can lead to the cancellation of roots on both sides of the equation, resulting in unnecessary complexity. AR models are generally more interpretable, as they rely on the variable's own past values rather than unobserved shocks, which are typical of MA models.

From an estimation perspective, MA models involve non-linear parameters and typically require non-linear least squares and numerical optimization, which can result in unstable estimates or convergence issues, especially in models with many MA terms. In contrast, AR models are linear in their parameters and can be estimated using simpler techniques [Diebold 2007]. For these reasons, a parsimonious SARMA model was preferred, balancing model fit, predictive accuracy, and adherence to ARIMA Box-Jenkins assumptions.

6.3. Model selection and forecast evaluation

To assess the performance of both baseline and proposed models, metrics from the training and test sets were compared. Training set performance reflects how well a model fits the observed data, but strong in-sample performance does not always translate to accurate out-of-sample forecasts. A model may still underperform on test data due to issues such as overfitting, structural changes in the variables, or unforeseen shocks not captured in the training set. To evaluate predictive accuracy, forecasts were generated up to twelve months ahead using unseen test data. This was repeated across ten different train-test splits, following the TSCV approach, to provide a more comprehensive view of model performance across various in-sample and out-of-sample scenarios.

For training set performance, the log-likelihood and AIC were compared among the competing models. The AIC is obtained with the expression $2k - 2ln(\hat{L})$ where k is the number of parameters in the model and $ln(\hat{L})$ is the maximized value of the model's log-likelihood function. It is a relative measure of goodness-of-fit as it balances model parsimony (number of parameters) and model fit (log-likelihood). The lower the AIC of a model, the better its fit relative to competing models. Meanwhile, the interpretation of the maximized log-likelihood is straightforward, and a higher value means improved model fit. Both the AIC and log-likelihood are standard goodness-of-fit metrics for MLE-based models.

For both train and test sets, the root mean squared scaled error (RMSSE) was computed. The RMSSE compares model forecasts with a naïve forecast. In this case, the models were compared to a seasonal naïve forecast. In a seasonal naïve forecast, the observation in the same month of the previous year is taken to be the prediction for the current period, i.e., $\hat{Y}_t = Y_{t\text{-}12}$. An RMSSE of less than one means that the forecast model is more accurate than the naïve forecast, while a zero RMSSE suggests perfect predictive ability. Formally, the RMSSE is taken to be:

$$RMSE = \sqrt{\frac{1/h \; \Sigma_{t=1}^{h} (Y_{t+h} - \hat{Y}_{t+h})^2}{1/T{-}s \; \Sigma_{t=s+1}^{T} (Y_{t+h} - \hat{Y}_{t\text{-}s})^2}} \tag{12}$$

Both RMSSE and AIC are relative measures of error. The advantage of RMSSE is that comparisons are done relative to a benchmark, although there is no direct interpretation. This complements the Mean Absolute Percentage Error (MAPE) metric, which shows forecast errors as a percentage of the actual level of a variable. The interpretation of MAPE is straightforward as a value of 0 suggests perfect predictive ability, and a large MAPE suggests larger errors as a proportion of the target variable.

$$MAPE = \frac{1}{T} \sum_{t=1}^{T} \left| \frac{Y_t - \hat{Y}_t}{Y_t} \right| \times 100 \tag{13}$$

7. Results and discussion

For the proposed models, the estimated coefficients for assets and LOTCI align with theoretical expectations derived from the central bank's balance sheet identity. Specifically, assets exhibit a positive relationship with CIC, while LOTCI shows a negative relationship, with both coefficients statistically significant at the 1 percent level. Additionally, the SAR(1) term is significant, and the MA(1) component is included to account for serial correlation. Table 1 presents the regression results using the full dataset for the ARIMA-based models.

TABLE 1. Regression output for ARIMA-based models (full data set)

Variable	ARIMA (baseline)	ARIMA Model 1 (contemporaneous)	ARIMA Model 2 (lagged)
Dependent Variable: Currency-in-Circulation (stationary-transformed)			
SAR(1)	-0.44*** (0.06)	-0.28*** (0.06)	-0.28*** (0.06)
MA(1)	-0.05 (0.07)	-0.08 (0.07)	-0.10 (0.07)
Assets		2.52*** (0.10)	2.56*** (0.10)
LOTCI		-1.81*** (0.07)	-1.85*** (0.07)
Number of Observations	259	259	247
AIC	-1,275.68	-1,604.70	-1,530.3
Log-Likelihood	640.84	807.35	770.15

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Figures in parentheses are the estimated standard errors of the regression coefficients

The performance metrics are summarized in Table 2, showing the average results across all ten TSCV splits. ARIMA Model 1 consistently outperforms the other models in terms of both goodness-of-fit and predictive accuracy for both training and test sets. Its AIC is markedly lower, and its training set MAPE is roughly half that of the competing models. The log-likelihood rankings closely follow those of the AIC. Moreover, ARIMA Model 1 has a significantly lower RMSSE, approaching zero, which indicates stronger performance relative to the seasonal naïve benchmark. Collectively, these results point to ARIMA Model 1 as having the best overall model fit.

These results extend to the test sets, where ARIMA Model 1 continues to outperform the other models based on MAPE and RMSSE, metrics used to evaluate predictive accuracy. In ARIMA Model 1, the exogenous regressors (assets and LOTCI) were forecasted using separate ARIMA models, allowing values to be generated for future periods $t + h$. Since these variables can be reliably projected within reasonable bounds, ARIMA Model 1 delivered better predictive performance than ARIMA Model 2, which instead relied on lagged values of the predictors.

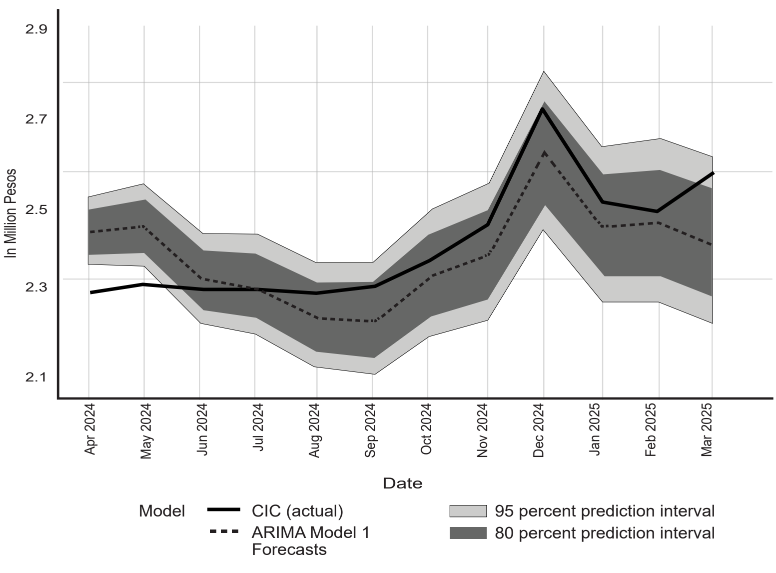
To show how ARIMA Model 1 might perform moving forward, we take the last 12 CIC observations as of writing to be the test set, augmenting the original data set used for TSCV. Model 1 is re-estimated with data points from January 2002 to March 2024, with the test set going from April 2024 to March 2025. Figure 9 shows the path of CIC, along with the forecasts from the preferred model, and its corresponding 95 percent and 80 percent prediction intervals. As expected, the prediction intervals successfully cover most of the actual CIC values in the test set. This indicates strong predictive accuracy.

TABLE 2. Model performance metrics (average in all splits)

	ETS (baseline)	ARIMA (baseline)	ARIMA Model 1 (contemporaneous)	ARIMA Model 2 (lagged)
Dependent Variable: Currency-in-Circulation (stationary-transformed)				
Train Sets:				
Log-Likelihood	-3,120.92	598.42	762.10	574.81
AIC	6,277.83	-1,185.10	-1,507.43	-1,134.07
MAPE	1.46	1.46	0.76	1.44
RMSSE	0.19	0.20	0.08	0.19
Test Sets:				
MAPE	2.75	1.66	1.56	1.80
RMSSE	0.73	0.46	0.45	0.50

Performance gradually decays over time as forecasting over a longer time horizon may lead to compounding forecast errors. In the first six months, the MAPE of ARIMA Model 1 averaged 1.90 percent, before climbing to 4.80 percent in the last six months when the model consistently underestimated CIC. On average, its MAPE is 3.33 percent for all 12 months.

FIGURE 9. Actual CIC vs Model 1 forecasts (April 2024 to March 2025, in million pesos)



Source: Authors' calculations.

8. Ways forward

The balance sheet approach in estimating CIC is useful in generating monthly forecasts as they do not rely on GDP figures that are released quarterly. It is also novel as it does not use demand-side factors anchored on the motives to hold physical currency. While the balance sheet-based models are not intended to replace demand-side models, the proposed models may generate more timely and accurate CIC forecasts for central banks. Improving the prediction of CIC could enhance currency management by aligning currency production more closely with market demand, and enabling more responsive monetary policy. Alternative modeling approaches are particularly valuable during periods of crisis when traditional patterns in the demand for cash break down. This is because demand-for-cash models are typically anchored on GDP, whose relationship with CIC may not hold during economic disruptions.

Future research on CIC modeling could explore alternative techniques such as deep learning models for sequential data, including Long Short-Term Memory networks. Non-linear and long-memory models may also be appropriate, especially for higher-frequency forecasting, referring to what Khatat [2018] calls "second-generation models for currency demand." One promising strategy involves forecasting balance sheet variables using machine learning methods and using those forecasts as inputs to a contemporaneous ARIMA model, preserving interpretability. This mirrors the approach proposed by Prayoga, Suhartono, and Rahayu [2017].

Further investigation into multiple-equation time series models such as Structural Vector Autoregressive Models and State-Space Models, as well as mixed-frequency approaches like Mixed Data Sampling, Dynamic Factor Models, and mixed-frequency VARs, is recommended. These frameworks could provide a means of integrating the demand-for-cash perspective with the balance sheet approach, preserving the role of macroeconomic indicators like GDP while also capturing higher-frequency dynamics present in the central bank's balance sheet.

This study highlights the potential of using the balance sheet as a reliable foundation for forecasting CIC, particularly by leveraging the currency creation process associated with "unsterilized assets" when the BSP accumulates foreign reserves. A logical next step is to expand the set of predictors to include both macroeconomic and currency-specific indicators, an approach already being adopted by other central banks, including the Bank of England [Miller 2017].

With the presence of multiple competing models, forecast averaging or model ensembling could be explored to determine whether combining forecasts leads to more accurate predictions than relying on individual models. Such combinations may produce forecasts that are more resilient to outliers and economic shocks. Since a single model might perform well on one test set but poorly on another, combining forecasts can help leverage the strengths of each model. This approach is particularly relevant here, as the proposed models show consistent accuracy up to six months ahead, with errors increasing beyond that point. Incorporating forecasts from other models that perform better at longer horizons could help improve forecast accuracy.

The proposed models in this paper may be operationalized with other algorithms such as the Hyndman-Khandakar algorithm [Hyndman 2021] for ARIMA order identification if forecasting at scale is the priority. This paper follows the Box-Jenkins algorithm with a stricter criterion that model residuals must follow a white noise process. Likewise, the inclusion of country-specific banking or currency management variables may augment the information provided by the balance sheet.

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Appendix[16]

TABLE A. Stationarity testing of time series variables

	Test Lag Order	ADF Test Statistic	*p*-value
$\widetilde{CIC}_t$	12	-8.18	0.00 (stationary series)
$\widetilde{Assets}_t$	12	-5.19	0.00 (stationary series)
$\widetilde{LOTCI}_t$	12	-5.14	0.00 (stationary series)

FIGURE B1. Correlogram of baseline ARMA model residuals

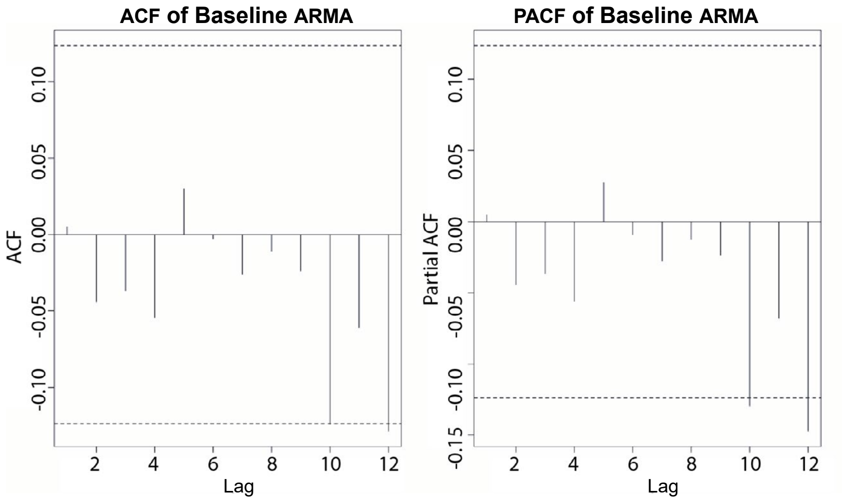

FIGURE B2. Correlogram of proposed Model 1 residuals (contemporaneous X's)

[16] For all statistical hypothesis testing, the type 1 error rate has been set to five percent (i.e., level of significance α = 0.05)

FIGURE B3. Correlogram of ARMA model for assets

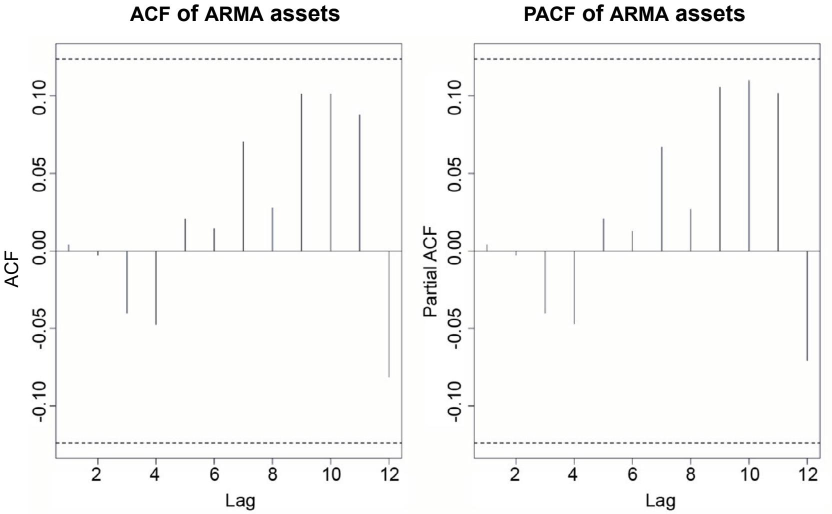

FIGURE B4. Correlogram of ARMA model for LOTCI

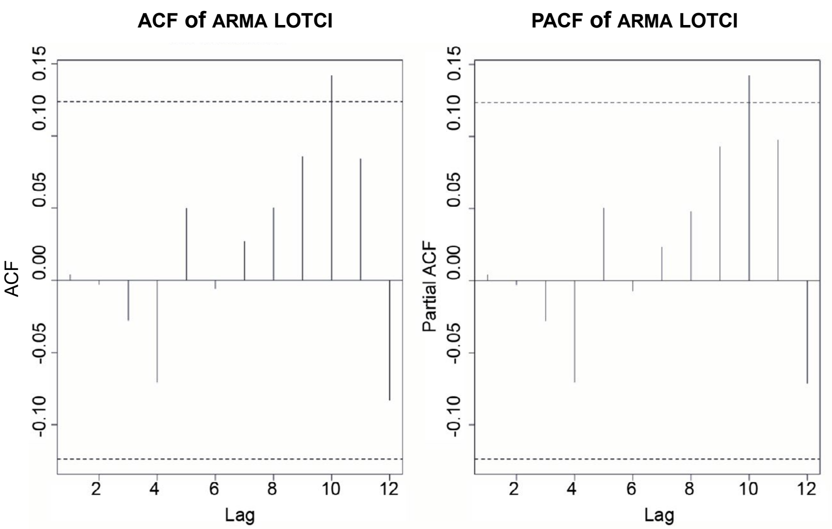

FIGURE B5. Correlogram of Model 2 residuals (lagged X's)

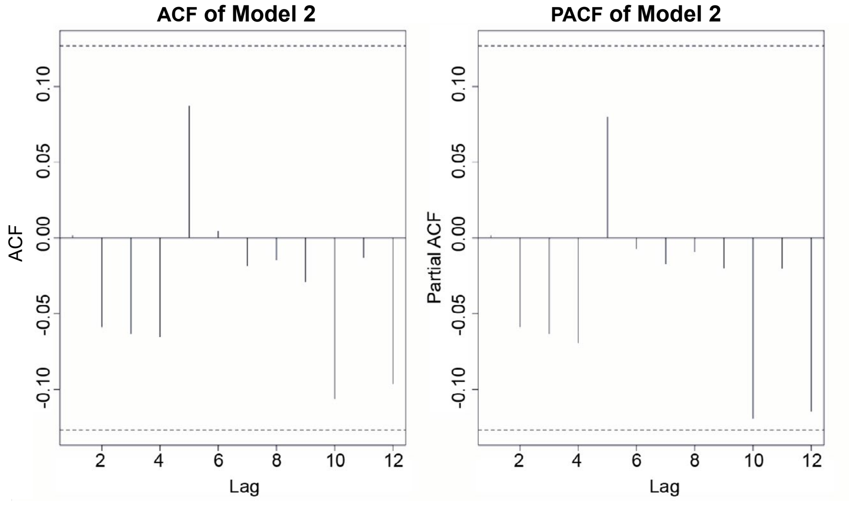

TABLE C. Ljung-box testing of model residuals

	Test lag and DF of test	Ljung-Box test statistic	*p*-value
Baseline ARMA	12	11.64	0.47 (white noise)
Model 1 (contemporaneous *X*'s)	12	7.95	0.79 (white noise)
Assets ARMA	12	11.81	0.46 (white noise)
LOTCI ARMA	12	13.91	0.31 (white noise)
Model 2 (lagged *X*'s)	12	10.33	0.59 (white noise)

FIGURE D1. Inverse AR/MA roots of the baseline ARMA model

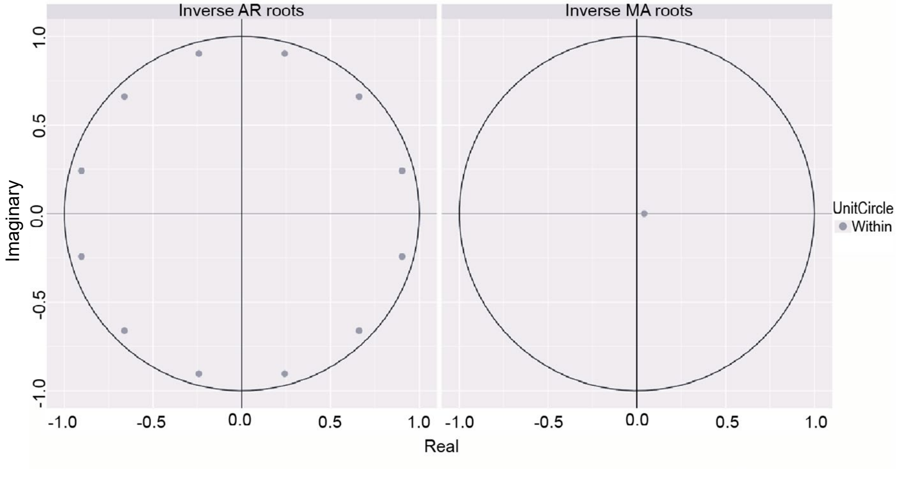

FIGURE D2. Inverse AR/MA roots of Model 1 (contemporaneous X's)

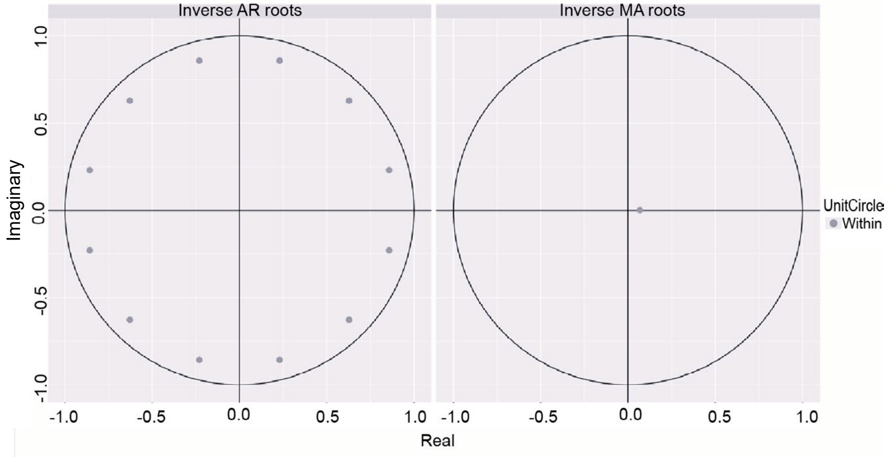

FIGURE D3. Inverse AR/MA roots of ARMA model for assets

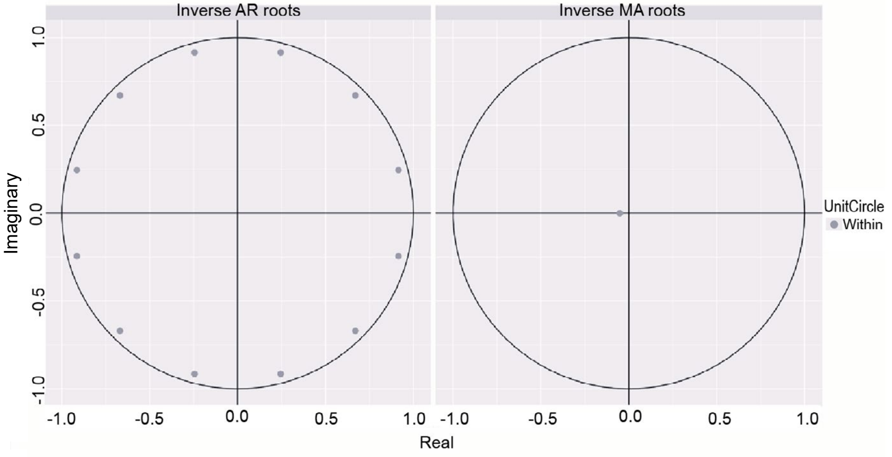

FIGURE D4. Inverse AR/MA roots of ARMA model for LOTCI

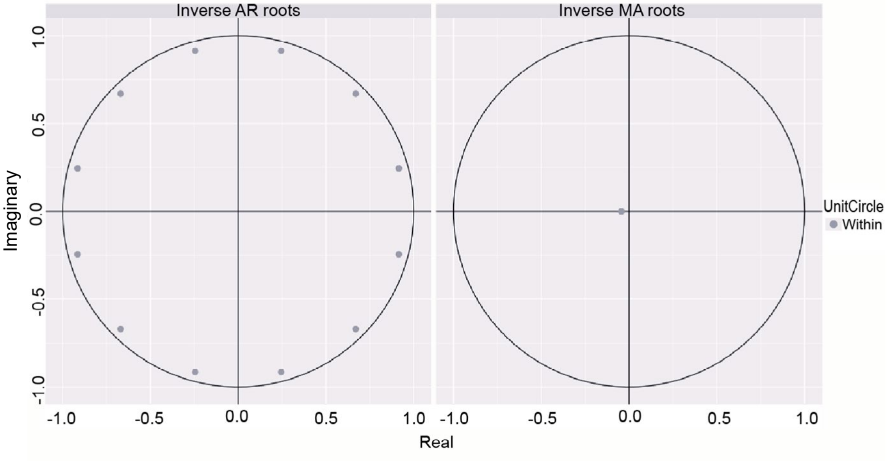

FIGURE D5. Inverse AR/MA roots of ARMA model for assets

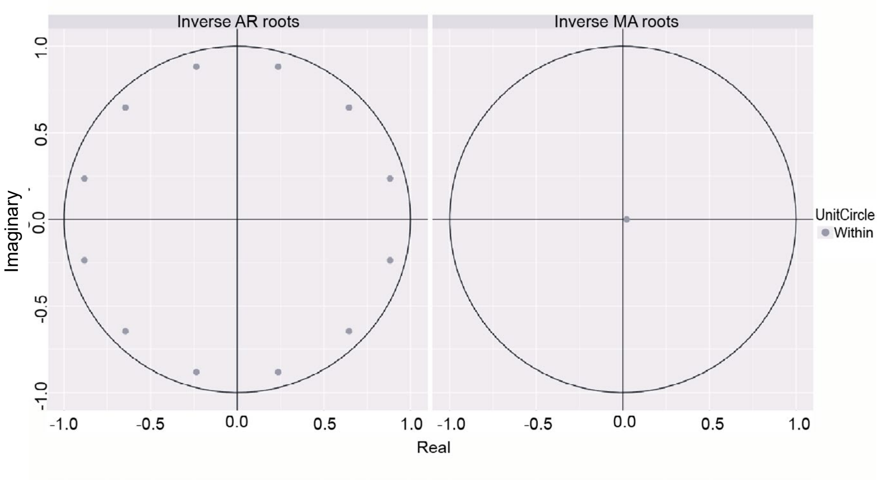

TABLE E. ARCH Lagrange multiplier test

	Test lag order	ARCH LM test statistic	*p*-value
Baseline ARMA	12	64.52	0.00 (ARCH effects))
Proposed Model 1 (contemporaneous *X*'s)	12	27.39	0.01 (ARCH effects)
Assets ARMA	12	12.59	0.40 (no ARCH effects)
LOTCI ARMA	12	11.36	0.50 (no ARCH effects)
Proposed Model 1 (lagged *X*'s)	12	45.61	0.00 (ARCH effects)

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