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Forecasting Currency in Circulation for the Maldives

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Abstract

Currency in circulation (CIC) is the amount of cash held by the public and the banking sector. The importance of forecasting CIC stems from central banks' remit to manage the operational target in order to achieve price stability through the management of the banking sector's liquidity. Given the autonomous nature of CIC, daily movements can greatly impact the liquidity of the banking system that is beyond the control of the central bank and therefore, requires strenuous effort to produce short-term forecasts. The main aim of this paper is to produce a short-term forecasting model CIC in the Maldives which can be used to assess the short-term impact of Rufiyaa liquidity. Various models have been used in the literature to forecast CIC, ranging from structural models to models based on transactional and portfolio demand for cash. However, autoregressive integrated moving average (ARIMA) models are often used by central banks for its relative accuracy in shortterm forecasting.

JEL classification: E41, E42, E58, E47, C22

Keywords: Currency in circulation, ARIMA, Time series forecasting, Maldives

Introduction

Central banks around the world are responsible for the formulation and implementation of monetary policy with the main objective of maintaining price stability within the economy. To pursue this objective, central banks need reliable forecasts of the banking sector's liquidity. This liquidity is partly affected by factors that are directly under the control of the central banks. However, there are autonomous factors, such as net foreign assets, CIC and net government position, which are largely beyond the control of the central bank. For instance, central banks' influence on both government deposits and excess reserves held by commercial banks is limited and large changes in these factors will increase fluctuations in the liquidity of the banking system.

Perhaps, the most challenging autonomous factor to forecast is the CIC, given its high volatility and direct link to the non-bank public sector. CIC as highlighted by Munawar (2014) is one of the main indicators used to measure the amount of cash in the economy, which is the total amount of notes held by the public (consumers

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and businesses) and the banking system. He further outlines the importance of understanding the short-term and long-term factors which affect the movements of CIC in order to effectively forecast liquidity when conducting weekly open market operations.[1]

This paper aims to formulate a suitable model that will improve the current CIC forecasting framework used by MMA. In general, forecasting with high-frequency data is susceptible to high volatility. Therefore, this paper will attempt to find the most suitable model that could reduce the forecasting error and provide reliable estimates for CIC. The rest of this paper is organized as follows. Section 2 briefly examines the econometric models used in forecasting CIC in other countries. Section 3 describes the behavior and patterns observed in the CIC of the Maldives. Section 4 lays out the model specifications for different possible variations to model CIC, while section 5 presents and analyses the estimation results. Finally, section 6 presents the conclusion based on the estimation result and forecast evaluation.

Theoretical Background and Literature

Forecasting CIC has been at the core of every central bank's monetary policy framework given its impact on the liquidity position of the banking system. Public's demand for money dictates the deviation in CIC and this underlying theory has been used as a basis for modelling the movements in CIC. While econometric analyses are important in understanding the nature of CIC and its main determinants, central banks often use univariate time series models to carry out CIC forecasts. The forecasting nature of liquidity necessitates producing forecasts for a short-term horizon, and univariate models such as autoregressive integrated moving average (ARIMA) and structural time series (STS) models perform better at high-frequency data, and in general, provide better out-of-sample forecasts compared to available alternative models. The literature on CIC is diverse in terms of the approach and requirement of the study being carried out.

Khatat (2018) identifies two types of CIC models; a first-generation derived from the theory of transaction demand for money and a second-generation aimed at producing daily forecasts of CIC. A vector autoregression (VAR) model was used to capture the dynamic link between interest rates and the demand for cash and an ARIMA model was used to forecast daily CIC for five countries. Similarly, Dheerasinghe (2006), Battacharya and Joshi (2001) classifies the models in the literature into two main categories; models based on demand theory and univariate time series, respectively. The former proposes an alternative approach in modelling high-frequency data by decomposing the trend, seasonal and cyclical components for Sri Lanka; while the latter proposes an alternative approach of modelling the growth of CIC, by incorporating the day-of-the-month effect to existing models in the literature for India.

The first-generation models as mentioned earlier are based on transaction and portfolio demand for money where level of money is determined by the price level, level of real output and the opportunity cost of holding cash. Cassino et al (1997) uses the money demand function $M_t^d = f(P_t, Y_t, R_t)$ to derive their final estimation equation $m_t = \alpha + \beta_1 p_t + \beta_2 y_t + \beta_3 R_t$ by using a log-linear transformation. They use an error correction

[1] Even though the open market operations have been temporarily suspended, MMA continues to assess the supply of liquidity in the banking system

representation to estimate the model and use it for in and out-of-sample forecasting to compare it with its univariate counterpart. The results for in-sample forecasting period show that the error correction model (ECM) outperformed the ARIMA models. This is because for a long-term horizon, structural relationships in ECM are expected to influence the data. However, for the out-of-sample forecasting period, all the ARIMA models used in the analysis outperforms the ECM, suggesting that the estimated parameters in the demand function are strongly influenced by the observations in this period. They argue that the weak performance of ECM can be attributed to the omission of innovations in payments technology that is not captured in the money demand function. This is also supported by Arrau et al. (1995) as they highlight the persistent over prediction, implausible parameter estimates and highly autocorrelated errors of the traditional specifications. The paper argues that some of the above mentioned issues stem from the failure to account for the impact of financial innovation and attempts to estimate the money demand for various developing economies using several proxies for the innovation process.

The second-generation models which aim to provide short-term forecasts for CIC using high-frequency data have been heavily analyzed and the implications thoroughly discussed in the literature. Dheerasinghe (2006) provides a detailed account of the difficulty in using high-frequency data for forecasting purposes. Firstly, the intra-month and intra-week variations in CIC may change from week-to-week and month-to-month. The author gives the example of Sinhala/Tamil New Year which falls in the first two weeks of April and therefore, CIC will be vastly different within this period compared to the corresponding weeks of any other month. Furthermore, modelling the effects of a particular day is difficult because of holidays and variations in lag effects. This issue is most prominent in analysis of daily or weekly data series. For instance, a central bank uses weekly data to analyse the variations in CIC and for an Islamic country it is understood that CIC will increase during and week prior to Eid holidays. Univariate time series models fail to capture the effects of one or two days if a weekly model is used (Dheerasinghe, 2006). The author also discusses the presence of seasonality with weekly, monthly and annual patterns which can be cumbersome to model. Given these constraints, the paper attempts to identify the short-term variation in CIC for Sri Lanka using a sample that covers the period 1 January 2000 to 31 August 2005. The results indicate a clear seasonality around April and December due to Sinhala/Tamil New Year and Christmas respectively. In addition, the number of special holidays in a given month affects CIC significantly and having a general election also affects CIC in Sri Lanka.

While the use of Gregorian calendar is universal, most Islamic countries arrange their economic, social and religious celebrations according to Islamic calendar and Gregorian calendar combined. This makes modelling CIC variation difficult for Islamic countries, especially around Islamic holidays, as it falls on different days in the Gregorian calendar. However, Balli and Elsamadisy (2012) develops a CIC model for the state of Qatar by incorporating intra-weekly cycles, monthly cycles, intra-monthly effects, holidays and major outliers in the model. Some of the holidays accounted for in the model includes, Ramadan, Eid al-Adha, Eid al-Fitr and Thanksgiving Day. By adopting the Box-Jenkins methodology and the seasonal ARIMA approach, they find that, in comparison to linear methods, seasonal ARIMA provides better estimates for short-term forecasts.

In forecasting daily CIC for Brazil, Kazakhstan, Morocco, New Zealand and Sudan, Khatat (2018) uses the ARIMA model with dummy variables used by Cabrero et al. (2002). The author models the effect of trading day, the intra-monthly behavior of the CIC related to payroll dates, as well as the holiday effects, and several dummy variables for each country. Five variables were created to simulate the intra-weekly behavior of CIC, that is, a dummy for each day in the week. To simulate the increasing pattern of the first two weeks in a month and the decrease in the latter half, a dummy variable was created for each week in a month. In addition, holiday variables were created to account for all the holidays in each country, as CIC usually increases prior to holidays. To take into account the fact that a holiday has a different impact on CIC depending on the day of the week it occurs, several other dummies were created. The results suggest that the daily model for the five countries provided good performances, suggesting that they can be adapted to the change of CIC under different monetary policy frameworks and macro-financial environments.

Currency in Circulation in the Maldives

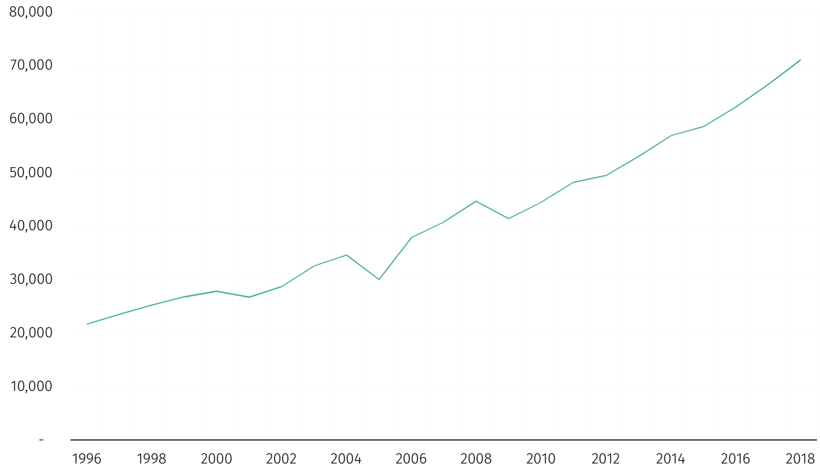
CIC in the Maldives has seen major developments in the last two decades reflecting significant economic and institutional changes that occurred during this time period. Munawar (2014) analyses some of the relevant economic and institutional factors that determine the long-term trajectory of CIC in Maldives. This includes level of economic activity, monetization of budget deficit, level of vault cash held in the banks, access to banking services and alternative mechanisms for cash payments.

The main purpose of holding cash or demanding cash is to make cash transactions within an economy and therefore, the positive relationship between growth in the economy and CIC must hold theoretically. The broadest measure of economic activity is Gross Domestic Product (GDP) or nominal GDP, which reflects both price developments and changes in real economy (Munawar, 2014). Looking at the development in CIC and nominal GDP over time, it can be seen that the aforementioned positive relationship holds for the Maldives. This can be seen in Figure 1 where growth rates of nominal GDP and CIC move in the same direction.

Figure 1: Growth in Currency in Circulation (CIC) and Nominal GDP, 2004 - 2019
(percent)

Source: Maldives Monetary Authority

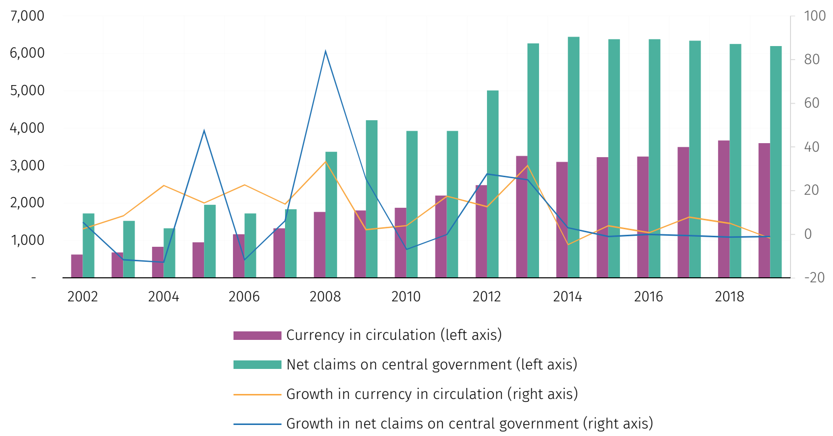
Figure 2: Growth in Real GDP, 1996 - 2018
(millions of rufiyaa)



Source: Maldives Monetary Authority

As seen in Figure 2, after a period of rapid growth in the latter half of the preceding decade, Maldivian economic growth moderated during 2000 and further slowed in 2001 following the September 11 incident[2], which left the tourism industry on a downward spiral for at least three quarters. This slowdown coincided with the contraction of narrow money during 2001, which projected a decline of 6% in annual terms, largely caused by a fall in both rufiyaa demand deposits of commercial banks as well as the CIC (Annual Report, 2001). Despite the slowdown in 2001, economic growth picked up in 2002[3] as a result of strong recovery in the tourism sector, which may have boosted economic activity in the domestic market, accelerating the cash circulation within the economy.

Figure 3: Net Claims on Central Government, Currency in Circulation and their Growth Levels, 2002 - 2019
(millions of rufiyaa, percent)



Source: Maldives Monetary Authority

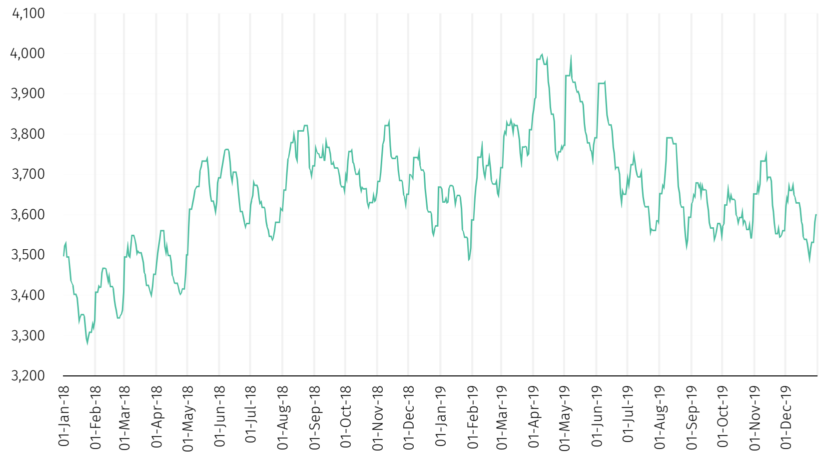
[2] Annual Report of the MMA 2001.

[3] Annual Report of the MMA 2002.

However, 2005 saw a decline in economic growth as devastation caused by the 2004 Tsunami propagated into the tourism industry and other related industries. This resulted in a fall of government revenues that significantly widened the government budget deficit, which was largely financed through borrowings from the MMA, otherwise known as monetization (Annual Report, 2005). Consequently, through monetization, more money was pumped into circulation as recurrent expenditure accounts for a large portion of the government fiscal budget. This can be seen in Figure 3, which shows an average growth of 21% and 23% of CIC and net claims on central government, respectively, over the period 2004 to 2008.

While the CIC presents a distinct long-term trajectory, there are weekly, monthly and other short-term variations that must be analyzed in depth, in order to properly model these patterns in a forecasting model. In Figure 4, we see that the daily CIC series is volatile in the short-term and is associated with recursive seasonal patterns and several one-off events.

Figure 4: Currency in Circulation, 2018 - 2019
(millions of rufiyaa)

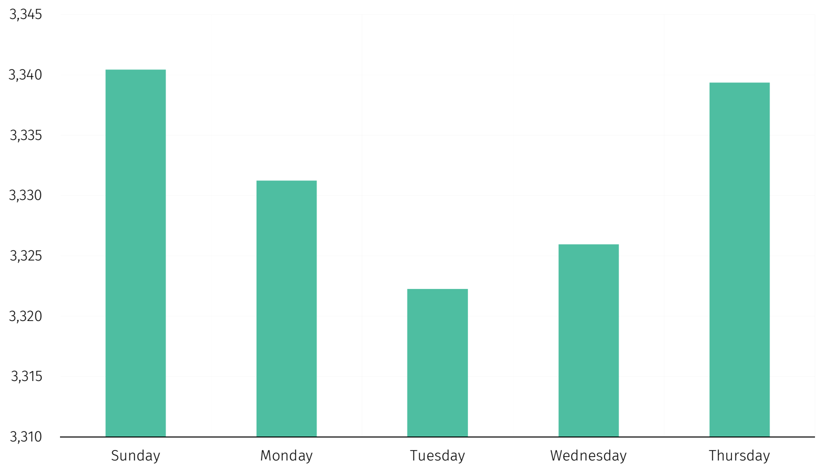


Source: Maldives Monetary Authority

Weekly pattern

In the literature, one of the most prominent patterns that can be seen is the weekly cycle, otherwise known as the trading-day effect. Figure 5 shows that, the demand for cash at the beginning of the week is lower than the latter half of the week. This can be attributed to an increase in demand for cash for the weekend ahead.

Figure 5: Average Weekly Cycle of Currency in Circulation, 2014 - 2018
(millions of rufiyaa)



Source: Maldives Monetary Authority

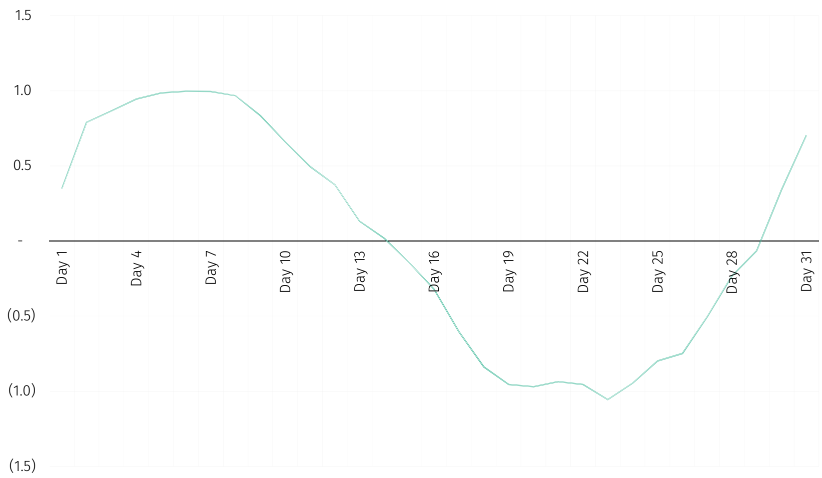
Monthly pattern

The second pattern that can be seen in Figure 6 is a monthly or intra-month cycle which resembles a "saw-tooth" pattern as suggested by Baumol (1952); Tobin (1956) in their inventory theory of money. The CIC increases during the first and the last week of each month linked with the salary period. Salaries are usually paid during the last two days of each month.

According to the current behavior, the public starts withdrawing money from the last week of the month in anticipation of the salary being received during the succeeding days. This process continues until the end of the first week of the following month. However, withdrawals in the first week of the month are more prevalent. This is referred to as cash outside the banking system. It denotes the amount of money outside the MMA and the banking system. CIC starts to increase around the last week of the month as banks withdraw more from their reserve accounts at the MMA in order to cater the demand by the public. Banks start to debit their account at the MMA before the public starts withdrawing their money. This generally happens during the period 19 to 30 of each month. For instance, in 2010, on average almost 60% of the withdrawals from the MMA by Bank of Maldives Plc. (BML) had taken place during this period each month (Munawar, 2014). Therefore, the CIC increases at the beginning of a month.

As the public purchases goods and services, the currency first flows into the corporate sector and from there to the banking sector. A major portion of the money flows back to the banking system during the middle of the month, associated with the due dates of different payments that a household or business has to pay. Hence, CIC decreases during this period as banks credit a portion of it to their accounts at the MMA once they receive it.

Figure 6: Normalized Average CIC, 2005 - 2019



Source: Maldives Monetary Authority

Holidays and festivals

There are several holidays and religious festivals celebrated in the Maldives throughout the year. With holidays, the corporate sector enjoys high sales as people make bulk purchases using cash, which result in significant circulation of cash in the economy during holidays. After the holiday ends, cash enters the banking sector which greatly reduces the circulation of cash as banks deposit the cash in accounts held at the MMA. For instance, CIC often increases a few days prior to Eid al-Adha as people prepare for the festive season by purchasing holiday packages and prepare for bank closures during the holidays. This impact is profound in the Maldives as the entire population observe this religious month, including Bangladeshi workers who make up the majority of foreign workers. During these periods, CIC does not move according to the usual norm of the saw-tooth pattern. Regardless of which point the holiday occurs, CIC usually escalates during that period. For instance, the household consumption increases during the month of Ramadan. The changes in CIC on average may stand at the same level during the month of Ramadan. However, the level of CIC would generally be higher than what it would have been on any other regular month. This effect is magnified if a holiday precedes a weekend or if the length of the holiday increases due to any other reason.

Model Specification

The model has been designed to forecast the daily CIC. With the availability of the CIC data in high-frequency, and thus more number of observations, one could argue that it can be used to predict a long-term horizon. However, it is not always advisable to do so as higher frequency data may not be able to predict the long-term trends in the data. Rather, it may be much better in picking up short-term trends like daily and weekly trends. In this sense, the seasonal ARIMA models perform better in forecasting CIC, particularly for short-term horizons (Cabrero et al, 2002). Although univariate time series models could theoretically be applied to any frequency, the main problem at high frequency seems to be an appropriate specification of the seasonality which may change from month-to-month or year-to-year (Bhattacharya & Joshi, 2001).

Prior to the development of any model, CIC was forecasted by the MMA using historical observations without the use of any econometric model. To carry out the liquidity management operations most effectively, the MMA relied on the liquidity forecasts, of which CIC is one of the determinants of the supply of liquidity. As the CIC was used as a determinant of supply of liquidity in the liquidity forecasting exercise of the MMA, the estimate was produced on a weekly-basis, every Monday, and three-day ahead estimates were produced.[4]

As efforts to the continued monitoring of CIC was further enhanced, it led to a development of an ARIMA model which thereon has been used to forecast the CIC. In the analysis of time series, autoregressive moving average (ARMA) models provide a parsimonious portrayal of a weakly stationary stochastic process. This process can be broken down into two parts; the autoregressive (AR) and the moving average (MA) processes. Hence, it is referred as an ARMA (p, q) model where p and q refer to the order of the AR and MA process, respectively. The ARMA process is not only applicable for the weak stationary process; researchers also apply the ARMA process including various trends, seasonal and other deterministic or stochastic components (Balli & Elsamadisy, 2012). An even more accurate method is the use of ARIMA-based approach, to forecast a short-term horizon when working with a non-stationary time series.

The general ARIMA process can be written in the following way:

$$Y_t = D_{t,i} + \eta_t$$

$$\eta_t = \frac{\theta\,(B)}{\Phi\,(B)\,\delta\,(B)}\,\varepsilon_t \qquad \varepsilon_t \sim \text{i.i.d}\,(0, \sigma^2)$$

where Yt is the daily CIC, Dt,i is the linear regression component, B is the backshift operator, θ and Φ are the moving average and autoregressive operators respectively and δ is a difference operator that can include a seasonal difference operator.

The model used previously was an ARIMA model with order (7, 1, and 0). This indicates that the model is integrated once and incorporates autoregressive terms up to AR (7). The current study builds on this model that was used for forecasting CIC which from here onwards would be referred to as the baseline for benchmarking purpose. Overtime, the prediction power of the baseline has diminished due to the changes in many factors within the economy. The improved model accounts for such changes and is compared with 3 other models; the baseline, a naïve model and an ARIMA (1, 1, 1). The naïve forecast equals to the previous period’s actual without adjustments or establishment of casual factors.

In an econometric time series, seasonality is mostly inevitable. There are two ways to deal with it. One way is to remove it and then model and forecast the seasonally adjusted series. The other common technique

[4] The liquidity forecasting was conducted weekly on every Monday, where the week starts from Thursday and ends at Wednesday, corresponding to the MRR period which is a two week cycle. Hence the weekly forecast effectively produces estimates for three days (Monday-Wednesday). Currently open market operations have been discontinued since May 2014.

used is to run a regression on seasonal dummies, (Dheerasinghe, 2006) enabling the forecaster to capture the seasonality in the model. In this paper, the second approach has been used to run the models.

In an economy, intra-month or intra-week variations may change from week-to-week or month-to-month. Countries almost universally follow the Gregorian calendar. However, in the Maldives, we expect that economic life will co-move with the Islamic events as well. Determining this effect is even harder because the Islamic calendar is lunar. This makes it difficult to model high frequency time series.

The estimation sample covers the period 1 January 2016 to 31 October 2018. The out-of-sample forecasts have been carried from 1 November 2018 to 31 December 2018. For each year, all 365/366 observations have been included. Holidays carry the same level of CIC as the last working day.

The regression model is expressed in first difference of CIC. The preliminary model of the linear regression is:

$$C = \gamma' D$$

where C refers to the CIC in first difference at time t, γ is an nx1 coefficient vector whose transpose is the row vector γ' and D is a column vector of dummy variables explained as follows.

- Intra-month effect (M): Intra-monthly patterns in the series of CIC are associated with the payments such as salaries and utility bills. The demand for cash is higher around the salary day. For each day; *i*=1 to 31, a dummy variable at time t is defined to take the value 1 if the day at time *t* is *i*, else 0. The dummy variable captures any intra-month effect present in CIC at time *t*.
- Intra-week effect (W): For each day, *j* = Sunday through Thursday, a separate dummy variable is assigned, taking the value 1 for the respective day of the week and the rest 0. This is important to capture the weekly patterns that may change depending on the day of the week.
- Interaction variable: A few interaction variables have also been tested to identify the impact of the interaction between the intra-month and the intra-week effect. In this regard, the following interaction variables have been identified to significantly impact the CIC
    - Day 7 * Thursday
    - Day 10 * Thursday
    - Day 11 * Thursday
    - Day 19 * Thursday
    - Day 31 * Monday

- Election (E): In the span of the sample period used in the analysis, presidential elections took place once, in 2018. A dummy variable is assigned to take a value of 1 on the days of the year that the election was conducted. The underlying assumption behind the selection of this variable is the belief that the demand for currency would increase substantially during the election period. However, it was noticed that the CIC was quite erratic prior to the months leading up to the election and also post-election in 2018.

- Fitr Eid (F) and Hajj_Eid[5] (HE): These are two of the notable holidays marked in the Islamic calendar. A dummy variable has been defined for each of these holidays separately.

- Holiday (H): This is a matrix of dummy variables for all the one-day holidays in the calendar of Maldives such as National Day, First day of Ramadan and Prophet Mohamed's Birthday.

- Consecutive holidays (C): If the number of consecutive holidays exceeds three, a dummy variable is allocated that takes the value 1 against the first day of the holiday.

- First day of Ramadan (FR): It is customary for Maldivians to increase their spending prior to Ramadan. These are usually for renovating the house, buying new utensils and as such in preparation of Ramadan. This type of expenditure mostly starts a few days prior to Ramadan and goes on till the first two or three days of the month.

- Back-to-work (BW): It is assumed that CIC would decrease after any holiday as the banks re-open and people get back to their daily schedule.

- Post the introduction of the Ran Dhihafaheh (RDF) new note series, there were a notable number of days where the change in CIC was very erratic. The paper regards such days as outliers where the change in CIC had gone beyond MVR100 million leaving a huge spike in the observed data. Such days have been identified in the paper, and controlled for in the estimation. In this regard, seven such spikes were identified and controlled apart from the day of introduction of the RDF.

The final regression model is expressed as:

$$\Delta(CIC_t) = \Delta(CIC_{t-1}) + \sum \alpha_i M_{i,t} + \sum \beta_j W_{j,t} + \theta_i(B)\,HE + \theta_i(B)\,C + \theta_i(B)\,FR + \theta_i(B)\,H + \theta_i(B)\,E + \theta_i(B)\,BW + RDF + D_7{*}W_5 + D_{10}{*}W_5 + D_{11}{*}W_5 + D_{19}{*}W_5 + D_{31}{*}W_2 + RDF1 + RDF3 + RDF4 + RDF5 + RDF6 + RDF7 + RDF8$$

where M refers to the intra-month effect, W refers to the intra-week effect, HE refers to Hajj_eid, C is the consecutive holidays, FR is the first day of Ramadan, H is the one-day holiday effect, E refers to Elections, BW refers to back-to-work variable, RDF is the Ran Dhihafaheh issuance date and θi (B) is the polynomial of the dummy variable B, where B is the standard backward shift operator which is also called the 'lag operator'.

[5] Eid al-Adha is preceded by Hajj day which is also a public holiday in the Islamic Calendar.

The backward shift operator captures the changes in the currency level before and after the holiday *i*. For example, B^k means backshift by k times.[6] In this regard, for the back-to-work variable, a polynomial multiplied by the backshift operator, $(\omega_0 I + \omega_1 B)*B^{-2}$ indicates that, starting from the first working day after the holiday, we include up to one working day succeeding the first working day after the holiday.[7] In this manner, the effect on CIC is captured by including the days that are statistically significant. Table 1 contains the backshift operators used in the model.

Table 1: Seasonal Factors and their Backshift Operators

Seasonal Factors	$\omega_i(B)$
Hajj_eid	$(\omega_0 I + \omega_1 B + \omega_2 B^2)* B^2$
Consecutive holidays	$(\omega_0 I + \omega_1 B) * B^1$
First day of Ramadan	$(\omega_0 I + \omega_1 B + \omega_2 B^2 + \omega_3 B^3 + \omega_4 B^4 + \omega_5 B^5 + \omega_6 B^6) * B^1$
Back to work day	$(\omega_0 I + \omega_1 B)*B^{-2}$
Election	$(\omega_0 I + \omega_1 B + \omega_2 B^2 + \omega_3 B^3 + \omega_4 B^4 + \omega_5 B^5 + \omega_6 B^6 + \omega_7 B^7 + \omega_8 B^8 + \omega_9 B^9 + \omega_{10} B^{10} + \omega_{11} B^{11} + \omega_{12} B^{12} + \omega_{13} B^{13} + \omega_{14} B^{14} + \omega_{15} B^{15} + \omega_{16} B^{16} + \omega_{17} B^{17} + \omega_{18} B^{18} + \omega_{19} B^{19} + \omega_{20} B^{20} + \omega_{21} B^{21} + \omega_{22} B^{22} + \omega_{23} B^{23} + \omega_{24} B^{24}) * B^{-10}$

The regression model includes those variables that are statistically significant and whose coefficients are economically justifiable. Nonetheless, there are some exceptions to this statement. For some variables like Ramadan, Hajj and a few other dummy variables, we retain the variables in the equation even though they are statistically insignificant at their individual lags and leads. This is because their joint F-test indicates that the dummy variables jointly have a significant impact on the CIC. As the key goal of the model is to forecast the CIC for the short-term, individual significance is not required.

After a suitable backshift operator is identified by dropping the preceding days and the following days that are not statistically significant or economically sensible, the final regression model is obtained. For example, for Eid al-Adha the backshift operator considered is (ω0 I + ω1B + ω2B2)* B2 and the coefficients are found to be positive. This means that starting from four days prior to the occasion, CIC will increase in preparation for the expected increase in consumer expenditure.[8]

Seasonal patterns in the model can also be identified to a certain extent through visual sources like the correlogram of the regression. The correlogram may be used as an indicator towards inclusion of ARMA terms

[6] Example: B2Eidt = Eidt-2. This means 2 days before Eid. This is usually referred to as lags while vice versa are referred as leads.

[7] It should be noted that when we consider the first working day after a holiday, it means one working day after the last day of the vacation.

[8] Banks may tend to increase the amount of cash in their vaults and ATMs by withdrawing from their accounts at the MMA in anticipation of withdrawals from customers ahead of different occasions.

and can act as a guide to the forecaster in making a preliminary decision regarding the order of the ARMA terms that can be included in the model. As mentioned earlier, the correlogram provides information on the order of the ARMA terms depending on the autocorrelation function (ACF) and the partial autocorrelation function (PACF). Since the CIC is an I(1) variable and has some seasonal patterns, it is integrated with order 1 to eliminate some of the seasonality. In the model, instead of the ARMA terms, we have used the lag of CIC, making the model an autoregressive integrated moving averages model with seasonal dummies.

Output and Results

For any econometric model, the first crucial assessment could be the ability of the model to make economic sense. With respect to the explanatory variables that have been used in the model, the CIC tends to increase prior to long holidays. This shows that a larger volume of currency is required prior to major holidays. As commercial banks remain closed during these days, they may withdraw more from the MMA, in anticipation of the public requirements for the impending holiday period. For example, the model portrays an increase in CIC two days prior to a long holiday and starting from four days ahead of Eid al-Adha holidays. This means that the banks withdraw currency from the MMA two and four days prior to respective holidays that have been aforementioned.

While the model shows that CIC tends to increase prior to such holidays, it also depicts the decline in CIC once businesses resume daily operations post the holiday. It could also support the argument that individuals tend to deposit any significant amount of cash balances that remains with them post the holiday. After a period of time, CIC decreases as banks increase their minimum reserve requirement (MRR) portion with the MMA based on their level of deposits. Further, the model also accounts for changes to CIC pre and post elections. The coefficient was highly significant although the direction of CIC varied throughout. In most cases, the effects of an election are usually very erratic in nature and hence, a judgment regarding the accuracy of the direction of CIC is rather unpredictable.

With respect to the intra-week effect, the base day is selected to be Wednesday.[9] A cyclical pattern can be seen, where the CIC is lowest on Mondays and highest on Thursdays. Except for Sunday, all other days are significant at 1%. The results are also in line with the natural assumption that CIC increases prior to a weekend and starts falling from the beginning of the week, until it reaches the lowest point before reverting back. Similarly, the intra-month effect also highlights the fact that generally the CIC tends to be lower than the first day of the month which is most likely to be pay day.

While most of the explanatory variables are highly significant at 1% level, a few variables are insignificant. For example, the model tests the effect on CIC starting from seven days prior to the first day of Ramadan. Although individually, these variables turned out to be insignificant, the joint F-test showed that the variables are jointly significant and thus affects the pattern of CIC.

[9] The MRR period starts from Thursday and ends on a Wednesday every fortnight. Hence, the last day of MRR period is considered as a base day for comparison of intra-week effect assuming that this day will have an impact on the level of MRR that the banks retain depending on their space for going short on balances. Thus affecting CIC.

With regards to the autocorrelation and partial correlation, the results showed that they lie within the specified confidence bands. Further, the Breusch Godfrey Serial Correlation LM test also reveals that no serial correlation exist between the variables, supporting the fact that the model is appropriate to be used (Table 2).

Table 2: Results of Breusch Godfrey Serial LM test[10]

Model	P-value
New model	0.2426
Baseline	0.0000

Test Statistics are reported
Significance levels: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$

Performance evaluation

In choosing an ideal model, it is always better to conduct an out of sample forecast along with the within sample forecast. As mentioned earlier, this model is compared with three other models; the baseline, the naïve and ARIMA (1, 1, 1). For each model, we calculate the root mean squared error (RMSE), mean absolute error (MAE), bias proportion, variance and covariance. While the MAE portrays the size of the error that can be expected from the forecast, the RMSE provides a measure of the size of the error that gives more weight to the large but infrequent errors than the mean. The RMSE will always be larger or equal to the MAE.

The paper focuses on three types of performance evaluations; monthly, weekly and three-day ahead forecast evaluations, the third category being the most relevant to the current forecasting procedure.

Monthly horizon

This out-of-sample forecast was conducted for the period, November to December 2018. With regard to both the within-sample and out-of-sample forecast, the new model was superior in four out of five criterion[11] (Table 3) in the two-month forecast evaluation. In terms of the explanatory power, the new model has an adjusted

Table 3: Forecast Evaluation between Models (Two-month Forecasts)

	Within Sample		Out-of-sample (November-December 2018)		Rsq adjusted	AIC	SIC
	RMSE	MAE	RMSE	MAE			
New	16,854,317	12,697,610	49,456,005	42,251,639	59%	36.3	36.7
Baseline	21,373,305	14,808,704	52,108,087	44,272,064	36%	36.7	37.1
ARIMA	26,754,084	15,553,082	77,272,764	63,534,009	6%	37.0	37.1
Naïve	27,597,459	15,048,225	80,512,474	67,286,119			

[10] H0 states that there exist no autocorrelation.

[11] In choosing the optimal model, the lowest value of the RMSE, MAE, AIC, SIC, variance and bias proportion is considered while the highest adjusted R squared and covariance is selected.

R-square of 59%, while the baseline has an adjusted R-square of 36%. This highlights the fact that the new model has more power in explaining the variations in CIC. The RMSE and MAE for both within and out-of-sample forecasts are also superior in the new model.

Weekly horizon

The weekly horizon was tested for four sample periods of January 2019. Pertaining to this horizon, the four models were run again and the superiority of the models were identified based on the aforementioned criterion. Table 4 indicates that while only the new model is superior for within-sample forecast and also the R-square, AIC and SIC, RMSE for new model is also for out-of-sample forecast. However, the results from the MAE cannot be concluded against the new model as the performance varies in all the models throughout the month.

Table 4: Weekly Evaluation between Models – January 2019

	Within-sample		Out-of-sample		Rsq, AIC,SIC
January	RMSE	MAE	RMSE	MAE	
Week 1	New	New	ARIMA	Naïve	New
Week 2	New	New	ARIMA	ARIMA	New
Week 3	New	New	New	New	New
Week 4	New	New	New	ARIMA	New

Daily forecast evaluation

The current practice to forecast the value of CIC is to make a three-day ahead forecast. Since the forecasts are produced for liquidity forecasting purposes, the estimates are produced every Monday, for the period Monday to Wednesday. Hence, the most efficient method of comparing the results of the new model with the existing forecasts would be to reshape the new model in a way that it becomes comparable to the existing forecasts. Hence, the new model is iterated every time for three days. This process is repeated for all the succeeding days in the sample for each consecutive three days. These are then separated by combining all one-day ahead, two-day ahead and three-day ahead forecasts; each separately. These results have been compared to the forecasts that have been made in the past using the existing model, where in the one-day ahead of the current practice coincides with the one-day ahead estimate using the new model. In this section, RMSE has been chosen to evaluate the performance of the forecasting ability of both the models.[12] It determines the absolute fit of the model to the data and helps in deciding how close the actual data points are in comparison to the models predicted values. Thus, a lower RMSE indicates a better fit. The table below shows the results of the RMSE for each of the models with respect to one, two and three-day ahead forecasts respectively.

[12] The monthly and weekly forecast evaluation proved that the new model is superior to the baseline, Naïve and ARIMA models. But the daily forecast evaluation is compared only with the baseline model in order prove that the new model is still superior when compared with the prior practice of forecasting as well.

Table 5: RMSE for One, Two and Three-day Ahead Forecasts

	One-day ahead	Two-day ahead	Three-day ahead
New	20,822,664	31,561,587	34,501,180
Baseline	24,512,374	35,992,269	37,450,849

It is clear that the RMSE for each of the three days are lower for the new model. As the forecasting horizon expand the RMSE increases due to the increasing forecasting error. However, in comparison to the baseline model, the new approach is still superior. Prior to the usage of the baseline approach, the forecast for CIC was very static.

Conclusion

The results outlined in the paper show that the new model explains the variations in CIC better than the baseline approach which was used. This is evident from the higher adjusted R-square of 59% in comparison to 36% explanatory power of the previous approach. The new model is an improvement to the baseline approach whereby some explanatory variables have been included and omitted depending on the explanatory power of the model. For example, Eid al-Fitr and school holiday variable have not been included because the model performs better without it.

Prior to the development of an econometric model, total CIC for a particular week was taken as a simple average of CIC for the corresponding weeks of the past three years. This total was then equally distributed throughout the forecast week. Both the baseline and the new model are much superior to past techniques with the new model being an enhancement to the currently used baseline forecasting model. The model presented in the paper will boost the accuracy and reduce the variances while forecasting the CIC. As CIC is an important element of forecasting the liquidity of the banking system, this model will improve MMA's position in forecasting the weekly liquidity management. Nevertheless, it is also important to acknowledge the fact that the CIC is quite erratic in nature and may be subject to unforeseen events. Further, the model presented is most suitable for forecasting the very short-term and will not provide accurate results for a long-term forecast. This model should be evaluated and updated to account for the changes in trends.

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