Introduction

Central banks forecast liquidity to implement monetary policy. “Liquidity” is defined as on-call account of monetary counterparties (banks) at the central bank, also call “reserves.” Liquidity forecasts are an important input to calibrate monetary operations, the objective of which is to align monetary conditions with the announced monetary policy stance. This applies to most monetary policy frameworks and is particularly important when the operational target is short-term interest rates.

Statistical liquidity forecast consists in modelling the behaviors of the central bank non-monetary counterparties. Those counterparties are not supervised by the central bank and do not have access to the monetary policy operations of the central bank. Central banks can collect information directly from these counterparties. This is the non-statistical component of the liquidity forecast also called “institutional arrangements.” However, central banks also use time-series models to forecast the behaviors of those counterparties.

We focus on modeling the behaviors of three nonmonetary counterparties that can have an influence on liquidity conditions. First, the Government could have an impact on liquidity via the transfers between its account at the central bank and those of the banks due to public expenditures and collection of revenues. Second, the public influences liquidity by demanding banknotes and coins which are issued against banks’ reserves. Third, if the exchange rate is fixed and capital transactions allowed, a broad set of resident and non-resident counterparties could possibly influence liquidity via FX purchases and sales from and to the central bank. The items in the central bank balance sheet under the control of its nonmonetary counterparties are called “autonomous liquidity factors.”

Currency in Circulation follows distinct seasonal patterns due to calendar effects related to the work week as well as public and religious holidays. These effects make it possible to develop point forecasting models for the level of these factors. For this reason, we propose forecasting currency in circulation using models […]. Forecasting currency in circulation involved specific challenges such as treating mobile holiday (e.g., Ramadan or Chinese New Year) and structural break due to external shocks such as the COVID-19 pandemic.

On the other hand, net foreign assets do not display seasonal patterns, but do exhibit conditional volatility characteristic of financial returns data. For this reason, we propose forecasting net foreign assets, using models for conditional heteroskedasticity.

Finally, the state treasury account follows seasonal patterns for some of its determinants but also exhibit conditional volatility characteristics for others. Some items that determined the Treasury account have clear seasonal pattern such as the payment of salaries and pensions as well as the collection of taxes. On the other hand, capital expenditures and tax revenues usually do not follow regular patterns.

In addition to developing forecasting models for three individual autonomous factors, we also consider forecast combination through taking an equally weighted combination either of all forecasts or of a trimmed set of models. The forecast quality is tested based on predictive performance metrics reflecting accuracy, bias, and reliability, which will be explained in this paper. Models are, then, ranked based on their predictive performance to combine them.

Finally, we also apply the method of forecast reconciliation to the liquidity forecasting problem. This involves, first, generating forecasts for the aggregate (or net) liquidity due to net foreign assets, currency in circulation and state account balance, leading to four forecasts (one for each autonomous factor and one of the aggregates). In general, these four forecasts will not be coherent, i.e., the aggregate forecast will not be equal to the aggregate of the three individual factors. Reconciliation adjusts the four forecasts to ensure coherence. This method has been shown to improve forecasts in several contexts and is applied to liquidity forecasting for the first time here.

The remainder of the paper is summarized as follows. Section 2 introduces the data on the autonomous factors, highlighting the main features of each factor. Section 3 introduces the models and methods used both for forecasting and forecast reconciliation. Section 4 presents the results of extensive forecast evaluation and Section 7 concludes .

Data

There are several sources of liquidity in a banking system, those that are not under the control of a central bank and therefore represent sources of uncertainty. These are known as autonomous factors. The autonomous factors for which forecasting models are built in this study are currency in circulation, the state account balance, and net foreign assets. Our data were obtained from the Central Bank of the United Arab Emirates (UAE) and are collected at a daily frequency. We now discuss each of the autonomous factors in turn.

2.1 Currency in Circulation

Currency in Circulation (CIC) is the quantity of money issued by monetary authorities net of currency that has been removed from the money supply.

Currency in circulation consists of the banknotes and coins (maybe, one day, central bank digital currency) issued by the central bank and in the hand of the public. It excludes banknotes and coins in bank vaults or returned to the central bank.

RF to potentially expand on CIC data, how collected, measured etc. [I think it is enough]

Currency in Circulation tends to be influenced by calendar effects. In many countries, salaries are paid at the same time each week (or month) leading to a smooth weekly (or monthly pattern) whereby CIC increases after the pay date and slowly declines until just before the next pay date [Footnote : The relationship between the payment of salaries and the withdrawal of banknotes by the public is changing with the development of alternative payment methods]. The weekly pattern in CIC can also be influenced by a tendency of individuals to withdraw cash before the weekend. Public holidays can have a major impact on CIC. It is typical for CIC to increase in the buildup to a public holiday and, then, decline afterwards. These systematic features make it possible to develop models for forecasting CIC at horizons of 1 to 14 days that outperform naive forecasting techniques, [such as a random walk].

Figure 1 highlights CIC data for the UAE. Days with missing data include weekends (Friday and Saturday in the UAE) and major holidays. Data on these days are linearly interpolated. Other autonomous factors which may exhibit a different pattern of missingness (for instance data may be available on Fridays for net foreign assets since foreign exchange markets trade on Friday), are interpolated in a similar fashion. As such, interpolating rather than ignoring missing data guarantees a balanced panel of data, which becomes important for reconciliation steps later on. The daily pattern of CIC is apparent from the figure as are spikes around major holidays, in particular Eid al Fitr and Eid al Adha. In early 2020, there is a permanent level shift in CIC associated with measures at the onset of Covid to inject cash into the monetary system.

2.2 State Account Balance

State Account Balance (SAB) is the quantity of money held by the government in its account with the Central Bank. For an efficient resource management and to reduce counterparty risk, Governments often keep their money on a single account at the central bank. One implication of centralizing the government accounts at the central bank instead of leaving them with commercial banks is that changes in the Government account will have an impact on banks’ reserves at the central bank. In some cases, central banks finance the government in which case the net (central bank) claim on the government will need to be forecasted. However, the more interesting component of the net claim to forecast from a statistical point of view is the Government account with the central bank.

RF to potentially expand on SAB data, how collected, measured etc.

State Account Balance also tends to be influenced by calendar effects. Salaries and pensions are expected to be paid on a precise date, which will result in a decrease in the government account at the central bank and an equivalent increase of banks accounts at the central bank. Corporate and personal taxes are due for collection towards the end of the week, month, quarter of financial year which increase the government account and reduce the banks’ account at these times. Models accounting for these features can also outperform naive approaches in forecasting SAB.

Other budget items do not follow a regular schedule. Expenditures that are the most under the control of the government such as capital expenditures and capital revenues do not follow a preestablished schedule and could represent lumpy amount with large liquidity impact.

Figure 2 highlights SAB data for the UAE. Apart from spikes associated with seasonal factors, there is also a large one off spike in early 2019 associate with the sale of government assets (capital revenue [?]). In our modelling, such transitory effects can be accounted for via the use of dummy variables. When asset sales are scheduled to occur at some time in the future, this may motivate judgmental adjustments to model forecasts.

2.3 Net Foreign Assets

Net Foreign Assets (NFA) is the total foreign assets held by a central bank, net of their foreign liabilities. In a floating exchange rate, this factor is largely under the control of the central bank and, thus, either easy or not necessary to forecast. On the other hand, the central bank commits to buy and sell FX at fixed rate on the demand of any resident and non-resident agents, via authorized dealers (banks), in a fixed exchange rate arrangement without capital controls as in the UAE. In that context, forecasting NFA become a more challenging statistical exercise.

RF to potentially expand on NFA data, how collected, measured etc.

Compared to the two previous autonomous factors, NFA are not influenced by calendar effects and when forecasting the mean, it is often difficult to outperform a naive forecast of last observed value of NFA. However, the daily changes in NFA do resemble financial returns in that they often exhibit conditional heteroskedasticity and volatility clustering. This makes the GARCH family of models good candidates for forecasting the entire distribution of NFA data, which can be an important input into the calibration of liquidity buffers such as the reserve requirement to stabilize money market rate and reduce the liquidity premium.

Figure 3 shows both the level (top panel) and change (bottom panel) in net foreign assets. The bottom panel in particular shows evidence of conditional heteroskedasticity motivating the use of GARCH models and their extensions.

4.6 Model Averaging

It is well established in the forecasting literature that combining forecasts from different classes of models can improve forecast accuracy (Timmermann, 2006). While there is a long literature on finding optimal weights, even weights tend to perform more robustly since there is no additional uncertainty introduced by having to estimate combination weights (Smith and Wallis, 2009). As well as considering an equally weighted combination of all classes of models outlined above, we also consider trimming models by only taking the best K models. For this study we consider K = 2.