# TECHNICAL ASSISTANCE REPORT

# GUATEMALA

## The Statistical Component of Liquidity Forecasting

**JANUARY 2024**

**Prepared By**

*Daniella Gallardo (CAPTAC-DR), Romain Veyrune and Zhuohui Chen (MCMCO)*

**Authoring Department:**

**Monetary and Capital Markets Department**

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## GLOSSARY

| | |
|---|---|
| ARIMA | Autoregressive Integrated Moving Average Models |
| Banguat | Bank of Guatemala |
| BOM | Bank of Mexico |
| CAPTAC-DR | Regional Technical Assistance Center for Central America, Panama, and the Dominican Republic |
| CCB | Colombia's Central Bank |
| CiC | Currency in Circulation |
| CIMC | Monetary and FX Implementation Committee |
| COP | Colombian Peso |
| ETS | Exponential Smoothing |
| FX | Foreign Exchange |
| GARCH | Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) |
| GTQ | Guatemalan Quetzal |
| DMFX | Department of Monetary, Foreign Exchange and Credit Policy Implementation |
| DMAF | Department of Macroeconomic Analysis and Forecast |
| IBR | Banking Reference Indicator [Indicador Bancario de Referencia] |
| IT | Inflation Targeting |
| MCM | Monetary and Capital Markets Department |
| MCMCO | MCM's Central Bank Operations Division |
| ME | Mean Error |
| MAE | Mean Absolute Errors |
| Min T | Minimum Trace |
| MIS | Mean Interval Score |
| MPR | Monetary Policy Rate |
| MXN | Mexican Peso |
| NFA | Net Foreign Assets |
| NL | Net Liquidity |
| NOA | Net Other Assets |
| OLS | Ordinary Least Squares |
| OMO | Open Market Operation |
| RMSE | Root Mean Square Error |
| RR | Reserve Requirement |
| STA | Single Treasury Account |
| TA | Technical Assistance |
| TBATS | Trigonometric Seasonality, Box-Cox Transformation, ARMA Errors, Trend and Seasonal |

## PREFACE

At the request of Banco de Guatemala (Banguat), a Monetary and Capital Markets (MCM) Department/CAPTAC-DR technical assistance (TA) mission visited Guatemala City from June 12 to 16, 2023, to assist the Banguat in liquidity forecasting to calibrate its daily deposit operations.

The mission met with Mr. Vinicio Caceres, Banguat's Financial Manager, Mr. Marco López, Director of the Department of Monetary, Foreign Exchange and Credit Policy Implementation (DMFX), Mr. Ariel López, Deputy Director of the DMFX, and Mr. Juan Antonio Ibañez Deputy Director of the Department of Macroeconomic Analysis and Forecast (DMAF).

The mission wishes to thank the Banguat staff for their cooperation, productive discussions, and hospitality throughout the TA. Also, the logistical support and resources for coordinating and developing the work agenda were highly appreciated.

We also thank CAPTAC-DR donors for funding the project under which this TA was delivered.

## EXECUTIVE SUMMARY

**The mission assisted Banguat with the statistical component of liquidity management.** Central banks need to calibrate monetary operations to achieve their objectives in term of short-term interest rates. For this, they need to understand the behavior of their monetary policy counterparties (banks) and of their non-monetary policy counterparties (the public with currency in circulation, the government with its accounts at Banguat, and others). To predict their behaviors, central banks have tools to collect information directly from the counterparties and process it, including survey and information sharing systems. In addition, they should have their own statistical forecast to extract all the information available from time series.

**The reserve requirement in Guatemala presents some forecasting challenges.** The requirement, which is the main driver of the demand for reserves of banks, is not known before being due because the requirement is contemporaneous with the base, which presents a forecasting challenge for both the Banguat and the banks. On the other hand, the autonomous factors, which reflect the impact of the behaviors of non-monetary policy counterparties on banks' reserves at the central bank, are typical of those of other central banks.

**The mission deployed the statistical forecasting framework developed by MCMCO to calibrate operations.** Currently, the Banguat primarily allots its Open Market Operation (OMO) (24-hour deposits) based on a daily survey of the banks' demand for the operations. Additionally, Banguat conducts a weekly liquidity forecast based on institutional information and updates it daily. The MCM framework includes 12 forecasting models of three types: expositional smoothing (simple, with exogenous regressors, and seasonal), ARIMA (simple, with exogenous regressors, and seasonal), TBATS, and volatility models. It has an out of sample performance testing system based on four performance criterion reflecting accuracy, bias, and confidence intervals. The framework could produce forecasts and combine them. The mission introduced the main elements of all the models, and focused on the RR forecasting, while it also provided the codes for autonomous factors forecasting.

**The mission factored in the heterogeneity in the reserve requirement base in the reserve requirement forecast.** The mission forecasted the different banks' deposits included in the reserve requirement base. Then, it used statistical methods (e.g., OLS and MinT) to reconcile the forecast of four different types of deposits and obtain the reserve requirement assuming a constant reserve requirement ratio. The statistical reconciliation is more accurate than the aggregated forecast as it brings additional information that is useful to predict the behaviors of the relevant counterparties, i.e., banks' depositors.

**The reserve fulfillment pattern can be identified and should be incorporated when calibrating the daily deposit operations**. Banks have a clear preference for the amounts that they keep on account in excess of or less than the reserve requirement (and those that they invest on the deposit facility) depending on the day of the month. This pattern should be accommodated when calibrating monetary operations to avoid that banks' fulfillment profiles influence short-term interest rates. The mission forecasted the demand for excess reserves for each of the banks,[1] because this variable is under the discretion of their respective treasurers and applied statistical reconciliation. As with the deposit base, reconciled-bank forecasts are more accurate than the aggregate one.

**The Banguat forecasts autonomous factor relatively accurately.** The Banguat is forecasting more accurately the government account at the Banguat and the Net Foreign Assets (NFA) than the models provided in the MCMCO Framework. Therefore, the Banguat liquidity institutional framework provides information useful for the forecast and additional to the pure statistical forecasts. The framework forecast of currency in circulation (CiC) is slightly better that the Banguat's because the contribution of the institutional framework is limited for that factor and MCMCO framework has more statistical models than the alternatives. In addition, the MCMCO Framework provides additional forecasts of Net Other Assets (NOA), Net Liquidity (NL) with reconciliation, and information on prediction uncertainty.

**A liquidity table could help bringing together demand and supply forecasts to calibrate the open market operations.** Autonomous factors determine the liquidity that would be available in the system while the reserve requirement and excess reserve forecasts determine how much banks would want of it at a given date. The allotment of the open market operation is simply the difference between both if a "neutral" liquidity allotment is the objective.

**Publishing aggregated forecasts would inform banks' bidding at the daily deposit auctions of the Banguat.** After following an adoption process of the framework (testing, evaluation, internal approvals, and procedures design), Banguat should consider publishing the forecasts. While banks know their short-term cash flows, they do not know those of the other banks when they bid at the auction. Publishing banks' opening balance as well as the forecast of: (i) autonomous factors; (ii) the reserve requirement; and (iii) the preferred fulfillment would inform banks of the aggregate liquidity condition when they bid at the operations. Initially, the forecast horizon could be limited to one day (usually high-quality forecast) and extended once the forecast quality at longer horizon would have been vetted.

[1] Currently there are 18 banks on operation. The mission provided forecasts for 16 banks with enough data. For the banks recently added, the mission left the codes ready for the estimation for Banguat to use when the sample is large enough.

**Table 1. Key Recommendations**

| Recommendation and Responsible Department | Timeframe[2] |
|---|---|
| **Liquidity Forecast** | |
| 1. Complement the Banguat's bank survey with statistical models to produce a daily reserve requirement and demand for excess reserve forecasts (#6 and 57). DMFX | Short term |
| 2. Complement Banguat's forecasts with statistical models to produce a daily forecast for autonomous factors (#7 and #37). DMAF | Short term |
| 3. Evaluate forecast performance periodically (#38). DMFX &DMAF | Medium term |
| **Open Market Operations** | |
| 4. Complement the survey of banks' demand for daily deposit operations with a calibration based on the forecasting of the autonomous factors and the demand for reserves (#37). DMFX | Medium term |
| **Information to the Monetary Counterparties** | |
| 5. Publish daily the forecasts of the autonomous factors, the reserve requirement, and the demand for excess reserves for the next day (#42 & 43). DMFX & DMAF | Long term |
| | |
| 6. Publish daily the forecast of the autonomous factors, the reserve requirement, and the demand for excess reserves at the one-week horizon (#42 & 43). DMFX & DMAF | Long term |

[2] Short term: < 6 months; Medium term: 6 to 12 months; Long term: more than 12 months.

# I. Introduction

1. **An MCM mission visited Guatemala City from June 12–16, 2023, to help Banguat with monetary policy implementation.** Banguat targets an interest rate to implement monetary policy in the context of an Inflation Targeting (IT) framework. It daily conducts open market operations, which consist in offering 24-hour deposits to monetary policy counterparties (banks). Recourses to the deposit facility averaged 20 percent of the daily auctioned amounts, The use of the deposit facility is due to banks forecast errors and other reasons, including precaution and it represents one percent of the banks' total position with Banguat.

2. **Central banks, like the Banguat, implement monetary policy by influencing the marginal funding rate in the economy via their control over liquidity.** Central banks issue liquidity (account balances in their books thereafter called "reserves") and can control the reserves available to monetary counterparties (e.g., banks) via their market operations. On the other hand, banks demand reserve for several reasons including a regulatory motive (the reserve requirement, RR) and for precautionary motives (as an insurance against unexpected outflows). There are levels of reserves on the demand curve for which short-term interest rate volatility is lower for than others. If the central bank keeps liquidity on the "stable point," it would keep the marginal funding cost of the financial intermediaries (short-term rates) stable and close to it policy rate and, thereby, influence financial conditions in the economy. The "stable points" that the central banks typically target are either:

- *The middle of the corridor* defined by the rates of the deposit and lending facilities, assuming that those are in place. Open market operations provide just enough reserves to satisfy the demand for reserves arising for the reserve requirement and, possibly, a small a demand of excess reserves. The allotment is, then, said "neutral."

- *The bottom of the corridor* by providing reserves via open market operations in excess of what banks need for the reserve requirement and precautionary reasons and enough to pin short-term interest rates to the deposit facility rate.

- *The top of the corridor* by providing less than what banks need to satisfy the reserve requirement and the precautionary demand for reserves such as to force banks to borrow at the lending facility and pin short-term rate to the rate of that facility.

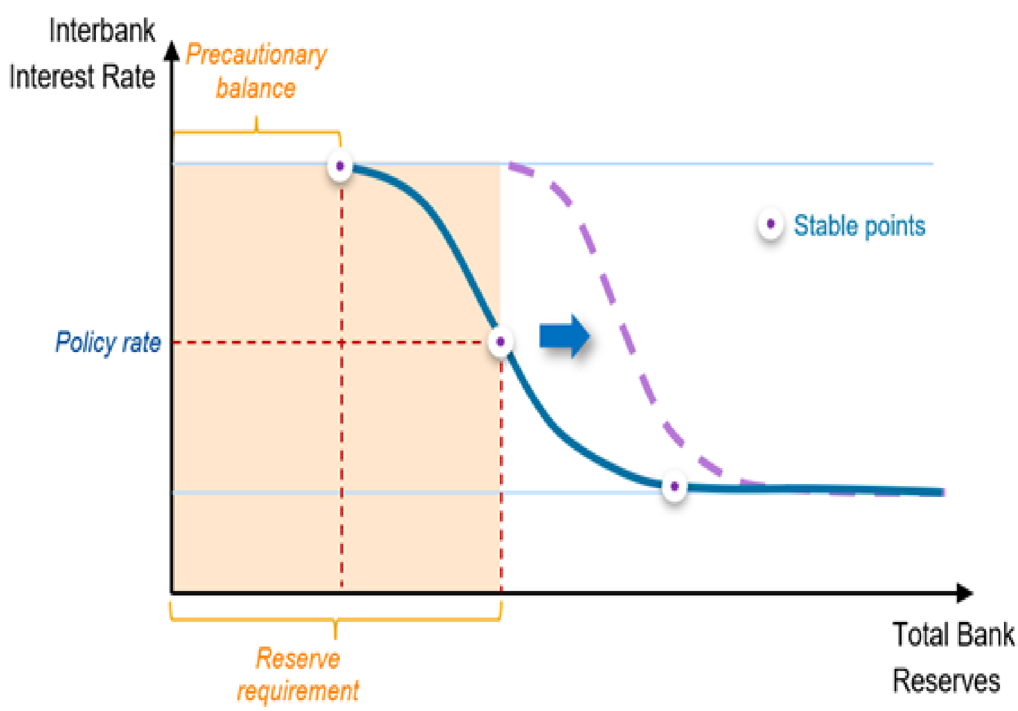
3. **The setup of the reserve requirement in Guatemala creates forecasting challenges for both the Banguat and the banks.[3]** Every day, banks must maintain an equivalent in reserves of 14.6 percent of the deposits that they have on the same day.[4] Neither the Banguat nor

[3] For a detailed description of Banguat's monetary policy implementation framework, see the TA report: "Guatemala CAPTAC-DR—TA Report 2022 Aug—Monetary Policy Implementation Framework Evaluation."

[4] Banks' balances at the central bank (excluding the deposit facility) are eligible for RR fulfillment, and up to 25 percent can be fulfilled with the cash vault.

the banks know what the exact requirement would be until the end of the day. In addition, the banks are allowed to under fulfill the reserve requirement for up to 14 days of a calendar month, provided the sum of deficiencies divided by 14 does not exceed 20 percent of the average monthly reserve requirement. As a result, the Banguat needs to forecast how much reserves banks would need to decide how much deposit to offer at its daily deposit operations. On the other hand, banks need to know how much the requirement would be to decide of their participation at the Banguat's daily deposit operations and of their participation in the interbank market.

**Figure 1. Demand for Reserves and Interbank Interest Rate**




Source: IMF staff.

**4. The Banguat calibrates its operations based on a daily survey of banks.** Fundamentally, forecasting consists in understanding and, thus, anticipating the behavior of important counterparties of the central banks. The "institutional" component of liquidity management channels the information from the sources, i.e., the counterparties themselves, to the central bank. They take the forms of surveys of monetary counterparties (banks) as well as information sharing agreement with non-monetary counterparties (chiefly the National Treasury). In Guatemala, banks daily inform the Banguat of the amounts of deposits that they would likely request at the auction via a survey. The Banguat announces an operation of a total size that is equivalent to the sum of banks' net declared demand. It allots the same amount or less if the demand turns our lower than expected.

**5. This mission assisted the Banguat in developing the statistical component of liquidity forecasting.** Like other central banks, Banguat forecasts the components of its balance sheet with an impact on liquidity, obtaining information from institutional arrangements and sources. For example, Banguat receives weekly information from the government about the expected outflows. On NFA movements, Banguat has information about contractual payments and income related to foreign-denominated debt. In complement of the "institutional" component, the central banks should have statistical forecasts to process all information that could be extracted from time series. It could be used as a default to establish a benchmark for the information provided by other sources.

**7. The mission forecasted the different components of the demand for reserves.** The demand is broken down between the regulatory demand, arising from the reserve requirement, and the demand for excess reserves as reflected in banks' preferred fulfillment profile of the reserve requirement. The latter needs to be incorporated in the OMO calibration to avoid that it impacts short-term interest rates. The mission forecasts: (i) the different deposits of the RR base as depositors are the interest focus whose behavior should be predicted to forecast the RR via its base (assuming a constant ratio); and (ii) the demand for excess reserve of each bank because this variable is more directly under the control of each bank's treasurer. Then, we use statistical reconciliation technique to obtain an aggregated forecast.

**8. The mission forecasted the "autonomous factors."** Besides the demand for reserves coming from the monetary counterparties (banks), central banks should also forecast the behaviors of its non-monetary counterparties that can have an impact on banks' reserves. The latter are called autonomous factors and include banknotes (the general public), the Treasury account at the central bank, Net Foreign Assets, and the net position of other non-monetary policy counterparties, e.g., the social security institution that has an account at the Banguat. The mission used the suite of models developed by MCM's Central Bank Operations Division (MCMCO): (i) to forecast autonomous factors; and (ii) to statistically reconcile them in one liquidity forecast. Then, the mission compared the forecast errors of the Banguat with the forecast errors of the MCMCO forecasting framework.

**9. The rest of the report is organized as follow.** The first section covers the estimation of the demand for reserves. The second section presents the methods to forecast autonomous factors. The third section concludes by explaining how the different statistical results could be combined in a liquidity table to provide a neutral liquidity allotment at the Banguat's daily deposit operation.

## II. ESTIMATING THE DEMAND FOR RESERVES

**10. The RR creates a regulatory demand for reserves.** This regulation imposes on banks to hold certain balances in reserve at the central bank. This amount is defined as a percentage of the reserve requirement base, which includes demand, saving, term, and other deposits. The mission forecasted the reserve requirement on an aggregated basis and based on the different deposits of the reserve requirement base. In addition, the mission forecasted the demand for excess reserves on an aggregated basis and for each bank. Then, it tested whether the statistically reconciling disaggregated forecasts provide more accurate forecasts than the aggregate one.

## A. The Reserve Requirement

### On an Aggregated Basis

**11. The RR follows an historical trend with some quarterly seasonality.** There is a clear undamped upward trend with an average annual growth rate of 10 percent across the year (Figure 2). The reserve requirement seems to be significantly lower during Q2 and Q3 than the rest of the year, which could reflect the seasonality of the RR deposit base (Figure 3).

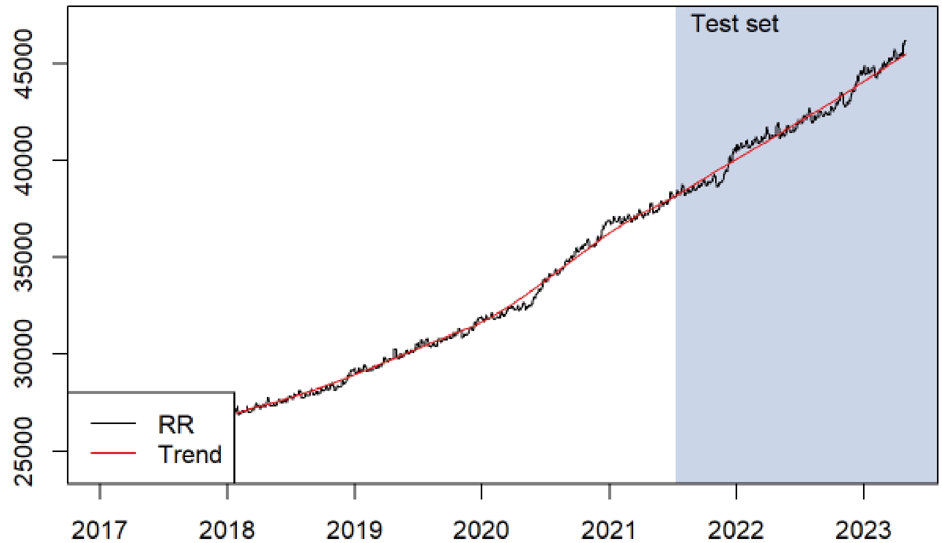
**12. ARIMA with regressor emerges as the best model to predict the reserve requirement across time horizon and performance metrics (Figure 4).** The performance metrics include two indicators of accuracy, including Root Mean Square Error (RMSE) and Mean Absolute Errors (MEA),[5] one indicator of bias (Mean Error, ME), and one indicator of the confidence interval (Mean Interval Score, MIS). ARIMA with regressors has the best out of sample performance, considering improving forecast compared to a random walk (the Naïve), except in term of bias for which seasonal ARMIA fares better.

**13. The forecasting framework allows the presentation of the best forecast or a combination of forecasts to avoid model dependence over a flexible period.** Figure 5 presents the daily forecast as of April 30, 2023, up to the 30 days horizon, which is approximately the under-fulfillment allowance period (one calendar month). The framework could also produce the combination of the best three models or all models available (Figure 6).

**14. Below the performance of the models across the various metrics is plotted.** The forecasts are ordered from worst to best according to each criterion for producing forecasts for 1 to 4 weeks ahead (Figure 4). The best forecast for each horizon is highlighted with a green circle. When a Naïve forecast is available the errors are provided relative to it. Any forecast less accurate than the Naïve (performance equal to 1) should not be considered.

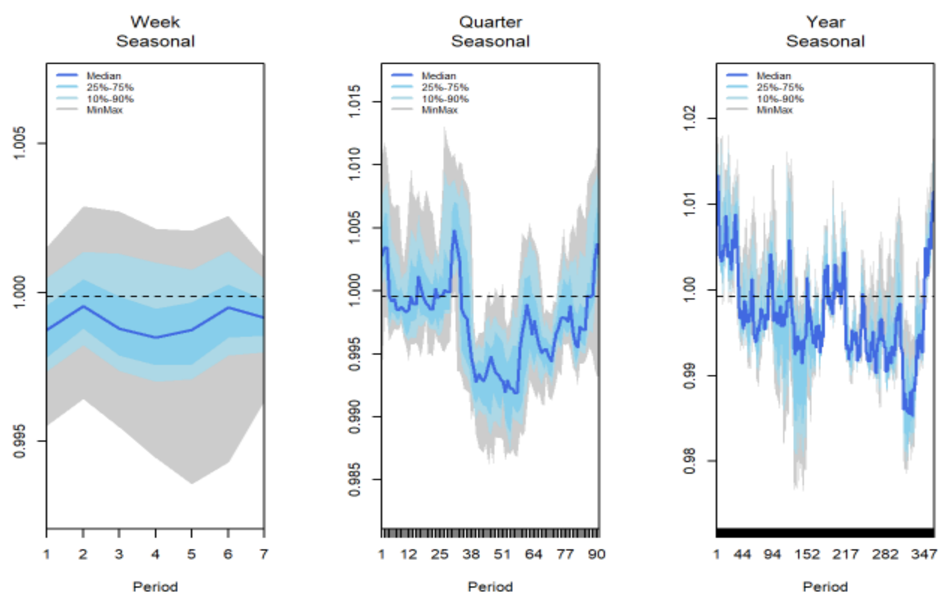
[5] MAE is less sensitive to outliers.

**Figure 2. Historical Trend of RR (Million GTQ)**



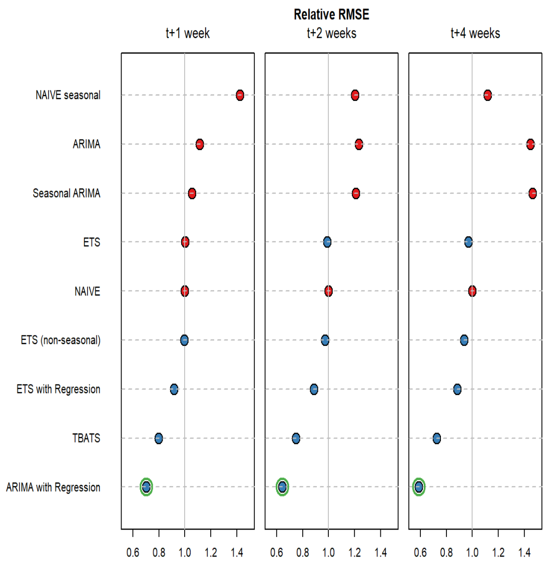

Source: Banguat and staff calculation.

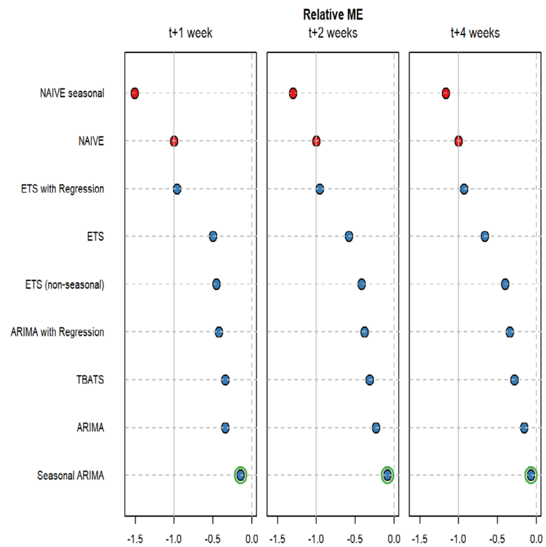
**Figure 3. Seasonality Analysis for RR**




Source: Staff calculation.
Notes: Y axis is normalized detrended RR.

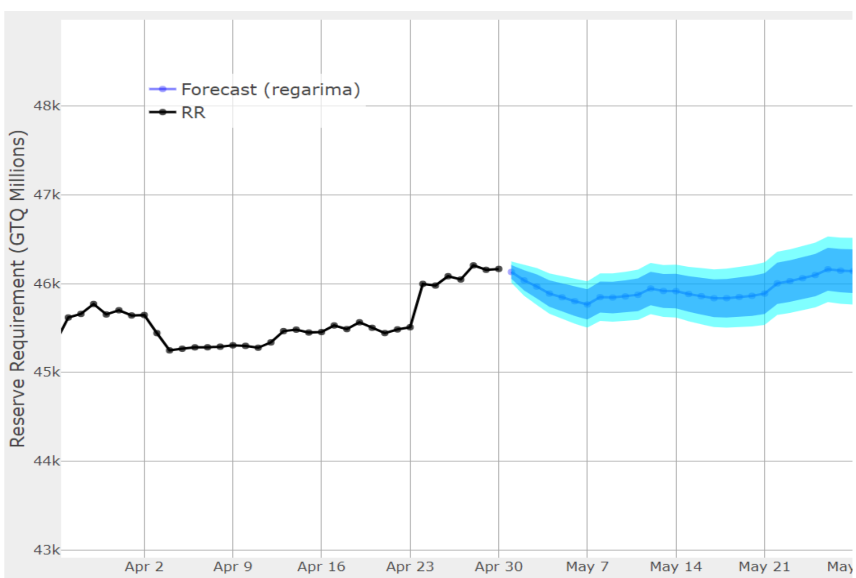
## Figure 4. Predictive Accuracy and Bias of Forecasting Models for Reserve Requirement



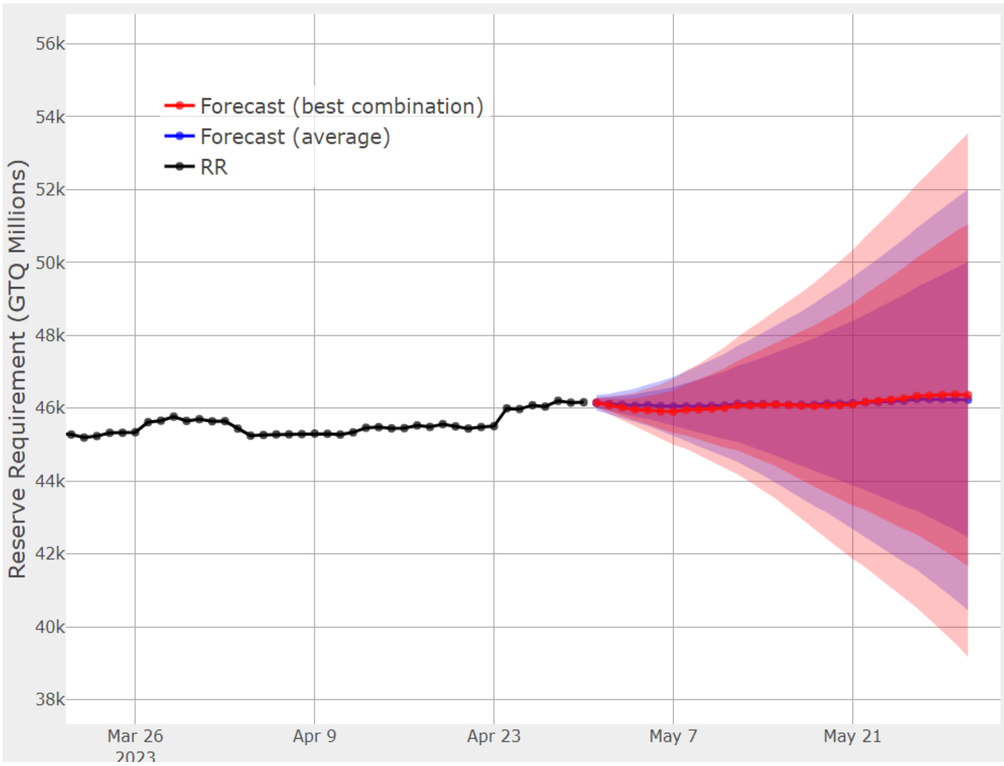

Source: Staff calculation.
Notes: X axis is relative scores of RMSE or ME.

## Figure 5. Reserve Requirement Forecast Using the Selected ARIMA with Regression Model




Source: Staff calculation.

**Figure 6. Reserve Requirement Forecast Using Best Three Models and Average of All Models**



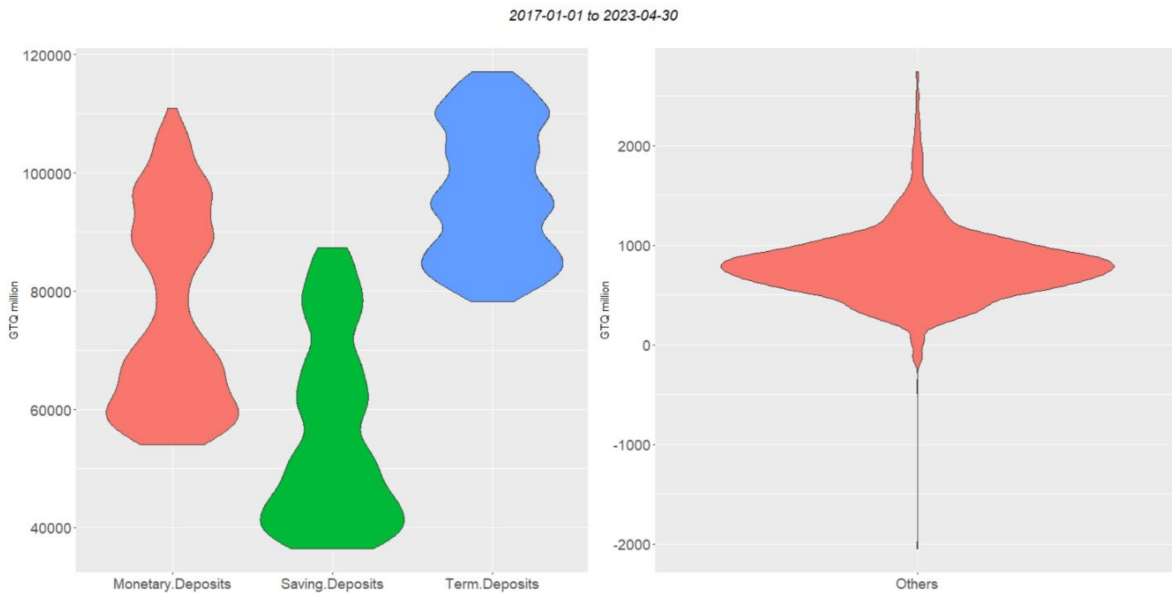

Source: Staff calculation.

## By-Deposit Type Approach

**15. Assuming a constant ratio, the Banguat could derive the reserve requirement from a forecast of its deposit base.** The economic agents, which behaviors we intend to forecast, are the banks' clients, i.e., the depositors that control the RR base. The by-deposit type approach consists in forecasting directly the different type of deposits included in the base, namely demand, term, saving, and other deposits and then, applying the uninform 14.6 percent ratio to obtain the reserve requirement forecast. One could assume that that the different deposits would have different behaviors and factoring this heterogeneity would improve the forecast.

**16. Descriptive statistics confirms that there is significant heterogeneity across types of deposits.** Saving deposits appear more widely distributed in term of sizes than term deposits, which tend to be larger. Demand deposits stand in between term and saving deposits in term of size and seem to have a bi-modal distribution (Figure 7). Other deposits are smaller and concentrated around the similar amounts.

**Figure 7. Distributions of RR Base by Types of Deposits**




Source: Staff calculation.

**17. The best model selection per type of deposits confirms the heterogeneity.** Based on RMSE out of sample testing, three different models best forecast the behaviors of the four types of deposits, including a TBATS model (Table 2). TBATS is short for Trigonometric seasonality, Box-Cox transformation, ARMA errors, Trend and Seasonal component, which serves as a time-series model with capability to model complex seasonalities and error patterns (Appendix I).

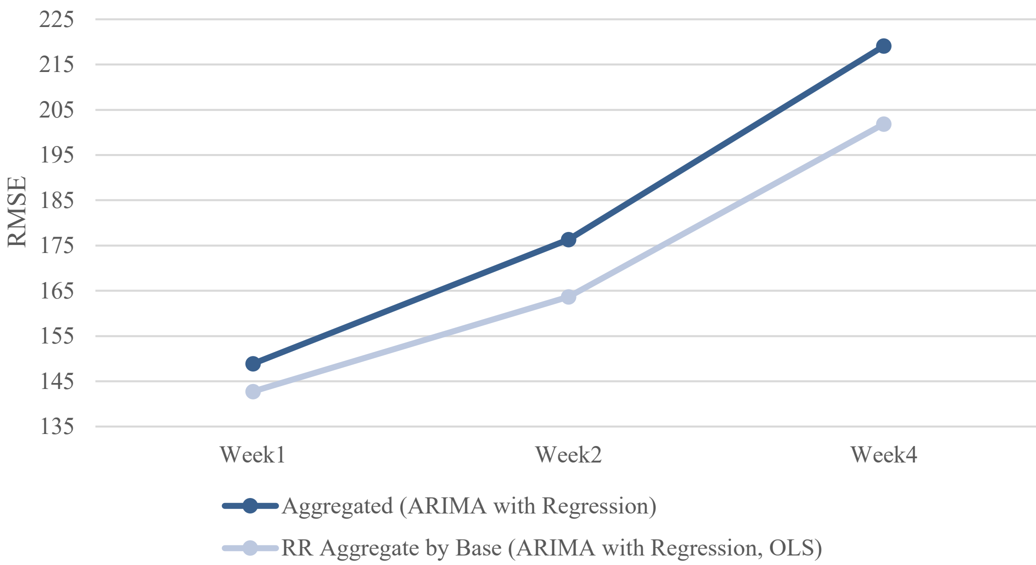
**Table 2. Selected Models for Reserve Requirement Base**

| **Component** | **Average (GTQ million)** | **Selected Model (RMSE, Horizon = 30)** |
|---|---|---|
| Monetary Deposits | 76,564.25 | ARIMA with Regression |
| Saving Deposits | 56,205.56 | TBATS |
| Term Deposits | 96,734.47 | ETS with Regression |
| Others | 801.71 | ARIMA with Regression |

Source: Staff calculation.

**18. The model aggregation improves the forecast quality.** RMSE at the 1, 2, and 4-week horizons are lower for the deposit-base reconciled RR forecasts (Table 3) than non-reconciled aggregated one, confirming that additional information is processed (Figure 8). With by-deposit type information, one could simply add up the forecasts of deposits in a bottom-up fashion (each type of deposit for which there is a requirement) and obtain the estimates for RR with the RR coefficient, 14.6 percent in Guatemala. As each deposit type will be forecasted independently, there is no guarantee that the forecasts of each deposit types will add up to the forecasts of aggregated RR. Using the reconciliation techniques will make sure that both by-deposit forecasts and aggregated RR forecasts are used, and, at the same time, ensure that the accounting relationship among them holds true (Appendix I). Across specifications, by-deposit ARIMA with regression reconciled with OLS performs the best at the 1-week horizon while deposit-base ARIMA with regression bottom up performs the best for the 2 and 4-week horizons.

**Figure 8. RMSE Comparison for Forecasts (Million GTQ)**




Source: Staff calculation.

**Table 3. RMSE For Reserve Requirement Forecasts by base: Reconciled vs. Unreconciled (Million GTQ)**

| | | Week 1 | Week 2 | Week 4 |
|---|---|---|---|---|
| **Unreconciled** | RR Aggregate (ARIMA with Regression) | 148.90 | 176.30 | 219.10 |
| **Reconciled** | RR Aggregate by Base (ARIMA with Regression, OLS) | **142.77** | 163.65 | 201.89 |
| | RR Aggregate by Base (ARIMA with Regression, Bottom Up) | 142.81 | **163.43** | **201.78** |
| | RR Aggregate by Base (ARIMA with Regression, Min T) | 143.93 | 166.39 | 204.52 |

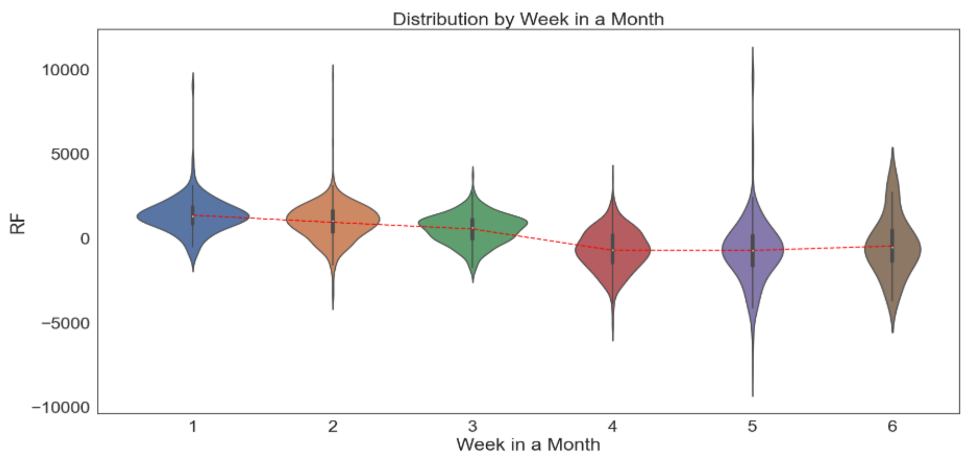
Source: Staff calculation.

## B. The Reserve Requirement Fulfillment Profile

### On an Aggregated Basis

**19. The excess reserves exhibit a clear monthly pattern.** Excess reserves defined as the daily difference between the balance on account and the reserve requirement objective. They are held on unremunerated account voluntarily because banks always have the option to place them at the deposit facility of the Banguat. Banks tend to exceed the requirement early in the month (front loading) and they seek to reduce the unremunerated balance on account by placing reserves on the deposit facility as much as possible afterward (Figure 9).

**Figure 9. Intra-Monthly Distribution of Reserve Fulfillment (Million GTQ)**

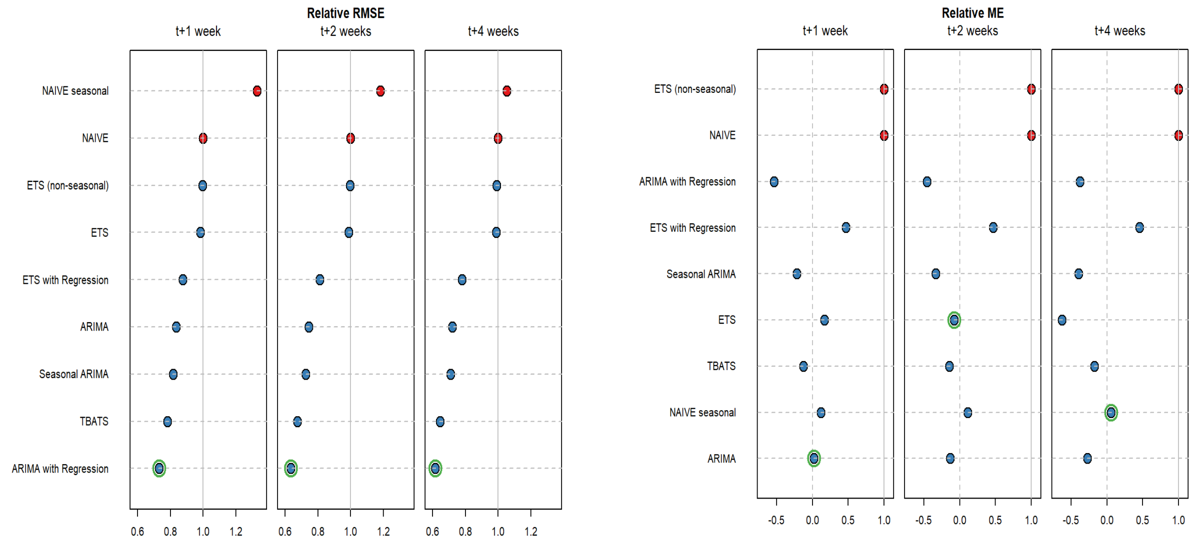



Source: Banguat and staff calculation.

**20. The demand for excess reserves needs to be accommodated to stabilize short-term interest rates.** The allotment of the open market operations should be relatively reduced when banks want to keep more reserves at the beginning of the period; otherwise, the participation in the open market operation would be low and the rate may increase. Conversely, the Banguat should issue more at the end of the period to avoid that the lower demand for reserve results in an increase in the demand for daily deposits that would push their rates down and increase recourse to the deposit facility.

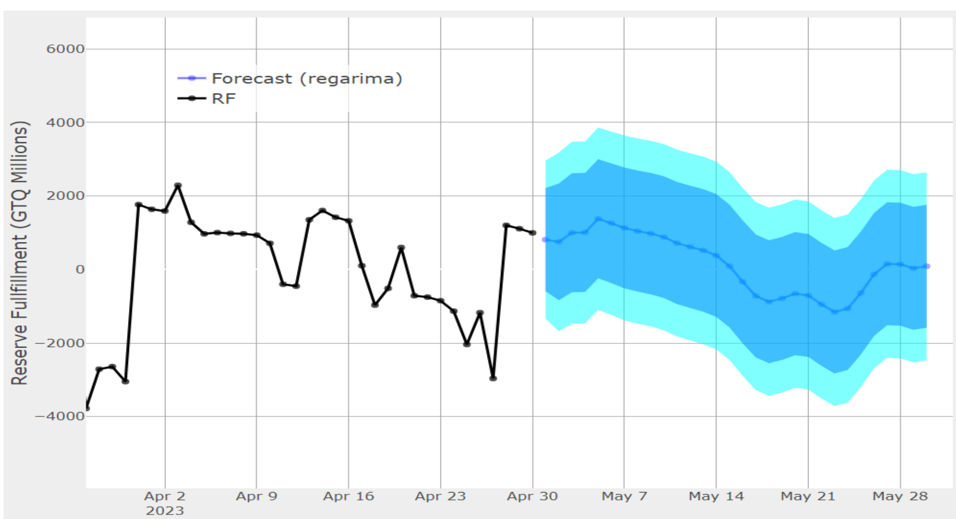
**21. Similar forecasting models as previously presented could be used for excess reserves.** Across out-of-sample performance metrics, ARIMA with regressor is the best model, except for bias (ME) in which case simple ARMIA perform better (Figure 10). Based on that model, the Banguat could forecast the daily fulfillment up to the end of the month. Figure 11 presents the 30-day forecast as of April 30, 2023.

**Figure 10. Predictive Accuracy and Bias of Forecasting Models for Reserve Fulfillment**




Source: Staff calculation.
Notes: X axis is relative scores of RMSE or ME.

**Figure 11. Reserve Fulfillment Forecast Using the Selected ARIMA with Regression Model**

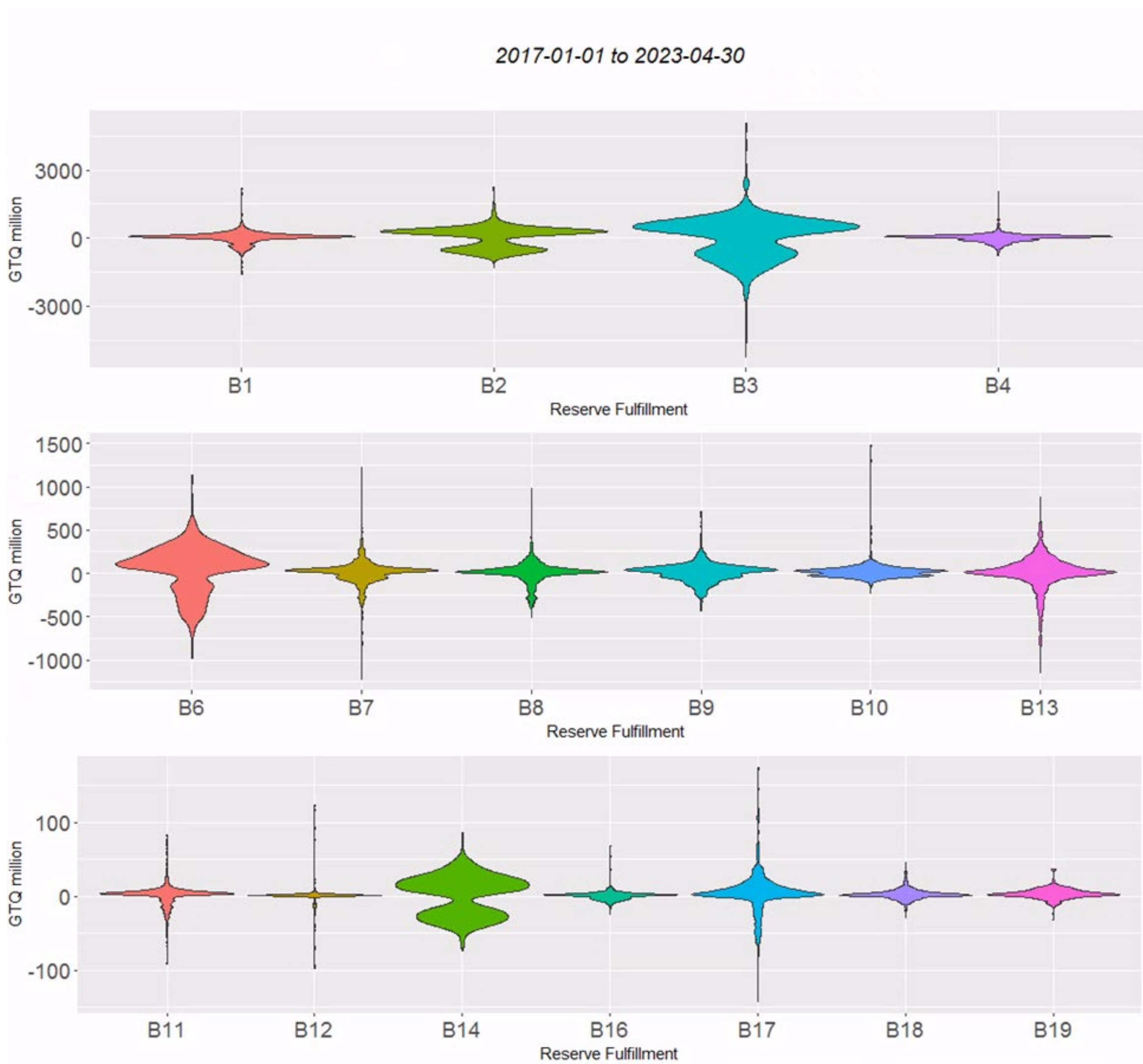



Source: Staff calculation.

## By Bank

**22. Descriptive statistics confirm that there is a significant heterogeneity in the demand for excess reserves across banks.** Each bank keeps reserves in excess or below the reserve requirement on a daily basis, but the distribution of excess reserve varies across banks. Some show wide and bimodal distributions while others keep less and less volatile excess reserves (Figure 12). The heterogeneity arises from the preference of each bank treasurer in terms of the fulfillment profile for the reserve requirement. Some prefer to front load the requirement while other could prefer a more linear or backloaded maintenance profile.

**Figure 12. Distributions of the Reserve Requirement Fulfillment Profile**




Source: Staff calculation.

**23. The best model selection per bank confirms the heterogeneity.** Based on RMSE out of sample testing, four different models best forecast the behaviors of the 19 different banks, for which enough data are available (Table 4). However, TBATS performs best for most banks, 9 out of 19.

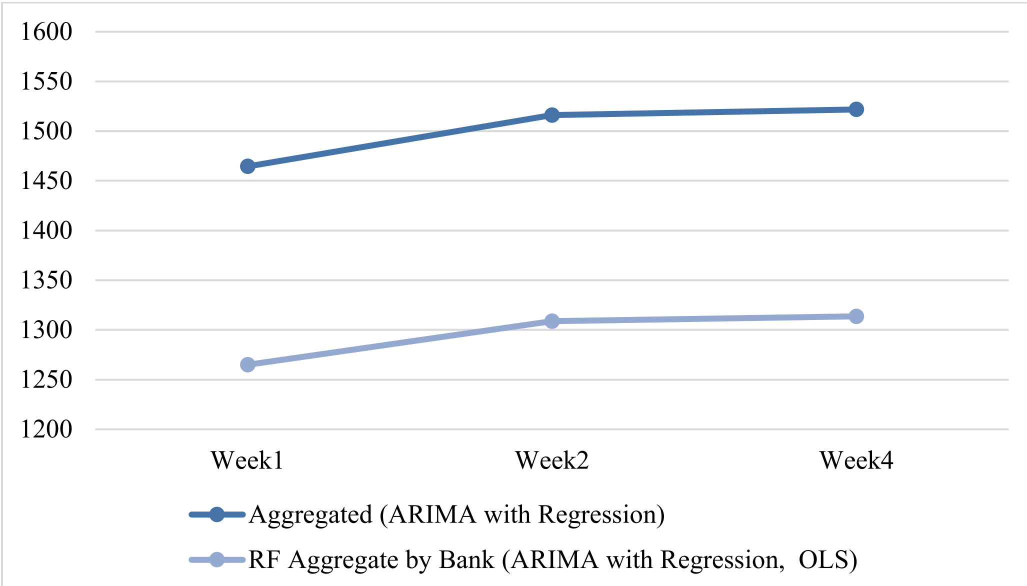
**Table 4. Selected Models for RR Fulfillment Profile by Bank**

| Bank# | Average RF (Million GTQ, 2017-01-01 to 2023-04-30) | Selected Model (RMSE, Horizon = 30) |
|---|---|---|
| 1 | 28.67 | **Seasonal ARIMA** |
| 2 | 44.40 | **ARIMA with Regression** |
| 3 | 51.87 | ARIMA with Regression |
| 4 | 17.63 | **Seasonal ARIMA** |
| 6 | 55.47 | **TBATS** |
| 7 | 7.22 | **Seasonal ARIMA** |
| 8 | 7.22 | **TBATS** |
| 9 | 10.37 | **Seasonal ARIMA** |
| 10 | 24.62 | **TBATS** |
| 11 | 1.65 | ARIMA with Regression |
| 12 | 0.36 | **ETS** |
| 13 | 6.01 | **TBATS** |
| 14 | 1.19 | **ARIMA with Regression** |
| 16 | 0.84 | **TBATS** |
| 17 | 5.19 | **TBATS** |
| 18 | 2.70 | **TBATS** |
| 19 | 1.33 | **TBATS** |

Source: Staff calculation.

**24. Model reconciliation improves the forecast quality at the short horizon.** RMSE at the 1, 2, and 4-week horizons are notably lower for the by-bank reconciled forecasts (Table 5) than non-reconciled one, confirming that additional information is processed at all horizons (Figure 13). ARIMA with regression reconciled by OLS appears to be the best performing specification in term of RMSE at all horizons.

**Figure 13. Reserve Requirement Fulfillment RMSE: Aggregated vs. by Bank (Million GTQ)**




Source: Staff calculation.

**Table 5. RMSE for RR Fulfillment Profile: Reconciled vs. Unreconciled (Million GTQ)**

| | | Week 1 | Week 2 | Week 4 |
|---|---|---|---|---|
| **Unreconciled** | RF Aggregated (ARIMA with Regression) | 1464.5 | 1516.0 | 1521.8 |
| **Reconciled** | RF Aggregate by Bank (ARIMA with Regression, OLS) | **1264.9** | **1308.8** | **1313.6** |
| | RF Reconciled by bank (ARIMA with Regression, Bottom up) | 1368.8 | 1423.2 | 1442.9 |
| | RF Reconciled by bank (ARIMA with Regression, Min T) | 1439.3 | 1472.2 | 1453.7 |

Source: Staff calculation.

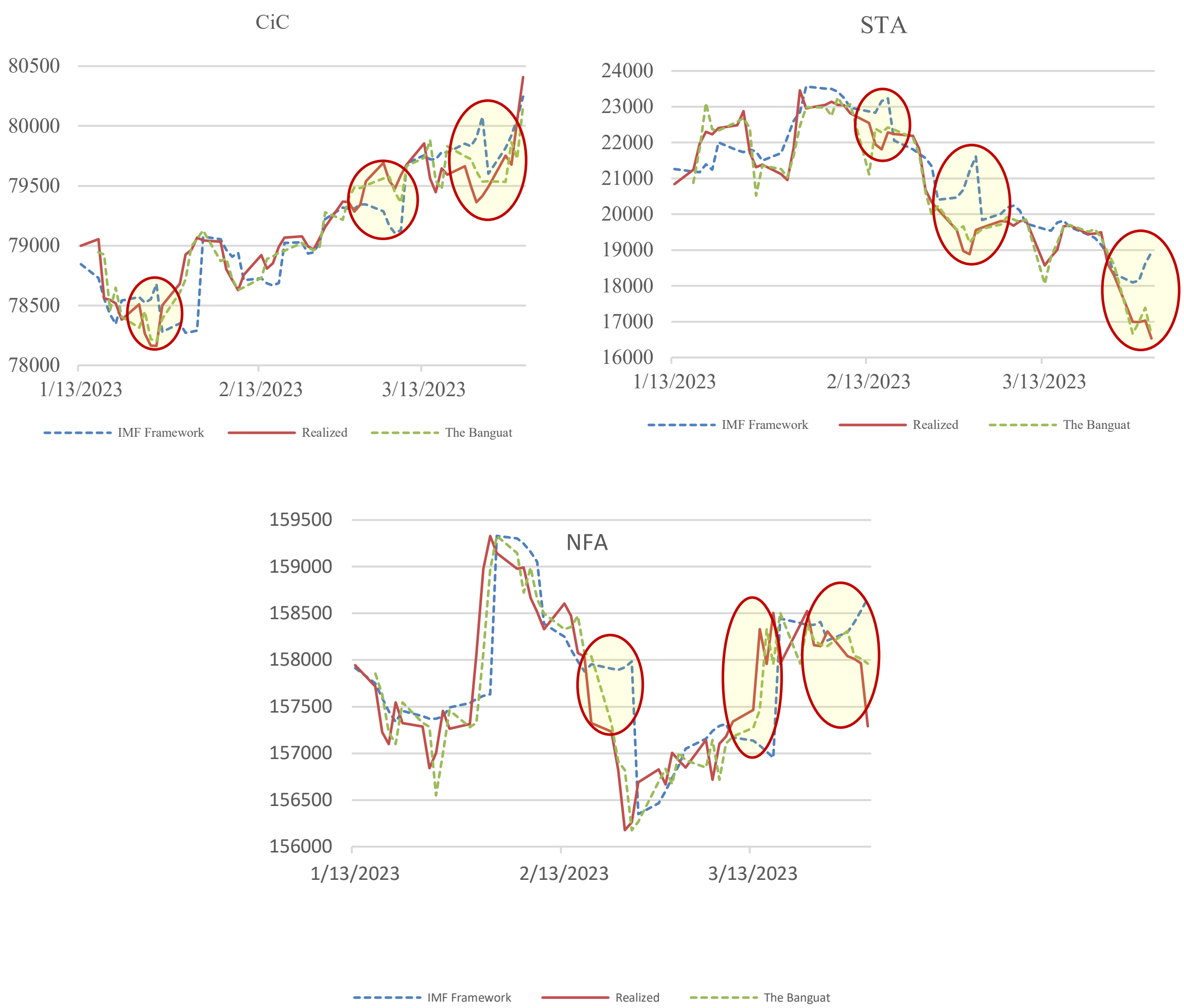
## III. FORECASTING AUTONOMOUS FACTORS AND NET LIQUIDITY

25. **The first objective of adopting a Liquidity Forecasting Framework (e.g., the IMF framework used during the mission) is to benchmark the performance of Banguat's current models.** Compared to pure statistical estimations generated by the MCMCO Framework, the Banguat's current models have better forecasts benefiting from the qualitative input such as the settlement date of foreign exchange (FX) operations and prior notification of large transaction by the government (Figure 14). Such information is more instrumental to NFA

and STA forecast. T tests on the absolute errors also suggest that the error differences on NFA and STA between two models are statistically significant, but the performances on predicting CiC are not statistically different (Table 6).

**26. The second objective is to introduce reconciliation techniques to obtain the forecast of the aggregated effect of autonomous factors on liquidity or NL.** The framework adds a forecast of Net Other Assets (NOA) to complete the full set of autonomous factors. Then, it uses statistical technique to reconcile the sum of the autonomous factors with the forecast of total NL. Finally, the framework also provides information of forecast uncertainty (the confidence interval).

**Figure 14. Predictions for CiC, STA, and NFA (Million GTQ)**




Source: Banguat and staff calculation.

**Table 6. T Test P Values on Mean of Absolute Error by Models**

| | CiC | NFA | STA |
|---|---|---|---|
| **Unpaired** | 0.11 | 0.12 | 0.00* |
| **Paired** | 0.10 | 0.04* | 0.00* |

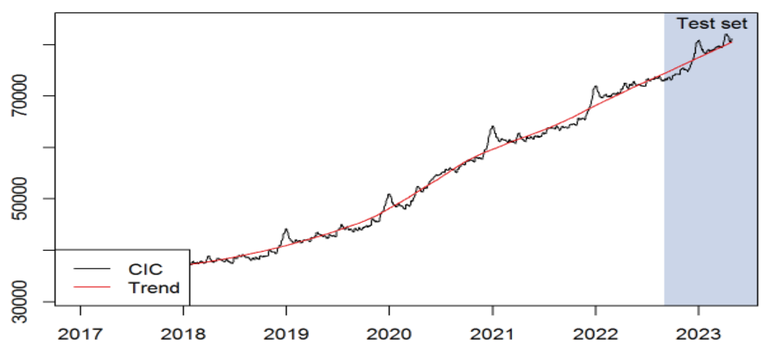
Note: * indicates significant difference at 5 percent.
Source: Banguat and Staff Calculation.

Source: Banguat and staff calculation.

## A. Currency in Circulation

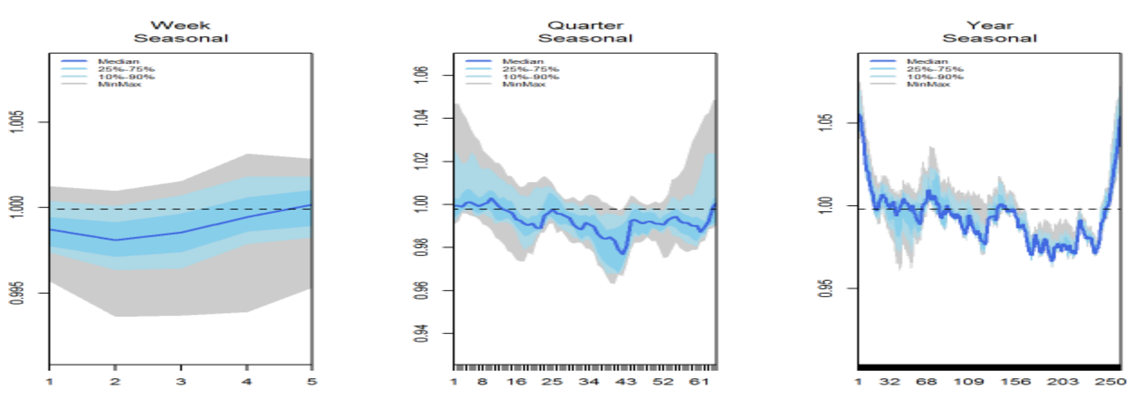
**27. A clear upward trend and seasonal pattern can be detected in the CiC time series, which indicates the suitability of time series models with seasonality components.** More specifically, the CiC series demonstrates strong weekly seasonality with an increasing demand towards the end of the week and showed seasonal jumps starting from the previous yearend to the beginning of new year (Figure 15 and 16).

**Figure 15. Historical Trend of CiC (Million GTQ)**




Source: Banguat and staff calculation.

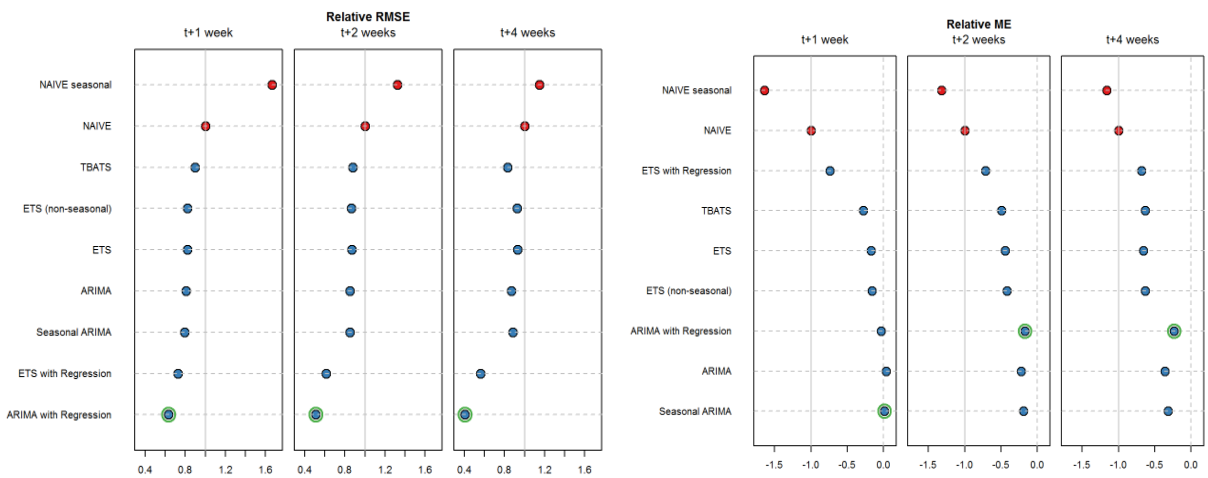
**Figure 16. Seasonality Analysis for CiC**




Source: Staff calculation.
Notes: Y axis is normalized detrended CiC.

**28. ARIMA with Regression is selected for CiC for all one-week, two-week and four-week forecasts.** Along with two benchmarking models Naïve and Naïve seasonal, 7 models were tested for CiC. Figure 17 visualizes the average performance of the forecasts across the complete test set. The ARIMA with Regression and ETS with Regression are ranked the top in terms of accuracy, testifying to the valuable addition of regressor. Based on information criteria, the MCMCO Framework determines a list of regressors to be included for the model and there are trigonometric terms, weekly seasonality, and holidays (New Year, Assumption Day, Revolution Day, All Saints Day, Good Friday, and Christmas). The selected ARIMA with Regression has a closer to 0 score for ME, indicating the model is relatively unbiased.

**Figure 17. Predictive Accuracy and Bias of Forecasting Models for CiC**

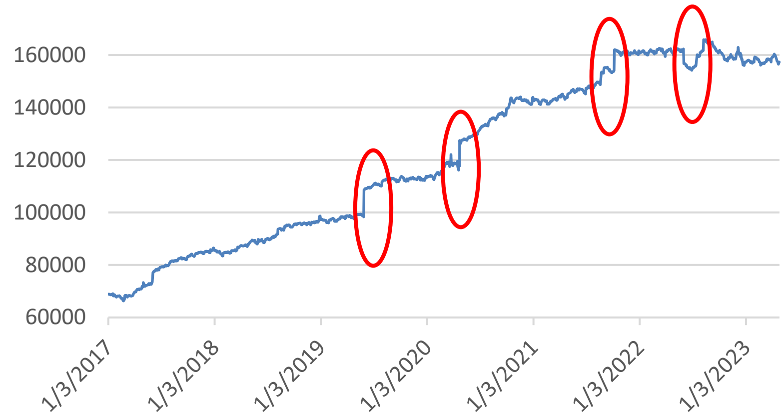



Source: Staff calculation.
Notes: X axis is relative scores of RMSE or ME.

## B. Net Foreign Assets

**29. The NFA series is ascending before 2022 and then levels off with four historical drastic jumps and drops.** Due to activities such as Eurobond issuance and FX purchase, the NFA data witnesses four sharp changes in its trend (Figure 18), which will bring uncertainty during the modelling and forecasting process. The mission team experimented using corresponding structural breaks dummies to capture these conspicuous changes, but the forecast results were not satisfactory enough. As a result, the mission removed these jumps and reconnected the series before inputting it into the forecasting models.

**Figure 18. Historical Jumps and Drops in NFA (Million GTQ)**

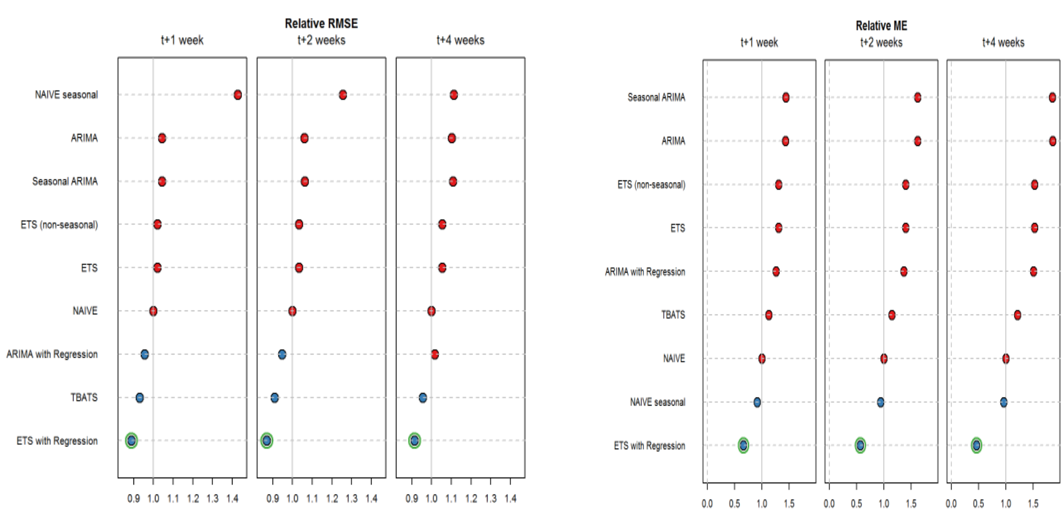



Source: Banguat and staff calculation.

**30. Times series models, rather than volatility models, were employed to forecast NFA.** Usually, volatility models such as Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model fit better for NFA prediction because NFA series often show high volatility and have no trend or clear seasonal pattern. However, none of the volatility models outperformed the simple Naïve benchmark; hence, the mission team switched to time series models.

**31. Figure 19 summarizes the results for the NFA, with the ETS with Regression being the recommended forecasting method.** Like the CiC, the inclusion of regression benefits the predictive accuracy of the models. For NFA, only trigonometric seasonality is picked out as regressors. And across three different horizons, the ETS with Regression model has the lowest averaged RMSE and closet-to-0 ME among all models, making it most accurate and unbiased.

**Figure 19. Predictive Accuracy and Bias of Forecasting Models for NFA**

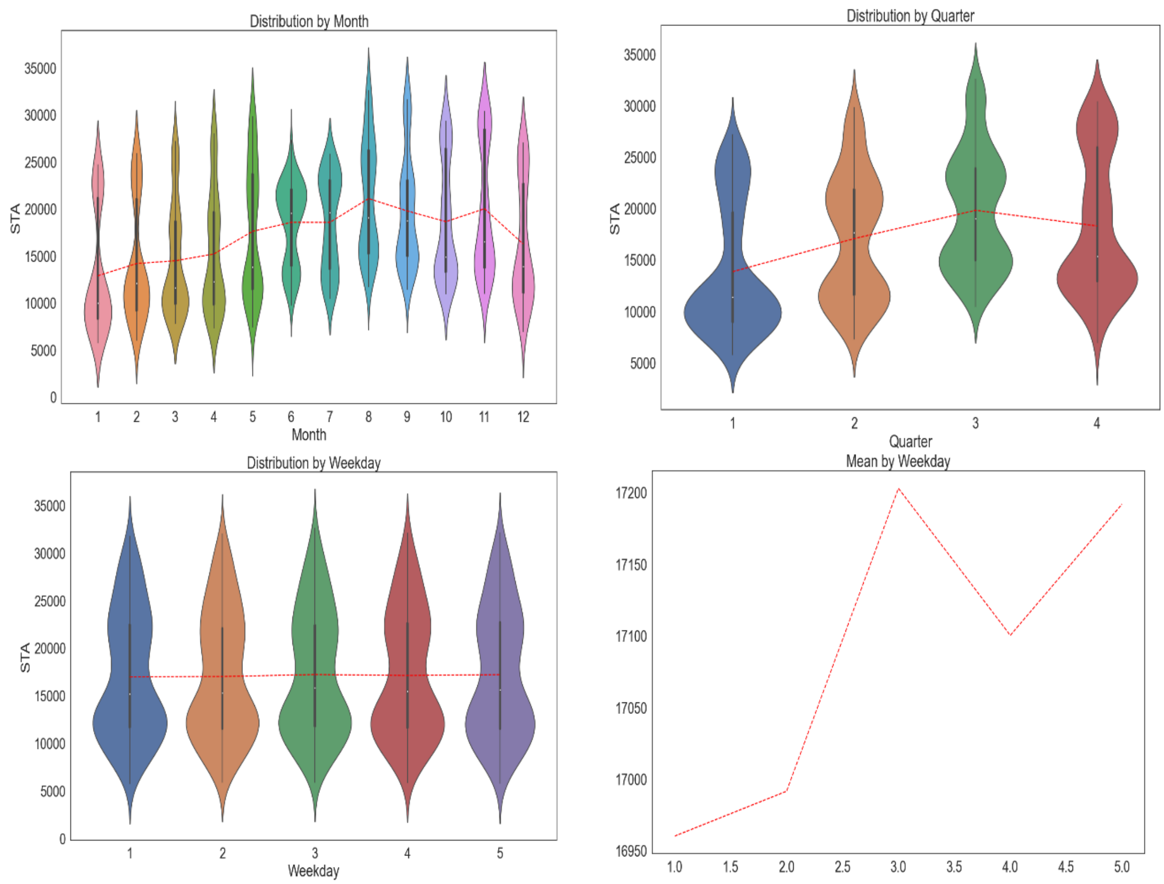



Source: Staff calculation.
Notes: X axis is relative scores of RMSE or ME.

## C. State Treasury Account

**32. Monthly and quarterly seasonality is obvious in STA data, while intraweek pattern is weak.** Figure 20 illustrates the distribution by different frequency. While the monthly and quarterly patterns are pronounced, the intraweek distribution is relatively stable. The mean dynamic within a week, however, indicates the deposit is higher midweek than the beginning of a week and, hence, possible existence of intraweek seasonality.

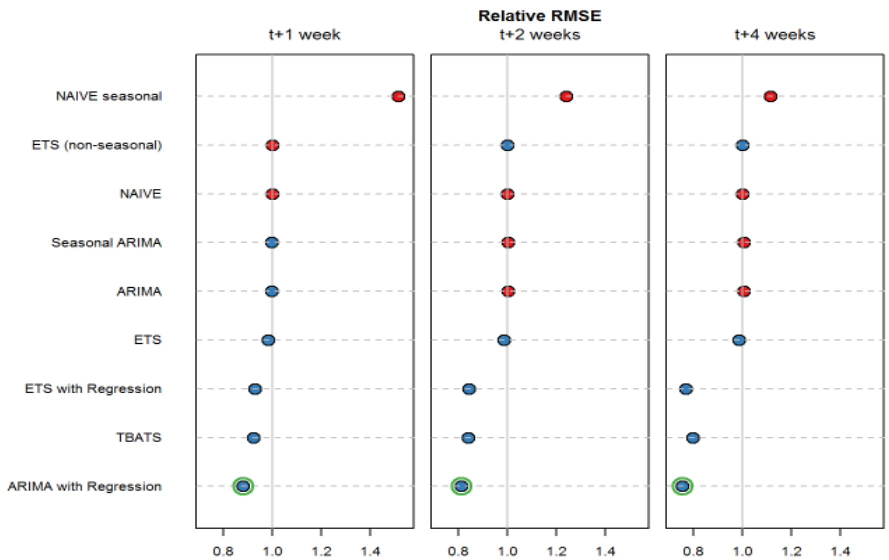
**Figure 20. Seasonality in STA (Million GTQ)**




Source: Staff calculation.

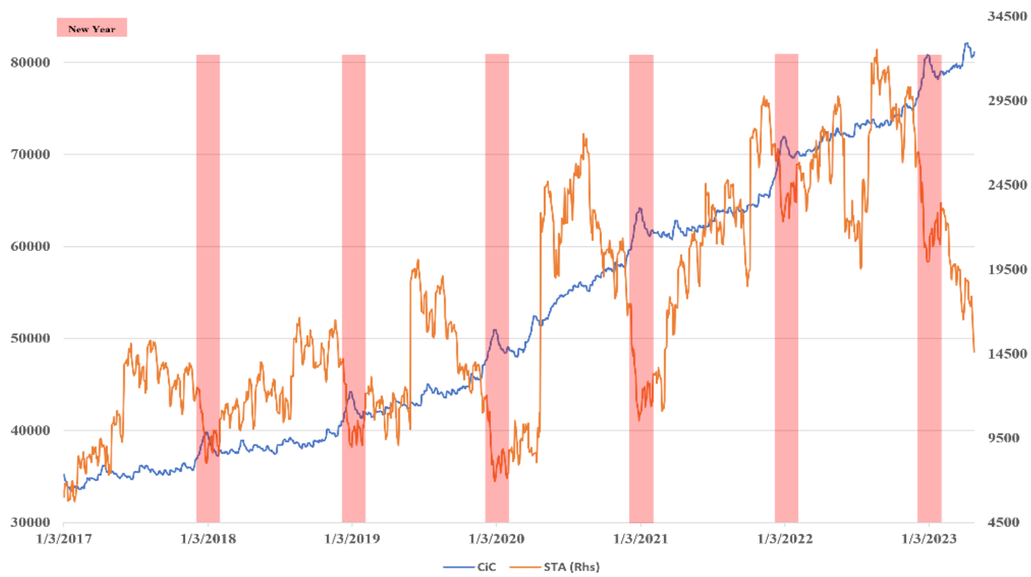
**33. ARIMA with regression ranks the best for STA in terms of predictive performance.** Fourier terms to gauge multiple seasonalities and weekly dummies are incorporated with both ARIMA and ETS models (Figure 21). And both have better accuracy among all models tested. It is reasonable that holiday and special events are omitted since compared to CiC, for example, the STA data does not show solid jumps or drops during the New Year holiday periods but transitory drops with fluctuations (Figure 22). Fourier terms are more appropriate to model such patterns.

**Figure 21. Predictive Accuracy of Forecasting Models for Single Treasury Account**




Source: Staff calculation.
Notes: X axis is relative scores of RMSE.

**Figure 22. Single Treasury Account Behavior vs. CiC during New Year Holiday (Million GTQ)**



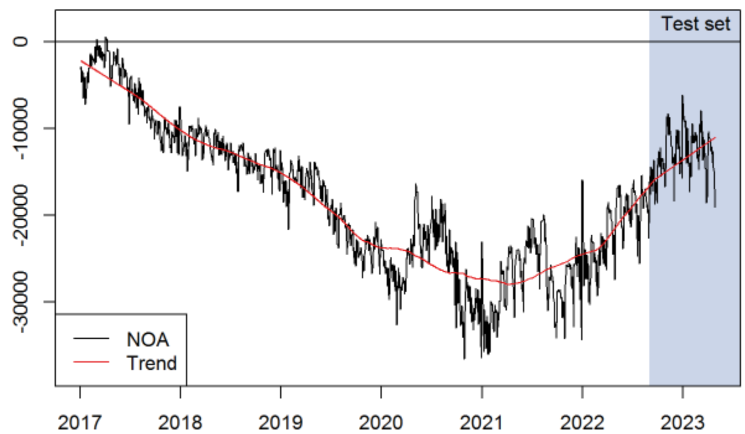

Source: Banguat and staff calculation.

## D. Net Other Assets

34. **Net Other Assets series does not exhibit strong volatility either and volatility models are not best fit for its prediction**. Before 2021, the NOA stock is on a downward trend but

starts to climb after 2021 (Figure 23). As for seasonality, intraweek seasonality is not evident but there are monthly and quarterly patterns.

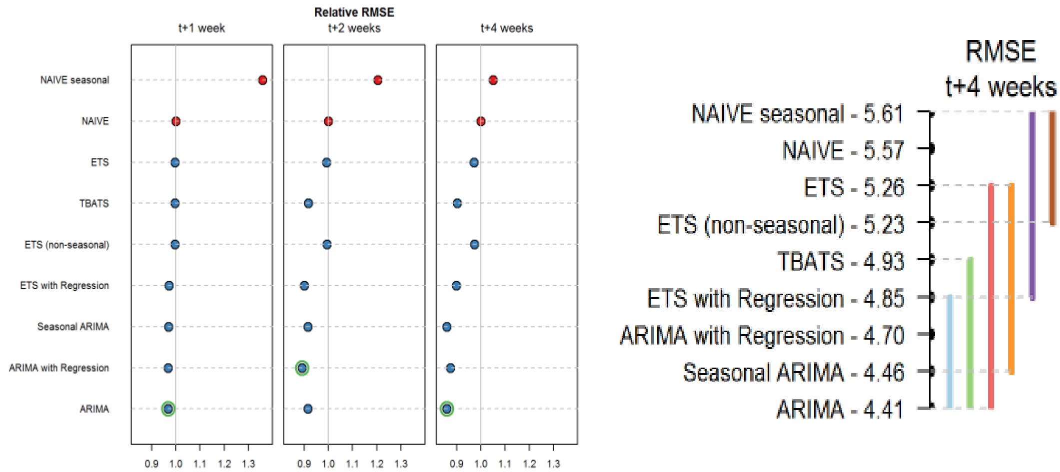
**Figure 23. Historical Trend of Net Other Assets (Million GTQ)**




Source: Banguat and staff calculation.

**35. Even though multiple seasonalities exist, a more parsimonious model ARIMA was selected to forecast NOA.** The RMSE scores are summarized below for each model and the ARIMA model is better performing for 1 and 4-week horizon. Seasonal ARIMA and ARIMA with Regression are following but only produce more accurate forecast on average at two-week horizon. However, as the statistical tests (Figure 24) demonstrated the much simpler ARIMA has no significant differences from the more complex model with regressors or seasonality, and, therefore, is the recommended forecasting method. In general, when a simpler forecasting method performs equivalently to more complex ones, the simpler is preferable, as it is easier to parameterize, and maintain, and is typically more robust, not to mention now simple ARMA has relatively better predictions for two out of three different horizons.

**Figure 24. Predictive Accuracy and Statistical Difference of Forecasting Models for Net Other Assets**

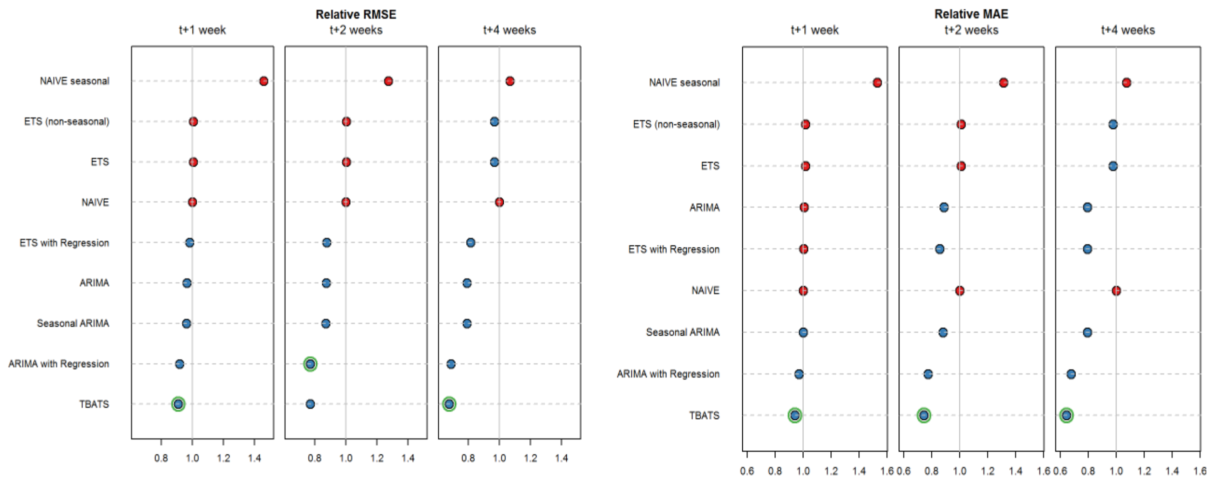



Source: Staff calculation.
Notes: X axis is relative scores of RMSE.

## E. Net Liquidity

36. **The MCMCO Framework also runs statistical forecast for NL and TBATS is selected based on lowest RMSE score.** Assuming NL = NFA + NOA – CIC – STA, the series of NL can be obtained and then be input into the Framework to determine a best model for its prediction. For both 1 and 4-week horizon, TBATS produces lower error on average, while ARIMA with Regression ranks better if the horizon is of two weeks (Figure 25). However, if another metric MAE is examined, the TBATS is constantly the best. A possible cause of such difference is that TBATS model may generate several extreme forecasts for two-week horizon and entail larger penalty in RMSE, which is more sensitive to outlier.

**Figure 25. Predictive Accuracy of Forecasting Models for Net Liquidity**




Source: Staff calculation.
Notes: X axis is relative scores of RMSE or MAE.

37. **The forecasts for the autonomous factors and NL are reconciled to produce a more coherent NL forecast, with OLS being the recommended reconciliation method for longer forecast horizons and Bottom-Up for one-week forecast.** Table 7 provides the results for the alternative reconciliation methods. The best result in each column is highlighted in bold. Red signifies the result without any reconciliation. For longer horizons such as two weeks and four weeks, OLS provides gains over the unreconciled construction of NL, where it is forecasted directly. But the forecast horizon is shortened to one week, the Bottom-Up approach, i.e., forecasting the components of the NL separately and then, aggregating them to the NL, will be enough. In terms of bias, the OLS approach has lower ME scores across all horizons.

**Table 7. Predictive Accuracy and Bias of Forecasting Models for NL (Million GTQ)**

| Method | RMSE | | | MAE | | | ME | | |
|---|---|---|---|---|---|---|---|---|---|
| | +1 week | +2 weeks | +4 weeks | +1 week | +2 weeks | +4 weeks | +1 week | +2 weeks | +4 weeks |
| **OLS** | 1873.8 | **2214.0** | **2597.9** | 1461.6 | **1795.7** | **2166.1** | **65.0** | **-10.3** | **-56.7** |
| **Base (Unreconciled)** | 1959.7 | 2312.7 | 2687.9 | 1553.6 | 1850.7 | 2210.4 | 110.0 | 62.6 | -66.8 |
| **Bottom Up** | **1814.8** | 2300.0 | 2732.1 | **1378.6** | 1827.0 | 2244.9 | -114.8 | -301.9 | -550.9 |
| **MinT** | 2135.9 | 2574.2 | 2952.2 | 1704.6 | 2021.2 | 2382.9 | 145.7 | 180.1 | 286.2 |

Source: Staff calculation.

38. **The mission recommends that Banguat complements its institutional forecast and bank's survey with the proposed statistical models to produce forecasts for autonomous factors and the RR and to calibrate daily auctions.** The mission provided Banguat with the codes to estimate all the models for each variable, the reconciliation for liquidity, and RR. With the codes, Banguat staff can also test the performance of each model and do out-of-sample forecast evaluation and select a model to do the forecasts.

39. **The mission recommends that Banguat periodically evaluates the selected models to conduct the forecasts.** The best model selected can change throughout time due to new information or structural changes. The mission recommends periodically evaluating the models' performance (i.e., quarterly, semiannually) to corroborate or change the selected model. Banguat staff can rely on MCM for technical support.

## IV. LIQUIDITY TABLE AND CALIBRATION

40. **The "liquidity table" summarizes information on reserves available in the system and the demand for reserves to calibrate the daily deposit operations.** The first four lines under Autonomous Factors (Table 8) determine the reserves available in the system at each forecasted date. Then, under reserve requirement, we have the predicted demand due to regulation (the RR) to which we add the banks' preference regarding the reserve requirement fulfillment. In conclusion, Banguat would roll over an amount of daily deposit corresponding to the difference between available reserves (from autonomous factors) and how much the banks want to keep (for regulatory reasons or predictable preferences for excess reserve holdings). This is the "neutral allotment" based on which banks have exactly what they need.

41. **The facilities are expected to capture the forecast errors under neutral allotment.** Ex-ante, the open market operations are calibrated to leave no excess or shortage of reserves; therefore, the recourse to the facility should be expected null. However, in case of forecast errors from the Banguat, the recourse to the facilities could be non-null. If the market functions well, banks' forecast errors would not matter, and an accurate aggregate calibration is enough as any excess or shortage would be sorted out in the market. On the other hand, banks' liquidity forecast

could lead to recourse to the facilities even though the aggregate calibration is accurate if the interbank market does not seamlessly redistributed liquidity.

**42. Here are presented data in flows but the table could be also prepared in levels.** Liquidity tables in levels translate the full balance sheet of the central bank while the tables in flows only focus on the most important factors. The full tables ensure that no liquidity factor is omitted (comprehensive approach) but is more cumbersome to implement.

**43. Some items of the liquidity table should be published to inform banks' bidding at the open market operations.** Banks may know relatively exactly their short-term cash flows but they unlikely know the cash flows of the other banks. Therefore, the sum of individually optimal bids may not be optimal at the market level. On the other hand, central banks have private information on both the demand and supply of liquidity because it is an instrument that they issue. By disclosing some of this information, they could inform auction participants on expected aggerated liquidity conditions, thereby improving their bidding. From the illustrative liquidity table, the most important items to published would be:

- Observe data such as the opening banks' balances at the Banguat.
- Liquidity forecast including of:
  - The total autonomous factors.
  - The daily reserve requirement objective.
  - The demand for excess reserves.

**44. The Banguat would gradually increase the published forecast horizon once forecast quality would have been vetted.** Forecast quality declines with the forecast horizon. Banguat could, thus, start with publishing forecast for the next day, and consider publishing them once forecast quality appears sufficient to be published, starting with the 1-week horizon.

**45. Several central banks publish liquidity data.** Those publication could be consulted on the web site of European Central Bank or Bank of Mexico (BOM),[5] for instance.

[5] Appendix II contains a brief description of Colombia's Central Bank and Bank of Mexico liquidity management and forecasting.

## Table 8. Liquidity Table

| | Flows | source | T (Actual) | T + 1 (Forecast) | T + 2 (Forecast) | T + 3 (Forecast) | T + (Forecast) |
|---|---|---|---|---|---|---|---|
| **I** | **Autonomus Factors (1. + 2. + 3. + 4.)** | **Sum** | **-140** | **-220** | **-350** | **-240** | **770** |
| 1. | Currency in Circulation | IMF forecast | 60 | -30 | -130 | -100 | 60 |
| 2. | Central Government Deposits | IMF forecast | -150 | -100 | -200 | -150 | 700 |
| 3. | FX Operations with monetary impact ( 3.a + 3. b) | Sum | -70 | -100 | 10 | 0 | 0 |
| 3. a | Central Bank's FX Purchases | IMF forecast | 0 | 0 | 10 | 0 | 0 |
| 3. b | Central Bank's FX Sales | IMF forecast | -70 | -100 | 0 | 0 | 0 |
| 4. | Other autonomus factors | IMF forecast | 20 | 10 | -30 | 10 | 10 |
| **II.** | **Maturity of previous operations** | **Banguat** | **5,000** | **4,260** | **3,740** | **3,390** | **3,175** |
| **III** | **Total flows (I. + II.)** | **Sum** | **4,860** | **4,040** | **3,390** | **3,150** | **3,945** |
| **IV.** | **Reserve Requirement (1.+ 2.)** | **Sum** | **600** | **300** | **0** | **-25** | **-70** |
| I. | Reserve Requirement Objective | IMF forecast | 100 | 200 | -50 | 75 | 80 |
| 2. | Reserve Requirement Fulfillment preference | IMF forecast | 500 | 100 | 50 | -100 | -150 |
| **V** | **Total Open Market Operations (III. - IV.)** | **Sum** | **4,260** | **3,740** | **3,390** | **3,175** | **4,015** |
| **VI** | **Deposit Facility Estimated** | **Banguat** | **0** | **0** | **0** | **0** | **0** |
| **VII.** | **Credit Facility Estimated** | **Banguat** | **0** | **0** | **0** | **0** | **0** |

## Appendix I. Statistical Methods Used in the Liquidity Forecasting Framework

1. **The time series models are normally forecast CiC and STA, which focus on modelling the trend and seasonality.** The MCMCO Liquidity Forecasting Framework include 4 types of time series models: the Naïve, Exponential Smoothing, ARIMA and TBATS.

2. **The Naïve model (random walk) is often used as the simplest forecast benchmark.** The Naïve forecast assumes that the time series has no structure, while at the same time requires no parameter estimation or any other modelling choices. The forecast is generated as:

$$\hat{y}_{t+h} = y_t,$$

Where $y_t$ is the observation at time $t$, $\hat{y}_{t+h}$ is the forecast for period $t + h$, and $h$ is the forecast horizon. The intuition behind the Naïve forecast is that all forecasted values are equal to the last observation, and therefore there is no additional information to model. Arguably, this is an inappropriate model to forecast liquidity, but it does make it a useful benchmark. More complex modelling approaches are often not transparent or intuitive enough in what they do. Therefore, at a minimum, they must outperform such a simple forecast. A helpful modification of the Naïve is its seasonal counterpart, where instead of repeating the last observation, the last seasonal period is repeated:

$$\hat{y}_{t+h} = y_{t-s+h},$$

Where $s$ is the seasonal period, corresponding to the number of days in the week (5 without the weekend).

3. **Each observation in a time series contains both structure and noise.** The structure makes up the part of the series that can be modelled and used to inform our forecasts. The noise part is inherently random and unforecastable. Let $y_i$ be an observation of a time series at period $i$, and:

$$y_i = \mu_i + \varepsilon_i,$$

Where $\mu_i$ denotes the structure of the time series and $\varepsilon_i$ the randomness. In forecasting, the main challenge is to identify a model that can separate the structure from noise, as well as to correctly characterize the patterns in the structure (e.g., slope, seasonality). If the forecasting model is appropriate for the data, the noise part should have no patterns and be random. Therefore, the noise can only be characterized in terms of the statistical distribution it follows. Usually, it is assumed to follow the normal distribution, and therefore $\varepsilon \sim N(0, \sigma^2)$. In other words, the noise is normally distributed with zero mean and standard deviation $\sigma$. A well-specified model should provide a function for $\mu_i$ as well as an estimated $\hat{\sigma}$. Note that neither $\mu_i$ nor $\varepsilon_i$ are observable, and therefore it is the task of the modeler to specify a forecasting model that clearly separates them from the observed $y_i$.

4. **Exponential smoothing models operate by modelling the time series as a collection of patterns, namely level, trend, and seasonality.** Usually, exponential smoothing (ETS) is framed within a state-space model, where each component of the time is a state, and together they produce the forecast $\hat{y}_i$, as:

$$\hat{y}_i = f(\hat{\mu}_i, \varepsilon_i)$$
$$\hat{\mu}_i = g(level_i, slope_i, season_i)$$

The functions $f(\cdot)$ and $g(\cdot)$ can be either additive, multiplicative, or have some mixed form. The figure below provides an example of the decomposition of a time series into separate components by exponential smoothing. Observe that the level, slope, and season components together can explain most of the time series, with any unexplained part attributed to the noise component. The level tracks the local mean of the time series, while the slope models how the level increases or decreases over time (e.g., a slope of +2 suggests an upward movement by two units per period). Finally, the season component models any periodic patterns in the data. Not all time series require all components to be modelled, as some may be absent.

In the fully additive case, the model becomes:

$$\hat{y}_i = \hat{\mu}_i + \varepsilon_i$$
$$\hat{\mu}_i = level_i + slope_i + season_i$$

Each of the states ($level_i$, $slope_i$, and $season_i$) is structured similarly. For example, the additive $level_i$ is:

$$level_i = level_{i-1} + \alpha e_{i-1},$$

Where α is a smoothing parameter between 0 and 1 and $e_{i-1}$ is the previous period error. Intuitively, this equation suggests that the current level estimate is updated by α times the last error. Given that the error is the difference between the actuals ($y_i$) and the forecast ($\hat{y}_i$) for the case of the exponential smoothing that has only an additive level, the model can be written in two alternative forms to help explain its function:

$$\hat{y}_i = \hat{\mu}_i + \varepsilon_i$$
$$\hat{\mu}_i = level_i$$
$$level_i = level_{i-1} + \alpha e_{i-1}$$

Or equivalently:

$$\hat{y}_i = \hat{\mu}_i + \varepsilon_i$$

$$\hat{\mu}_i = level_i$$
$$level_i = \alpha \cdot actuals_{i-1} + (1-\alpha)level_{i-1}$$

The second set of equations suggest that the smoothing parameter α decides by how much to update the previous level with the last observed actuals. Noting that $0 < \alpha < 1$, a percentage contribution interpretation becomes possible. For example, if $\alpha = 0.2$, the last estimated level is updated by 20 percent of the last observation. All other states operate similarly, requiring an additional parameter for each additional state, and a model may have any of these states on their own or together.

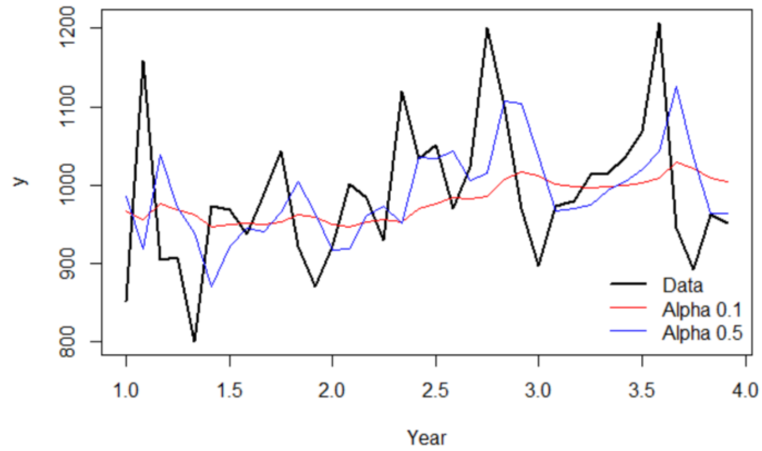
5. **A useful way to see how exponential smoothing operates is to consider the equations across time, which makes each component an exponentially weighted moving average.** For example, using $\alpha = 0.2$, the most current actual is weighted by 0.2, while the one before is weighted by $\alpha(1-0.2)^2$. The calculation becomes apparent if we replace (in the equations above) the $level_{i-1}$ with its respective state equation:

$$level_i = \alpha \cdot actuals_{i-1} + (1-\alpha)level_{i-1}$$
$$level_{i-1} = \alpha \cdot actuals_{i-2} + (1-\alpha)level_{i-2}$$

$$\rightarrow$$
$$level_i = \alpha \cdot actuals_{i-1} + (1-\alpha)(\alpha \cdot actuals_{i-2} + (1-\alpha)level_{i-2})$$

$$\rightarrow$$
$$level_i = \alpha \cdot actuals_{i-1} + \alpha \cdot actuals_{i-2} + (1-\alpha)level_{i-2} - \alpha^2 \cdot actuals_{i-2} - \alpha(1-\alpha)level_{i-2}$$
$$level_i = \alpha(1-\alpha)^0 \cdot actuals_{i-1} + \alpha(1-\alpha)actuals_{i-2} + (1-\alpha)^2 level_{i-2}$$

and so on. More generally the $j$th previous observation is weighted by $\alpha(1-\alpha)^{j-1}$. All weights will by construction be between 0 and 1, and sum up to 1, forming a weighted moving average. Therefore, each state in exponential smoothing models is a component of the time series (level, slope, or season) and achieves that by filtering the noise by using long averages. As the noise is randomly distributed, a sufficiently long average will tend to cancel out the positive and negative "errors," leaving the underlying structure. This is exemplified in the figure below, where the models for $\alpha = 0.1$ and $\alpha = 0.5$ are presented for a simulated time series (with a mean of 1,000) and additive normally distributed noise (with a standard deviation of 100). Observe that the model with $\alpha = 0.1$ is closer to the underlying mean, using a long average of historical values and therefore canceling out the noise. On the other hand, with $\alpha = 0.5$ the model is very reactive to noise, giving the wrong impression of additional fluctuations in the underlying time series structure (where all these fluctuations are due to the unforecastable noise). Naturally, in this case, a simulated time series was used with a known underlying data generating process. In practice, setting the appropriate parameters is a more challenging task as the underlying structure is unknown.




Source: IMF staff computations.

6. **The smoothing parameter for each component defines how reactive that component is to new information.** It is helpful to consider the extremes of 0 and 1. A 0-value smoothing parameter suggests that the component (e.g., level) is not updated at all by the observed data. On the other hand, a smoothing parameter of 1 suggests that the component is fully updated by the last observation and does not retain any underlying structure. More generally, low parameters can be interpreted as long-weighted moving averages that are resilient to increased noise and outliers. High parameters function oppositely, resulting in very reactive components. Although the parameters could be set manually for simple models (e.g., level-only exponential smoothing), numerical optimization is typically preferable. This is especially true for models with more parameters, which can automatically identify reasonable parameters for both simple and complex models.

7. **For numerical optimization, an appropriate loss function needs to be specified, typically based on quadratic errors.** To do this, the errors for the in-sample data that were used to fit the model are recorded. Quadratic errors, as summarized in the Mean Squared Error (MSE), track the mean of a time series. The numerical optimization provides the smoothing parameters—one corresponding to each state of the model—minimizes the number of errors.

8. **The appropriate exponential smoothing model form can be identified using a suitable information criterion, such as the Akaike Information Criterion (AIC).** The intuition behind such metrics is that they attempt to balance how well a model fits the data against the complexity of the model, as captured by its various parameters. A model without enough complexity—in the case of exponential smoothing, one without the appropriate states that capture the level, slope, and seasonality in a time series—will underfit the time series and provide poor forecasts. On the other hand, a model with superfluous complexity will overfit the data, which means that it will attempt to model the normally unforecastable noise and thus mistakenly model non-existing patterns in the

time series structure. In general, a more complex model (i.e., a model with more parameters) is more flexible to fit better to the in-sample data, and therefore potentially overfit. Overfit models can provide substantially inaccurate forecasts. A simplified view of the AIC is:

$$AIC = 2\sqrt{MSE} + 2k,$$

Where $k$ is the number of model parameters. For exponential smoothing. k is connected with the number of states/components in the model. The first half of the equation improves as the model fit becomes better, minimizing the errors between the in-sample observations and the model output. This typically correlates with the model having more parameters. The second half of the equation is minimized when the number of parameters is as small as possible, which typically happens when the model underfits, and therefore has larger in-sample errors. The model with the lowest AIC is preferable because it forces a balance between model fit and model complexity. This results in selecting models that can forecast well.

9. **To include regressors, the model can be augmented by adding them to the description of $\mu_t$ in the same fashion as with conventional regression modelling.** Additional details about ETS can be found in Hyndman et al. (2008)[1] and Ord, Fildes, and Kourentzes (2017).[2]

10. **The Autoregressive Integrated Moving Average (ARIMA) family of models is a flexible class of models used for time series forecasting in a wide range of settings.** In general, the ARIMA model is defined as:

$$(1 - \phi(B))(1 - B)^d y_t = (1 + \theta(B))\epsilon_t$$

Here $B$ is the backshift operator that lags a variable, i.e., $By_t = y_{t-1}$,$By_t = y_{t-2}$, etc. The order of differencing $d$ is typically equal to 1 (or in rare cases 2) for nonstationary series and 0 for stationary series. The term $\left(1 - \phi(B)\right) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$ is known as the autoregressive (AR) polynomial (or order $p$) and the term $\left(1 + \theta(B)\right) = 1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_p B^p$ is known as the moving (MA) polynomial (or order $q$). The term $\epsilon_t$ is a random "noise" or "innovation" term. The nomenclature ARIMA (p,d,q) is used to describe an ARIMA model. For example, an ARIMA model with $p = 2$, $d = 1$ and $q = 2$ would be referred to as an ARIMA (2,1,2) model.

[1] Hyndman, R., A. B. Koehler, J. K. Ord, and R. D. Snyder. 2008. *Forecasting with Exponential Smoothing: The State Space Approach*. Berlin: Springer Science and Business Media.

[2] Ord, K., R. Fildes, and N. Kourentzes. 2017. *Principle of Business Forecasting*, 2nd ed. New York: Wessex Press.

For all ARIMA models, the order of $\boldsymbol{p, d, q, P, D, and\ Q}$ must be made. The estimation is done using the stepwise algorithm of Hyndman and Kandakar (2008):[3]

i. Find $d$ using the KPSS (Kwiatkowski–Phillips–Schmidt–Shi) test.

ii. Estimating four initial models and choose the best.

iii. Expand the candidate model set by considering models that have $p$ or $q$ differing from the current best by 1.

iv. Iterate until no improvement is made.

The criterion for selection is the Akaike Information Criterion corrected for small sample size (AICc). The algorithm implemented in auto.arima function within the forecast package in the R software environment. The same algorithms can be modified and applied to seasonal ARIMA and seasonal ARIMA using the regression described below.

An important extension to ARIMA models is seasonal ARIMAs (SARIMA), which allows for the modelling of patterns that repeat themselves every $\boldsymbol{m}$ observations. In general, SARIMA take the form:

$$(1-\phi(B))(1-\Phi(B^m))(1-B)^d(1-B^m)^D y_t = (1+\theta(B))(1+\theta(B^m))\epsilon_t$$

Where $P$, $D$, and $Q$ are the orders of the seasonal AR component, seasonal differencing, and seasonal MA component. The nomenclature ARIMA(p,d,q)(P,D,Q)[m] is used to describe such models, for instance an ARIMA(1,0,0)(0,1,1)[5] model would be equivalent to

$$y_t = y_{t-5} + \phi(y_{t-1} - y_{t-6}) + \epsilon_t - \epsilon_{t-5}$$

Seasonal ARIMA models of this form are only capable of explicitly capturing one form of seasonality. Fortunately, the ARIMA model can easily incorporate covariates by extending its equation in the same manner as with conventional regression modelling. Additional details for ARIMA models can be found in Ord, Fildes, and Kourentzes (2017).

11. **Seasonality can be modelled using indicator variables.** This approach is particularly well suited when the length of the seasonal pattern is short and when the pattern is not necessarily smooth. For example, flexible day of week effects can be modelled using only four variables of the form:

[3] Hyndman, R. J., and Y. Khandakar. 2008. "Automatic Time Series Forecasting: The Forecast Package for R." *Journal of Statistical Software* 27 (3): 1-22.

$$D_t^{(Sun)} = \begin{cases} 1 \text{ if day t is a Sunday,} \\ 0 \text{ otherwise.} \end{cases}$$

Similar dummies can be defined for Mon, Tue, Wed, Thur. These indicators are then included in a vector of covariates $x'_t$ and the ARIMA model has the same specification as before, but with $y_t$ replaced by $y_t - x'_t\beta$. A similar modification occurs for ETS. A similar approach is used to encode holidays and special events. Structural breaks can be encoded using a continuous indicator:

$$\mathrm{D}_t = \begin{cases} 1 \text{ if t occurs after the structural break,} \\ 0 \text{ otherwise.} \end{cases}$$

12. **Daily time series can exhibit multiple seasonal cycles that must be accounted for in the modelling.** These include day in the week, day in the month, and day in the year, corresponding to different cyclicities in the data. This substantially complicates the creation of forecasts, as many models typically incorporate a single seasonal periodicity. Three elements are of interest in modelling multiple seasonalities: the length of the seasonal cycles, their encoding, and the efficiency of the latter, as we aim for parsimonious models. To resolve questions raised by the first element, one counts how many days are in each periodicity. For example, there are five days in the week (without weekends). However, day in the month seasonality is more challenging as months have a different number of days. To overcome this, quarterly seasonality is used, as a quarter contains a fixed number of weeks, and by extension days.

13. **The multiple seasonal cycles are encoded using trigonometric indicator variables.** Given the length of a season of $s$ periods, $s/2$ pairs of trigonometric variables are constructed, with $i = 1, \dots, s/2$:

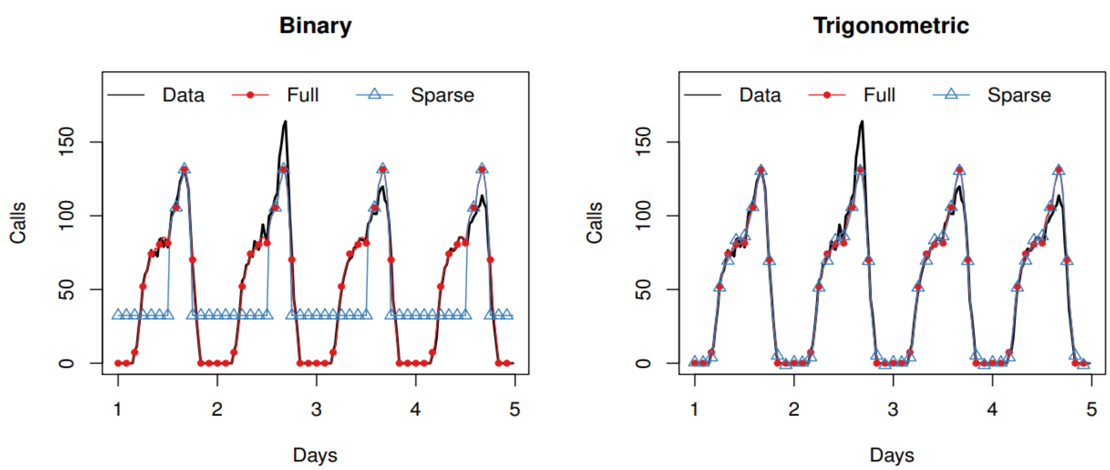
$$d_i = cos\left(\frac{2i\pi t}{s}\right),$$

$$d_{i+s/2} = sin\left(\frac{2i\pi t}{s}\right),$$

Where $t = 1, \dots, n$ (with $n$ being the sample size). When $s$ is an odd number, $s/2$ is rounded up to the closest integer. This encoding is mathematically equivalent to using $s$ binary indicator variables, in which case each binary indicator would encode the level of a particular day in the season. Note that in some cases one of the indicators will correspond to a constant, resulting in $s - 1$ informative indicator variables. One major advantage of the trigonometric representation is that it can encode complex seasonal effects, such as leap years. This is not possible with binary indicator encoding. For binary encoding, the number of trigonometric pairs is calculated as the floor of the true $s$. For example, for the day in the year we will have 260/2 cosines and 260/2 sines (five-day week years contain 260 days).

14. **To obtain parsimony, redundant seasonal indicators are filtered.** To do this, the time series trend is removed using a centered moving average (Ord, Fildes, and Kourentzes 2017). The centered moving average simply calculates the average of all values within a season that effectively models the trend in the time series. This is subtracted from the data, and the residuals are then modelled with different trigonometric indicator variables as explanatory variables. This is done using a regression model. However, they eliminate less informative inputs and help obtain a sparse representation, a lasso regression is used. Lasso regression is tasked to find a good compromise between how well the model fits the data and its complexity as measured by the number of parameters it has. The idea is that models with more parameters (and therefore input variables) are better able to model the observations, but can potentially overfit, capturing the randomness in the time series instead of just the structure. More details about the lasso regression can be found at Ord, Fildes, and Kourentzes (2017) and Kourentzes and Sagaert (2018).[4]

15. **An advantage of trigonometric indicator variables is that they provide an efficient sparse approximation of seasonal patterns.** The figure below exemplifies this. Using all indicators, binary and trigonometric variables (for integer *s*) provide the same output. However, when terms are eliminated, binary encoding omits all seasonal information for that period, while the trigonometric encoding merely provides a smoother approximation of the seasonal profile.




Source: IMF staff computations.

16. **The TBATS model incorporates many of the features of the models already introduced.** With TBATS, seasonality and trend are handled via exponential smoothing (using trigonometric terms for the former), a Box-Cox transformation is used, and ARIMA innovations are incorporated. This allows seasonality to change over time. A particularly attractive feature of the TBATS model is its ability to handle multiple

[4] Kourentzes, N., and Y. R. Sagaert. 2018. "Incorporating Leading Indicators into Sales Forecasts." *Foresight: The International Journal of Applied Forecasting* 48: 24-40.

calendars. Additional details about the TBATS model can be found in de Livera, Hyndman, and Snyder (2011).[5]

17. **Volatility models are appropriate for forecasting series with high volatility.** Normally, these models will be applied to forecast Net Foreign Assets. However, for this mission, times series models are more suitable for the NFA series at the Banguat. Three classes of models are fitted.

18. **The most popular family of conditional volatility models is the GARCH model.** The variance is modelled as

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \beta_i \, \sigma_{t-i}^2 + \sum_{i=1}^{p} \alpha_i \, e_{t-i}^2$$

The specification of the exponential GARCH model (eGARCH) is given by

$$\log\sigma_t^2 = \omega + \sum_{i=1}^{p} \beta_i \log\sigma_{t-i}^2 + \sum_{i=1}^{q} \alpha_i \, g(\epsilon_{t-i}).$$

Where $g(\epsilon_t) = \theta\epsilon_t + \lambda\big(|\epsilon_t| - E(|\epsilon_t|)\big)$. An advantage of this specification is its asymmetry since the sign and magnitude of innovations have different effects on the variance.

The GJR (Glosten-Jagannathan-Runkle)-GARCH specification is given by

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

Where $I_{t-1} = 0$ if $\epsilon_{t-1} \geq 0$ and $I_{t-1} = 1$ if $\epsilon_{t-1} < 0$. Like eGARCH, this specification allows for asymmetric effects.

19. **The generated forecasts (including prediction intervals) for all autonomous factors and NL can be reconciled together in a combined NL forecast.** The net liquidity injection (net foreign assets, currency in circulation, and state account balance) is the main quantity of interest. One approach would be to simply add up the forecasts of the autonomous factors in a bottom-up fashion, while a second approach would be to develop a forecasting model for the total of the autonomous factors. Alternatively, forecasts can be produced for each autonomous factor and the total. An advantage of this approach is that it hedges against model misspecification in the forecasting of the total if the

[5] De Livera, A. M., R. J. Hyndman, and R. D. Snyder. 2011. "Forecasting Time Series with Complex Seasonal Patterns Using Exponential Smoothing." *Journal of the American Statistical Association* 106 (496): 1513-1527.

misspecified features are captured in the forecasts of the individual autonomous factors. It also hedges against misspecification in the bottom level (due to noise) by forecasting the smoother total series. The downside of this approach is that the forecasts are no longer guaranteed to add up correctly.

Let the vector of four points forecasts that do not add up according to the hierarchical structure be given by $\hat{y}$. Let the matrix

$$S = \begin{pmatrix} 1 & 1 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

be the summing matrix. By construction, reconciled forecasts that are guaranteed to add up correctly can be found via:

$$\tilde{y} = S(S'S)^{-1}S'\hat{y}.$$

This approach is referred to as OLS reconciliation due to its resemblance with the matrix in Ordinary Least Squares regressions that project data onto fitted values.

20. **The MinT method is an even better approach because it exploits the correlation between forecast errors.** Forecasts that are guaranteed to add up correctly are found as $\tilde{y} = S(S'\Sigma^{-1}S)^{-1}S'\Sigma^{-1}\hat{y}$. The matrix $\Sigma$ is the covariance matrix of one-step-ahead forecasting errors. More details about the MinT method can be found in Wickramasuriya, Athanasopoulos, and Hyndman (2019).[6]

[6] Wickramasuriya, S. L., G. Athanasopoulos, and R. J. Hyndman. 2019. "Optimal Forecast Reconciliation for Hierarchical and Grouped Time Series through Trace Minimization." *Journal of the American Statistical Association* 114 (526): 804-819.

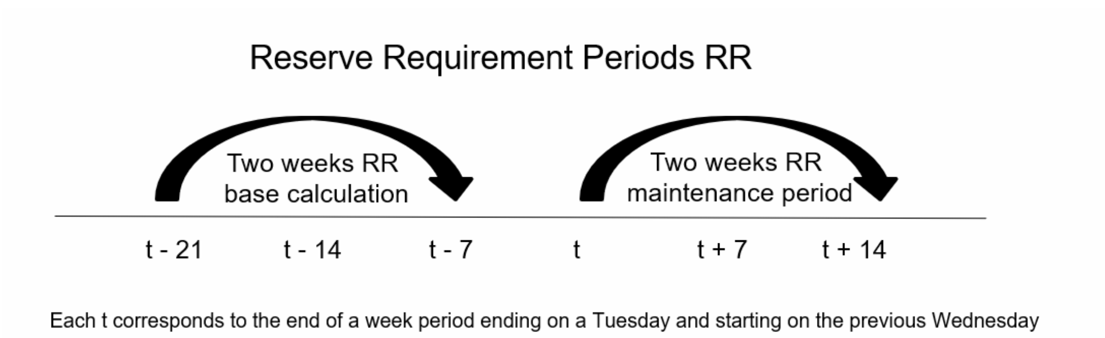
## Appendix II. International Practices with Liquidity Management

### Colombia

1. **Colombia's Central Bank (CCB) has had an IT regime since 1999.** To implement its monetary policy, CCB targets the interest rate as an operational target. The Monetary Policy Rate (MPR) currently stands at 13.25 percent. To steer the overnight market rate (IBR: Indicador Bancario de Referencia) towards the MPR, the CCB conducts temporary and permanent OMO calibrated on a 12-month liquidity forecast.

2. **The CCB has a net creditor position in the money market, mainly from the reserve requirement (RR).** There is an 11 percent requirement for current and saving deposits and 4.5 percent for term deposits up to 18 months. The base is calculated biweekly, starting on a Wednesday, and ending on the second Tuesday afterward. The maintenance period is biweekly, starting the second Wednesday after the base period ends (Figure 1). There is a full averaging allowance, and the RR can be fulfilled with unremunerated deposits at the CCB and vault cash.

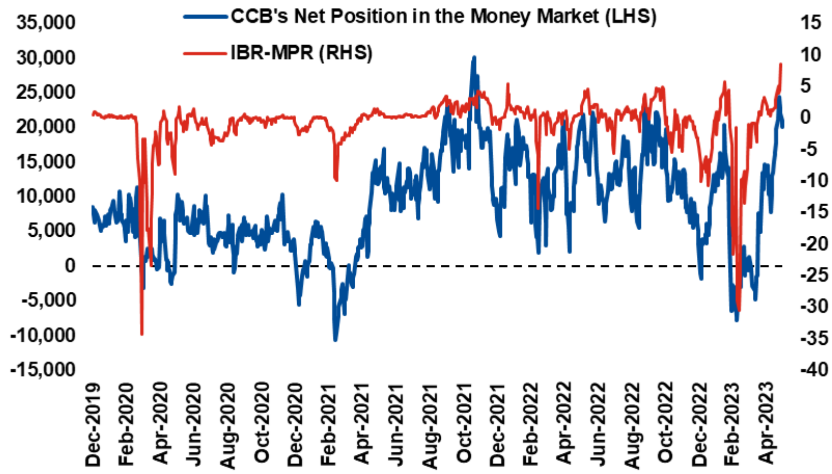
**Figure 1. Colombia Reserve Requirement Base and Fulfillment Periods**




Source: Colombia's Central Bank.

3. **To better steer the IBR toward the MPR, the CCB aims to maintain a creditor position in the money market when daily OMOs provide liquidity (Figure 2).** Liquidity shortages over a certain threshold push the IBR upwards. Conversely, market rates exhibit downward pressure with excess liquidity. Additionally, CCB avoids misleading the market with significant changes in the daily auctioned amount.

**Figure 2. Colombia's Central Bank Net Position in the Money Market and Market Rate Deviation from Monetary Policy Rate**




Source: Colombia's Central Bank.

**4. The Monetary and FX Implementation Committee (CIMC) authorizes the OMOs' details (types, amounts, timing).** The CCB Board and a Ministry of Finance representative integrate the CIMC. The CIMC meets monthly and authorizes daily average temporary (short-term) OMOs for the following four weeks. The CIMC allows the Operational Intervention Committee (COI) a margin to adjust the daily average to accommodate flows. The CIMC also approves OMOs with a permanent impact on liquidity.

**5. The CCB provides liquidity daily through short-term repo auctions.** The auctioned amounts are announced (Table 1) at the end of the previous sessions and are fixed for four terms (30, 14, and 7 days, and overnight). The first auction is the 30-day term. The unallocated amount is auctioned in the 14-day term, then for the 7-day term, with the remaining left for the overnight. There is a single price allotment with a minimum of the MPR as the minimum acceptable bidding rate.

**Table 1. Colombia's Central Bank Daily OMO Announcement**

BANCO DE LA REPUBLICA COLOMBIA

CONVOCATORIA DE LAS SUBASTAS PARA EL DÍA (*)
30 de mayo de 2023

OPERACIONES MONETARIAS

TRANSITORIAS DE EXPANSIÓN

| Tipo de Operación | Plazo | Cupo ($ miles de millones) | Tasa Efectiva Mínima % (con el márgen mínimo) (**) | Tasa Efectiva Máxima % (con el márgen máximo) (**) | Hora desde | Hora Hasta |
|---|---|---|---|---|---|---|
| Operaciones de Expansión - Repos Activos | | | | | | |
| Subasta (1) | 30 días | 21.200,00 | 13,25 | 14,25 | 09:00 AM | 09:15 AM |
| Subasta (1) | 14 días | (+) | 13,25 | 14,25 | 10:15 AM | 10:30 AM |
| Subasta (1) | 7 días | (+) | 13,25 | 14,25 | 11:15 AM | 11:30 AM |
| Subasta (1) | 1 día | (+) | 13,25 | 14,25 | 01:00 PM | 01:15 PM |
| Ventanilla (1) | 1 día | Ilimitado | 14,25 | 14,25 | 04:15 PM | 04:30 PM |

Source: Colombia's Central Bank.

6. **Standing facilities accommodate liquidity at the end of the day.** The overnight repo facility provides liquidity at the MPR + 100 bps. Banks can also place liquidity on the overnight deposit facility that pays the MRR - 100 bps.

7. **To withdraw transitory excess liquidity, the CCB auctions short-term deposits called DRNCE (Remunerated Deposits Outside the Reserve Requirement).** Deposits from these operations do not count towards the RR fulfillment and pay the allotted interest rate. The usual terms are 7 and 14 days, with maximum accepted interest rates equivalent to the MPR minus four basis points (bps) and three bps.

8. **The CCB conducts OMOs to offset permanent liquidity when the forecast indicates persistent deviations from the desired level for the daily auction.** When a forecasted permanent liquidity shortage is above a threshold, the CCB buys government securities (TES) to inject liquidity permanently. Alternatively, if the forecast indicates a permanent liquidity excess, the CCB sells TES from its portfolio to withdraw the liquidity permanently.

9. **The CIMC decides OMOs based liquidity forecasts with a 12-month horizon.** The CCB updates and presents its forecast to the CIMC monthly. The CIMC then determines the temporary OMOs' monthly average amount and permanent OMOs when appropriate. To produce this exercise, the CCB uses macroeconomic and statistical models to forecast the CiC. The government agreed to place its excess liquidity balances in term deposits at an account in the CCB. The CCB forecasts the income and outflows from the government account (Single Treasury Account (STA)) and receives government cash-flow projections. Debt flows (new issuance, interest payments, and maturity) in the STA are incorporated in the forecast. Finally, the CCB incorporates FX operations flow when it has an intervention program, like the 2012-2014 reserves accumulation through put options**.**

10. **The CCB does a forecast with a demand-supply approach for the RR period.** The CCB obtains a projection of the NL, subtracting the expected liquidity demand from the expected liquidity supply.

11. **For the regulatory demand for liquidity, the CCB forecasts the monetary base.** The CCB uses time series models conditioned to seasonal factors. The CCB estimates each institution's RR with the information on the deposits for the base period applying the relevant RR coefficient (0.11 or 0.45). Then, it aggregates individual RR forecasts to project the system's demand. Additionally, it incorporates an estimate of the precautionary level of reserves based on the historical over-compliance for the RR.

12. **For the liquidity supply, the CCB forecasts for the RR period.** The CCB includes its approved permanent monetary flows (government securities purchases and sales) and FX operations in this exercise. The government 's projected cash flow is also incorporated. The CCB net income statement flows that affect liquidity (interest payments/collections on monetary policy operations, payroll, operative expenses, among others). Finally, previous OMOs' maturity is incorporated into the forecast to project the liquidity before new OMOs.

**13.** The CCB does not publish either forecast but **announces the daily OMO amount for the following day, close to the average approved amount.** The calibration incorporates data points collected from OMOs 'market participants. The also constantly communicate with the government about the near-term expected flows on the STA.

### Mexico

**14. Bank of Mexico (BOM) formally adopted an IT regime in 2001.** In its implementation, it transitioned from signaling its monetary policy stance with a quantitative target for the banks' aggregated balances in their current account at the central bank to an interest rate target in January 2008. The quantitative target evolved from an accumulated target for 28 days (1995–2003) to a daily target (2003–2008). In either case, the quantitative target determined which part of liquidity would be channeled through OMOs and which part would be provided with an aggregated overdraft ("corto") or with positive balances ("largo") in the banks' current account. Regardless of the operational target, BOM uses liquidity forecast to calibrate its OMOs and manage short- and medium-term liquidity.

**15. Current BOM's monetary policy instruments and liquidity management are designed to steer the market's overnight interest rate towards the monetary policy target (currently 11.25 percent).** BOM follows an active sterilization strategy withdrawing excess liquidity not through standing facilities, but through OMOs, both in the short-term and in the medium to long-term. To calibrate each type of operation, BOM forecasts liquidity for the corresponding period.

**16. On the one-day horizon, BOM aims for neutral liquidity allotment.** As there is no reserve requirement, neutral liquidity implies an aggregate zero balance of the banks' accounts. Positive balances are not remunerated, and overdrafts are charged twice the market's overnight rate. Daily operations are calibrated based on a one-day forecast to offset the expected daily liquidity movement. BOM auctions a predetermined amount, with banks bidding for the interest rate, and there is a multiple price allotment. BOM injects liquidity with collateralized credit operations (overnight up to an average of 30 days). Liquidity-injecting operations have the policy rate as a minimum as the accepted bid rate. For liquidity absorption, BOM auctions overnight deposits with the policy rate as the maximum acceptance rate.

**17. Due to institutional arrangements, BOM has a high degree of certainty about each day's autonomous factors at the session's opening.** Foreign exchange (FX) operations affecting liquidity are settled on a T+2 basis. Regarding government flows, the BOM law requires a one-day preannouncement for credits and debits on the Sigle Treasury Account (STA). Even though the CiC changes are unknown, money demand's high seasonality makes it easy to predict. Nevertheless, BOM conducts a fine-tuning auction before the closure of the payments system to address any forecast error. As most liquidity operations are registered in the central bank operative systems at the session closing time, an in-house developed system expedites the daily forecast calculation. Before the morning auctions (around 7:30 a.m.), BOM publishes on its website daily liquidity forecast,[1] including the expected daily liquidity movement and the day's net OMOs amount to achieve a balance (Table 2).

**Table 2. Bank of Mexico's Intervention in the Money Market Announcement**

**Amounts in millions of pesos**
**May 30, 2023**

| Concept | Amount (*) |
|---|---|
| Expected change in the total balance of the credit institutions' current accounts on (30/05/23) resulting from the maturity of previous operations, Federal Government transactions and currency and coins' withdrawals or deposits. | 89,342 |
| Expected change in the total balance of the credit institutions' current accounts due to the total intervention of Banco de Mexico in the money market on (30/05/23) | -93,646 |

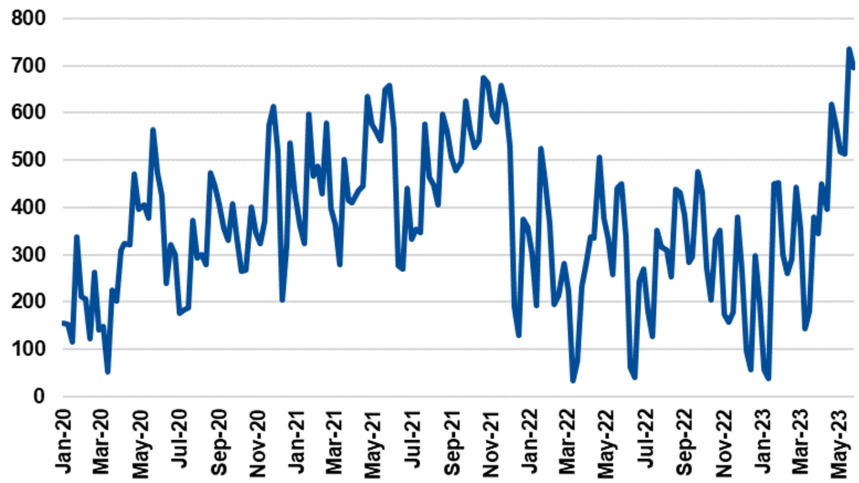
Source: Bank of Mexico.

**18. BOM pre-sterilizes excess liquidity for the medium horizon to achieve a net creditor position in the money market (Figure 3).** Banks must participate in BOM's liquidity-providing OMOs if the system has a short-term liquidity shortage. Therefore, OMOs can still steer market rates toward the target as they set the price of liquidity. Conversely, banks do not need to participate in a morning deposit-taking OMOs if the system has a short-term liquidity excess and they prefer to keep excess liquidity during the day, pushing the interbank interest rates downwards.

**19. Quarterly, BOM decides on and announces its medium-term sterilization policy.** Based on a liquidity forecast for up to two calendar years, BOM calibrates its medium to long-term liquidity operations to achieve a short-term creditor position. BOM starts with an annual forecast for each of the liquidity drivers. The annual forecast is broken down into monthly and daily forecasts using each factor's detailed information (seasonality, rules, predetermined arrangement). The monthly projections are constantly updated with the latest daily information.

[1] Few central banks publish short-term liquidity forecast or liquidity conditions. For example, the European Central Bank publishes every Monday the daily average aggregated autonomous factors estimates for the current and last week. The National Bank of North Macedonia publishes the daily aggregated flow of the autonomous factors. The Central Bank of Chile publishes the day's initial conditions of the reserves' accounts.

**Figure 3. Bank of Mexico's Net Position in the Money Market Announcement**
**MXN Billions**




Note: Balances of short-term liquidity-providing OMOs—short-term liquidity-absorbing OMOs.
Source: Bank of Mexico.

**20. BOM forecasts the autonomous factors individually:**

- **CiC:** Starting with an annual flow forecasted with econometric models considering expected values for macroeconomic variables (GDP growth, inflation, interest rates). The annual flow is distributed into monthly and daily flows using statistical models considering the money demand's seasonality across the year and the week and considering extraordinary events.

- **STA:** The annual flows are forecasted by category, income, expenses, and debt, linked to the Congress's approved figures. After Congress approves the budget, the Ministry of Finances publishes an expected monthly calendar for each category. BOM also relies on historical information to do the monthly distribution. The daily distribution is done based on historical data and operational rules (i.e., income taxes are due after the seventeen each month). BOM is in constant communication with the national treasury about its expected flows.

- **Net Foreign Assets (NFA).** BOM's FX interventions are usually carried on under pre-announced programs with known rules to accumulate reserves or sell dollars in the market. When such a program is in place, an expected annual flow is incorporated in the liquidity forecasts; Monthly and daily breakdowns can also be incorporated according to the rules, FX historical volatility, among others. Historically Pemex's, the state's own oil company, sales to BOM was the main source of NFA accumulation. Pemex's domestic currency needs are forecasted with estimations for the oil prices and production volume, along with the tax rate applied.