Modelling and Forecasting Currency Demand in Sri Lanka - An Empirical Study

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Abstract

The main focus of this paper is to examine the evolving determinants of currency demand and forecasting of Currency in Circulation (CIC) in Sri Lankan context using monthly and quarterly data for the period of 2001-2016. Using the Vector Error Correction Model (VECM), this study finds that variables such as the deposit rate, inflation, GDP and dummy variables for New Year/ Christmas and election were significant in explaining changes in CIC. Forecast produced by using Exponential Smoothing Approach and Auto-Regressive Integrated Moving Average (ARIMA) Model matches the monthly behaviour of CIC and capture seasonal and cyclical effects as well.

Keywords: *Currency in circulation, Demand for money, Vector Error Correction Model, Auto-Regressive Integrated Moving Average*

JEL Classification: *E20, E41, E52 and C22*

1. Introduction

Issuing currency is a function at the heart of all central banks (Norat, 2008). According to the Monetary Law Act (MLA), the Central Bank of Sri Lanka (CBSL) shall have the sole right and authority to issue currency in Sri Lanka. “Currency" means all currency notes and coins issued or circulating in accordance with the provisions of MLA. Under the current active Open Market Operation system (OMOs), an interest rate is achieved by appropriately managing market liquidity, by adjusting the volume of liquidity absorbed or injected through the auctions. Central banks should focus on forecasting on the CIC, because providing an accurate prediction for the CIC would enable central banks to plan monetary policy strategies in advance so they can manage liquidity efficiently (Balli and Elsamadisy, 2011). In monitoring and forecasting of CIC, data such as high-frequency time series, which are typically not available for macroeconomic variables such as output and inflation is important for more active liquidity management. Therefore, the importance of accurate forecasting for CIC emerged by the system to assess of the daily liquidity position in the banking system. A number of central banks of advanced, emerging and developing countries forecast the daily change of their CIC to calibrate the volume of their monetary operations (Kahatat, 2018).

The present study differs from the existing literature in the following ways. According to Nachane et al (2003), the literature on modelling currency demand functions constitutes a very small fraction of the literature on estimating money demand functions. In economic literature, only very few studies are available to examine the behavior of CIC in Sri Lanka. The current study has been undertaken with the motivation of fill this gap in Sri Lankan context. Dheerasinghe (2006) forecasted the currency demand in Sri Lanka by using Auto-Regressive Moving Average (ARMA) method. Accordingly, three models were estimated with monthly, weekly and daily time series, assembling tools for forecasting trend, seasonal patterns and cycles in individual series separately. Hence, no studies are available in Sri Lanka that attempts to examine behavior of CIC by using macro-economic variables. Considering this, the study attempts to examine the behavior of CIC in Sri Lanka using a set of macro-economic variables such as the GDP, interest rates and inflation; and dummy variables to capture seasonal and election effects. Moreover, in this study two methods namely, exponential smoothing and ARIMA has used to forecasting CIC in Sri Lanka. Hence, findings of this study would have several important implications for policy makers.

The rest of the article is organized as follows. Section 2 describes the objective of modelling and forecasting currency demand. Section 3 presents the literature review of the study. Section 4 summaries the modelling techniques and data that were used. Section 5 presents the empirical analysis and finally Section 6 provides a conclusion.

[1] The views expressed in this study are those of the author and do not necessarily reflect those of the Central Bank of Sri Lanka. Any errors and omissions are mine.

2. The Objective of Modelling and Forecasting Currency Demand

The purpose of this study is to investigate the empirical relationship between CIC and other macro-economic variables by deriving currency demand function. Moreover, it is expected to build an econometric model to forecast CIC. Although the central bank is in charge of distribution of the currency it can't assess the demand for the currency, as that demand is generated by the behaviour of commercial banks (Koziński and Świst, 2015). The CIC is one of the most significant factors influencing the liquidity of the banking system of Sri Lanka. Therefore, the amount of CIC has to be forecasted as accurately as possible. The CIC displays an increasing long-term trend and strong seasonal factors which can be forecasted (Guler, 2010).

In forecasting money market liquidity, for most central banks, the main autonomous items that need to be forecast are currency in circulation, statutory reserves, government transactions and net foreign exchange transactions. One of the most important autonomous factor in forecasting liquidity is CIC. Forecasting CIC accurately is one of the hardest tasks of a central bank, although the central bank has the monopoly of issuing currency. The reason is that the amount of currency circulating in the economy is determined by the public. Central banks need to forecast CIC, because providing an accurate forecast of CIC would enable the central banks to plan monetary policy strategies in advance so they can manage liquidity efficiently. In addition, having accurate forecasts of CIC help to stabilize the money market in the short run as they help design OMOs to minimize volatility in money market rates. This in turn helps the smooth functioning of markets which helps sustain economic activity, thereby helping raise economic growth in the long run.

CIC of the CBSL comprises the outstanding amount of bank notes and coins held by the public and Licensed Commercial Banks (LCBs). CIC and bank reserves are in the liability side of the balance sheet of the CBSL. On the other hand, assets side consists by Net Domestic Assets (NDA), Net Foreign Assets (NFA), Net Credit to the Government (NCG) and other items. Meanwhile the majority of the reserve money consists of CIC while emerging the importance of having accurate forecasting for that to assess the daily liquidity position of the banking system more accurately.

Table 1: Composition of Reserve Money (Rs.mn)

	2008	2009	2010	2011	2012	2013	2014	2015
Reserve Money (RM)	268.4	303.5	360.5	439.5	484.3	488.6	577.9	673.4
Currency in Circulation (CIC)	186.1	217.4	255.7	293.2	318.1	339.8	416.9	491.7
Commercial Bank Deposit	82.3	86.1	104.8	146.3	166.2	148.8	161.0	181.7
Contribution to RM by CIC	69.3	71.6	70.9	66.7	65.7	69.5	72.1	73.0

Source: Central Bank of Sri Lanka

As per the Table 1, contribution of CIC has varied in a narrow band between 66 per cent to 73 per cent of the reserve money during 2008 to 2015. CIC is the most important autonomous factor in the context of liquidity management, both in terms of size and volatility (Balli and Elsamadisy, 2011). As such estimating CIC is a crucial part of the reserve money in Sri Lanka in their liquidity management. More accurate liquidity management will reduce the volatility of money market rates and it facilitates price stability. Forecasting of CIC is important as an operational tool because the CIC directly impact on liquidity management. Modelling the daily CIC improves the quality of central bank's liquidity forecasts (Khatat, 2018). The currency deposit with the CBSL by LCBs is behave as a liquidity enhancing factor in contrast that currency withdrawal from CBSL by the LCBs behaves as the liquidity reducing factor. Factors mainly influencing for liquidity are shown in Table 2.

Table 2: Factors influencing for Liquidity

Liquidity Enhancing Factors	Liquidity Reducing Factors
CBSL purchases of T-bills	CBSL sales of T-bills
Foreign Loan Receipts	Maturing of CBSL holding of T-bills
Purchases of Fx in the market	Sales of Fx in the market
Retirement of CBSL Securities	Issuing of CBSL Securities
Conversion of the foreign currency proceeds	Foreign Loan Repayment
Currency deposit with the CBSL by Commercial Banks	Currency Withdrawals from CBSL by Commercial Banks
Release of CBSL profits to the Govt.	
Increasing provisional advances to Govt.	

Source: Central Bank of Sri Lanka

However, huge deviation of liquidity forecast may adversely affect the effectiveness of implementation of monetary policy. On any given day, getting the banknote forecast wrong would create misinformation about the accurate liquidity position. Therefore, the aim of an accurate liquidity and CIC forecast are to determine the appropriate level of liquidity management so as to stabilize overnight market interest rates in line with the policy rates and thereby ensuring price stability. Hence a study on variations in currency demand is important. A systematic study of both short and long run variations in currency demand is extremely important for the banking system, in particular, to the central bank (Dheerasinghe, 2006).

3. Literature Review

Due to the importance of CIC for conducting monetary policy, many central banks have developed and applied econometric models for forecasting purposes (Koziński and Świst, 2015). Accordingly, countries have used various methods for modelling and forecasting CIC (Table 3).

Table 3: Cross Country Experiences of Forecasting CIC

Methods	Country
Exponential Smoothing	Bank of England
Currency Demand Equation/ Money Demand Function	India Australia Nigiria Pakistan
Seosanal ARIMA / ARMA	Turkey New Zealand Qatar Sri Lanka Chechoslovakia Croatia

Source: Author's Calculation

Khatat (2018) estimate two types of CIC models namely (1) a first generation derived from the theory of money demand and (2) a second generation aimed at producing daily forecasts of CIC. Accordingly, it was transformed the currency demand function into a VAR to capture the dynamic link between interest rates and the demand for cash. Also applied ARIMA modelling to forecast the daily CIC for Brazil, Kazakhstan, Morocco, New Zealand, and Sudan. Empirical work shows that some of the conclusions in the economic literature on the impact of interest rates on the demand for currency do not necessarily hold, and that central banks would benefit from running both generations of CIC models. Cassino et al (1997) reviewed the results of a CIC forecasting study which employed different modelling techniques in the Reserve Bank of New Zealand. They implemented the traditional money demand model alongside two variants of the ARIMA model, one with seasonal moving average (SMA) terms and the other with seasonal autoregressive (SAR) terms. A univariate model, the ARIMA model's forecasts were mainly based on historical observations. Basing its modelling structure on the properties of a stationary time series process which rises and falls around a certain mean, it tended not to react to external shocks. The results of the different models (money demand model, ARIMA1 (SMA) and ARIMA2 (SAR)) produced out of sample forecasts with percentage root mean square errors of 2.62, 1.25 and 1.91 per cent respectively.

Dheerasinghe (2006) clarifies importance of having estimation of CIC for Sri Lanka. In modelling the stochastic trend in the data, Dheerasinghe utilized time and time-squared series to capture linear and non-linear trends in the data. The model selection was done by selecting the three models with the lowest Akaike and Schwartz information criterion, maximizing the R-squared and also minimizing the Mean Square error of the forecasts. Dheerasinghe noted from her results that all three approaches fit the data and captured various effects and seasonality properly, and also performed well out of sample in Sri Lanka. Hence the models identified that the Sinhala/Tamil New Year, elections, Christmas and the day prior to public and bank holidays have significant positive impact on demand for currency in Sri Lanka. Bhattachrya and Joshi (2000) reviewed various techniques of forecasting CIC in order to determine the best method of predicting the series due to the significance of CIC in maintaining monetary stability in the Indian economy. They used the money demand model and the univariate modelling approaches as the two main approaches to modelling CIC. These models had a tendency to perform poorly using high frequency data when compared to quarterly and annual data. Out of sample performance of the models using high frequency data were poor and due to a lack of income data beyond quarterly frequency in the money demand models. The paper proposed an alternative approach of modelling the weekly growth of CIC by incorporating day of the monthly effect. Nachane et al (2013) identify various factors influencing currency demand in India from 1989 to 2011 using vector error correction framework for modelling aggregate currency demand as well as for various currency sub-groups. There exists a cointegrating relationship between CIC, real GDP, prices and deposit rates in India. The income elasticity of currency is found to be somewhat higher than is observed in similar studies for advanced countries (Nachane, 2013).

In order to modelling the daily CIC in Turkey, Akinsi (2003) carried out Johansen multivariate cointegration analysis and error correction model using real money balances, real income, and the opportunity cost variables in Turkey. Results shows long run demand for real cash balances depends on real income, interest rate on government securities and the exchange rate. Single equation error correction model is specified and estimated based on the cointegration and the weak exogenity test results. As per the estimated models, the income and the interest rate effects is much smaller in the short run than the long run. Moreover, exchange rate influence is more pronounced in the short run.

According to Roseman (2010), domestic demand for currency in the US is largely based on the use of currency for transactions and is influenced primarily by income levels, prices of goods and services, the availability of alternative payment methods, and the opportunity cost of holding currency in lieu of an interest-bearing asset. Consumers frequently use smaller denomination notes for small transactions and alternative payment methods (for example, debit and credit cards) for larger purchases. In contrast, foreign demand for US currency is influenced primarily by the political and economic uncertainties associated with certain foreign currencies.

Ikoku (2014) examines forecasts of CIC prepared for liquidity management at the central bank of Nigeria. Forecasts were produced using ARIMA, ARIMA with structural variables, VAR and VEC models. They found that the most accurate models were mixed models with structural as well as ARIMA components, augmented by seasonal and dummy variables. In explaining the demand for currency; exchange rate, interbank rate, seasonality, holidays and elections were significant

Therefore, both short-term and long-term factors have been considered as influencing factors for CIC in economic literature. In fact, the majority of the empirical studies in this area define CIC by using one of following measures: such as payroll dates, weekends, holidays (seasonality), transactions variables (consumption or GDP), opportunity cost measures (interest rate, inflation and exchange rate) and technical and institutional factors (ATMs/electronic banking). Also various methods such as exponential smoothing, ARIMA, ARMA, VECM etc. have been used for forecasting CIC. A summary of empirical evidence on determinants of CIC is given in Appendix 1.

4. Methodology

5.1 The Model and Data

Several types of statistical techniques are used in modelling and forecasting CIC in economic literature. Many central banks use time series forecast models, often in the form of either first order autoregressive models, though more sophisticated approaches such as exponential or ARIMA type models (Norat, 2008). Some central banks apply econometric theoretical approaches. In this study, the currency demand of Sri Lanka is estimated using three different approaches; VECM and exponential smoothing model, which are common models used by central banks for forecasting CIC and ARIMA model; the most widely used econometric model in modelling CIC.

4.1.1 Vector Error Correction Model (VECM)

The demand for currency primarily relates to transactions demand in a country. Besides the transactions demand, a part of currency, being the most liquid form of money, is also held by the public and the firms as a precautionary measure. CIC is influenced by a host of factors primarily among them being the per capita income levels of people, prices of goods and services, opportunity cost of holding cash, financial innovations such as non-cash means of payment (e.g. smart cards, debit cards, credit cards, etc.) and extent of financial inclusion (Nachane et al, 2013). Understanding relationship between currency and various macroeconomic parameters is an essential in estimating currency demand model. A number of variables could affect aggregate currency demand; the most commonly used are interest rates (opportunity cost of holding currency), inflation (cost of living), national income or private consumption (to account for transactions demand), seasonal and cyclical effects (New Year, Christmas and elections) and financial innovations. In line with the general approach, it is concentrated on the first three candidate variables using two dummy variables to capture the effect of seasonal effects. To conduct this study, data from CBSL was used. On the basis of data availability, the model was estimated with data of a quarterly frequency for the period of 2001Q1 to 2016Q1. All variables are expressed in logarithmic form, except interest rate.

For the estimation, Average Weighted Deposits Rate (AWDR) has taken as interest rate. The Colombo Consumer Price Index (CCPI) is the official index of inflation in Sri Lanka. The seasonal effect is captured by dummy variable 1 (D1). Dummy variable 2 (D2) is presented to capture the effects of election on currency demand. The study uses the following currency demand function incorporating the factors described above.

$$lncic = \beta 0 + \beta 1 int + \beta 2 lnccpi + \beta 3 lngdp + \beta 4 D1 + \beta 5 D2 + \varepsilon t \quad (1)$$

Variables used in the empirical analysis, are defined in the following manner.

β = constant
int = interest rate (Average Weighted Deposit Rate - AWDR)
lnccpi = log of Colombo Consumer Price Index
lngdp = log of real Gross Domestic Product
D1 = a dummy variable to capture the seasonal effect (New Year and Christmas)
D2 = a dummy variable to capture the effect of elections

An increase in interest rates is expected to decrease in CIC due to increase in savings and deposits. Hence, a negative relationship is expected between currency demand and interest rates. An increase in price levels indicates increase in currency demand due to high cost of living. Therefore, a positive relationship is expected between inflation and currency demand. It is observed that the GDP has a positive relationship with currency demand that increase in income level. D1 is expected to have a positive relationship since seasonal demand causes higher demand in CIC. Moreover, D2 is expected to have a positive coefficient with currency demand as election causes higher currency withdrawals in the country. Descriptive statistics of data are given in Table 4.

Table 4: Descriptive Statistics

	CIC	INT	CCPI	GDP
Mean	214.52	7.948361	121.60	619,059.40
Median	180.47	7.400000	131.20	587,411.00
Maximum	498.34	11.63000	188.50	965,687.00
Minimun	70.42	4.840000	56.00	382,180.00
Std. Dev.	118.19	2.099843	43.95	171,761.00
Observations	61	61	61	61

Source: Author's Calculation

Table 4 shows that, on average CIC was around RS. 214.52 million and average interest rate was around 7.95 per cent per quarter. CCPI was around 121.60 index points and GDP was around Rs. 619,059.4 million in constant terms.

4.1.2 Exponential Smoothing Approach

Exponential smoothing is a forecasting technique that applies unequal weights to past data, with greater significance being placed on more recent data (Sewordor et al, 2007). As per the Norat (2008), this model is a weighted moving average forecasting technique where past observations decline in weight exponentially and the forecast for the next period is the forecast for the previous period plus an adjustment for the forecast error from the previous period. As per equation 2, Y_t refers the CIC in logarithmic form. Term α is a constant between 0 and 1where $0 \leq \alpha \leq 1$ is the smoothing parameter. The forecast at time t+1 is equal to a weighted average between the most recent observation yt and the most recent forecast $y_{t-1.}$

$$\begin{aligned}\hat{y}_{t+1} &= \hat{y}_t + \alpha(y_t - \hat{y}_t) \quad (2)\\ &= \alpha y_t + (1-\alpha)\,\hat{y}_t\end{aligned}$$

According to Norat (2008), substituting repeatedly for past forecast values in equation 2 results in the more general expression. As per Hyndman et al (2002), exponential smoothing models have good short-term forecast and seasonal time series predictability.

$$\begin{aligned}\hat{y}_{t+1} &= \alpha y_t + \alpha(1-\alpha)y_{t-1} + \alpha(1-\alpha)^2 y_{t-2} \quad (3)\\ &\quad +\alpha(1-\alpha)^3 y_{t-3} + \dots + \alpha(1-\alpha)^{t-1} y_1 + (1-\alpha)^t y_1\end{aligned}$$

As data points are weighted in accordance with an exponential function of their age, the smoothing is termed 'exponential'.

4.1.3Auto-Regressive Integrated Moving Average (ARIMA) Model

The ARIMA model is based on the methodology proposed by Box and Jenkins (1976). This methodology states that any weak stationary process can be broken down into autoregressive (AR) and moving average (MA) processes.

The models constructed using ARIMA are independent of any particular economic theory, and the forecast from the models are based purely on the past behavior of the series (Cassino et al, 1997). The model has been used extensively for the non-stationary time series. Hence one of the popular time series forecasting method that used by several is ARIMA. The linear ARIMA model is represented as follows:

$$y_t = D_t + \frac{\theta(B)}{\emptyset(B)\Delta(B)}\epsilon_t \qquad (4)$$

In the model, y_t refers the CIC in logarithmic form, and D_t represents the regression component. B is the back-shift operator, and θ and φ are the moving average and autoregressive operators, respectively. Δ is a difference operator, depending on the frequency of the difference. ϵ_t is assumed to be an independent and identically distributed stochastic process with zero mean and a variance of σ^2. The deterministic component describes intra-weekly, intra monthly and holiday effects and the stochastic component describes the correlation structure of the series and describes the remaining periodically (Cabrero et al, 2002).

$$D_t = \sum_{i=1}^{s} d_{i,t}, \qquad (5)$$

As per the equation (5), s is equal to the number of calendar variation effects, and $d_{i,t}$ is a function of all seasonal factors.

5. *Empirical Analysis*

5.1 Unit Root Tests

In the first stage, this study performs the unit root test on each variable in order to examine the stationary or non-stationary level in a time series data set. If both stationary and non-stationary variables were included in an equation and estimated by Ordinary Least Squares (OLS), this will lead to a spurious regression. Therefore, it is important to differentiate between stationary and non-stationary variables. There are various alternative tests for testing whether a series is stationary. Commonly used tests are Augmented Dickey-Fuller (ADF) and Philips-Peron (PP) tests.

This section conducts the unit root test using ADF test and PP test. Summary results of the unit root tests are presented in Table 5.

Table 5: Results of Unit Root Tests

Variable	Indicator	ADF Test		PP	
		Level	1st difference	Level	1st difference
LNCIC	t-Statistic	0.0569	-3.3068	0.8232	-18.1047
	P-Value	0.9594	0.0193	0.9937	0.0000
INT	t-Statistic	-3.1468	-3.7894	-2.2450	-3.3449
	P-Value	0.2285	0.0500	0.1931	0.0172
LNCCPI	t-Statistic	-1.2955	-5.3587	-19.9423	-5.4031
	P-Value	0.6261	0.0000	0.3112	0.0000
LNGDP	t-Statistic	1.1964	-11.1186	0.8211	-51.9150
	P-Value	0.9978	0.0000	0.9937	0.0001

Source: Author's Calculation

At levels, the null hypothesis of unit root cannot be rejected for all the variables. Therefore, the ADF and PP tests are conducted again for the first difference of each variable. The results show that the non-stationary hypothesis is rejected for the first difference of all the above variables. This indicates that each variable is integrated in order 1. This concludes that each variable in the study can be made stationary by taking the first difference. In summary, since all variables are integrated in the same of order ($I(1)$), and these variables are suitable for the long run cointegration test.

5.2Co-integration Analysis

Table 6: Normalised Co-integration Coefficients

Null Hypothesis	λ-Trace	λ-Trace 5% Critical Value	λ Max	λ-Max 5% Critical Value
r=0	149.9854	95.75366	61.66318	40.07757
r≤1	88.32225	69.81889	43.75880	33.87687

Source: Author's Calculation

As per the results shown in Table 6, both the Trace and Maximum Eigenvalue statistics confirm that there exists one cointegration between the variables. Hence the next step is to estimate the Error Correction Model to identify the normalised co-integrating coefficients with respect to currency demand. Table 7 shows the results of the Error Correction Model.

Table 7: Normalised Co-integration Coefficients

	LNCIC	INT	LNCCPI	LNGDP	D1	D2
β Coefficient	1	0.0048	-0.7081	-0.9154	-0.9590	-0.0512
Std. Error		0.0072	0.1379	0.1970	0.09660	0.0353
t-Statistic		0.6674	-5.1351*	-4.6467*	-9.9267*	-1.4519

**Significant at 5% level*

Source: Author's Calculation

It is expected that inflation, GDP and two dummy variables, new year/Christmas and elections exert a positive influence on currency demand in Sri Lanka and interest rates negatively relate to the CIC. As per the normalised co-integration equation of long run regression; all variables carry the expected signs during the review period. The results of long run model for CIC for Sri Lanka can be specified as follows.

$$LNCIC\,(-1) = 10.5414 - 0.0048INT\,(-1) + 0.7081LNCCPI\,(-1) + 0.9154LNGDP\,(-1) + 0.9590D1\,(-1) + 0.0512D2\,(-1) \quad (6)$$

As per the estimated equation above, a 1 per cent decrease in the interest rates would increase the currency in circulation marginally by 0.005 per cent, while an increase in inflation by 1 per cent, would increase the currency demand by 0.70 per cent. Currency demand increase by 0.91 per cents when real GDP increase by 1 per cent. The New Year and Christmas periods (April and December) had a positive effect of 0.95 per cent on the demand for currency. Moreover, elections had a positive effect of 0.051 per cent on CIC Sri Lanka.

5.3 Vector Error Correction Estimates (VECM)

In order to study the short run behavior of the variables and to measure their deviation from the equilibrium in the short run, VECM was used. The results of the VECM for currency demand model were given in the Table 8.

Table 8: Summary Results of VECM

	D(LNCIC)	INT	D(LNCCPI)	D(LNGDP)	D1	D2
β Coefficient	0.1170	0.7746	-0.0048	-0.1202	3.4464	0.2666
Std. Error	0.0304	0.7195	0.0282	0.0355	0.4339	0.8536
t-Statistic	3.8536*	1.0767	-0.1719	-3.3769*	7.9427*	0.3124

**Significant at 5% level*

Source: Author's Calculation

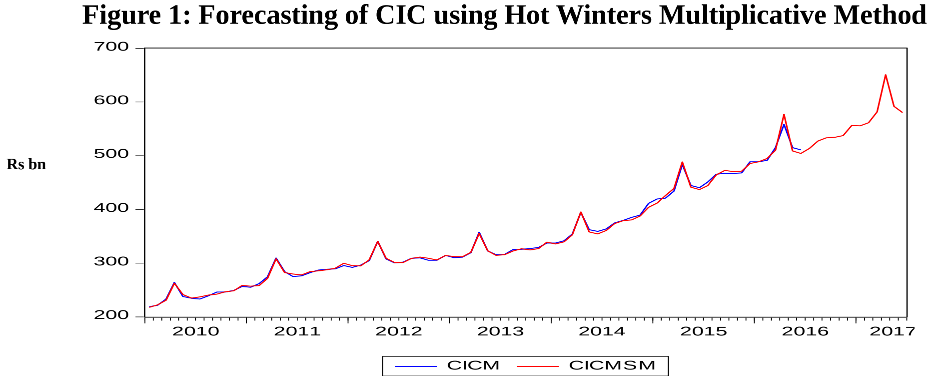
The coefficient of Error Correction Term of D(LNCIC) is 0.117. This indicates that 11.7 per cent of the deviation from the equilibrium is corrected within a quarter, taking around 2 quarters to reach long run equilibrium.

5.4 Forecasting of CIC

5.4.1 Forecast based on Exponential Smoothing Approach

Holt-Winters Multiplicative method was used to forecast CIC under exponential smoothing approach. For this study, monthly average data of CIC was used to forecast CIC. Accordingly, during the period of 2016:6-2017:6 can observe same seasonal trend for the month of April and December as shown in Figure 1

Figure 1: Forecasting of CIC using Hot Winters Multiplicative Method



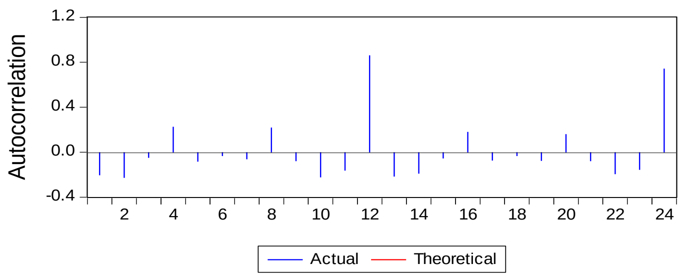
Source: Author's Calculation

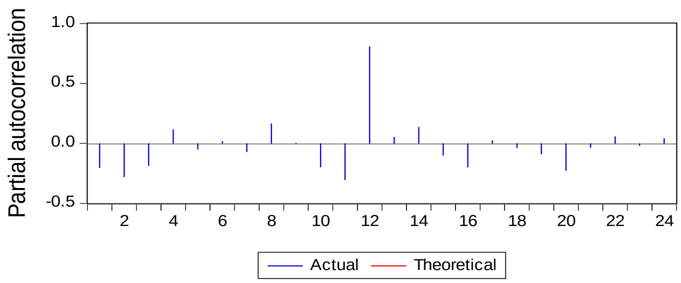
The forecast produced by this model accurately matches the shape of the monthly behavior and capture the seasonal effects as well. Further, this model evidenced clear seasonality in April and December mainly associated with the Sinhala/Tamil New Year and Christmas respectively.

5.4.2 Forecast based on ARIMA Model

ARIMA model which is a generalization of an autoregressive moving average is applied in this study. To perform the regression model; it is needed to have a stationary series. Therefore, it is used the Augmented Dickey-Fuller test to check if the CIC series is stationary or not. The results of the ADF test are shown in Table 9 in Appendix 2. The ARIMA model denoted by ARIMA (p, d, q) × (P, D, Q) can be expressed using the lag operator. p, d, q are the orders of non-seasonal AR, differencing and MA respectively. P, D, Q are the orders of seasonal AR, differencing and MA respectively. According to Nasiru et al (2013), the estimation of the model involves three steps, namely: identification, estimation of parameters and diagnostics. The identification step involves the use of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) to identify the tentative orders of both the non-seasonal and seasonal components of the model. Accordingly, after obtaining the order of integration of CIC, the order of the Autoregressive and Moving Average was determined. Based on the Box-Jenkins approach this was based on the ACF and PACF plots. Below Figure 2 shows that the ACF plot have significant spike at the non-seasonal lag 1 and 2 and seasonal lag 4 and 12 with some other spikes at other non-seasonal lags. Also, the PACF plot also has significant spikes at the non-seasonal lags 1 and 2 and seasonal lags 4 and 12 and also has spikes at other non-seasonal lags.

Figure 2: Results of ACF and PACF



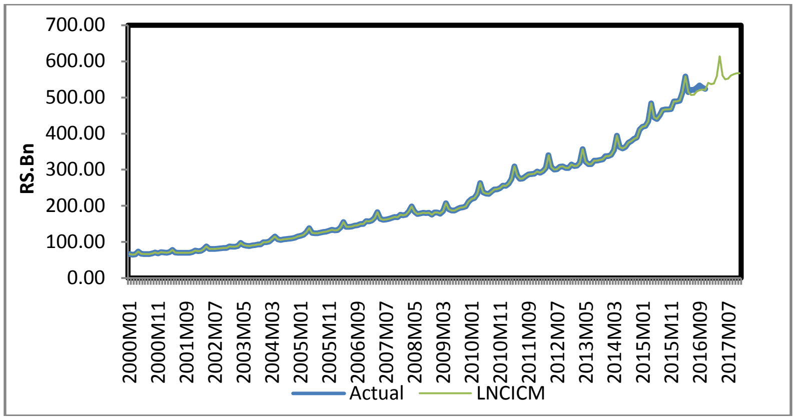


Source: Author's Calculation

The second step involves estimation of the parameters of the tentative models that have been selected. In this study, the model with the minimum values of Akaike Information Criterion (AIC), modified Akaike Information Criterion (MAIC) and Bayesian Information Criterion (BIC) is adjudged the best model. Accordingly using the lower significant lags of both ACF and PACF and their respective lags tentative models were identifying for CIC. The optimal lag length for both the AR and MA are selected using the AIC. Accordingly, six candidate's models are obtained. Out of these models the best model is obtained that was the lowest AIC. Accordingly, the result of Table 10 in Appendix 2 shows that ARIMA (212) (101) model is the best candidate models that has least AIC.

Accordingly, CIC is forecasted using the ARIMA (212) (101) model. Below figure 3 shows actual historical data for the period of 2001:1 – 2016:5 and the forecast for post sample estimates of 2016:6 – 2017:11 are used for testing the validity of the model. The forecast produced by this model accurately matches the shape of the monthly behavior and capture the trend, seasonal and cyclical effects as well.

Figure 3: Forecasting of CIC Using ARIMA



Source: Author's Calculation

ARIMA model based forecasts give reliable estimates of CIC. Hence, forecasting CIC considering behavior in similar periods in the past as well as seasonality and trends in economic activities using judgment would be more appropriate.

6.Conclusion

This research was undertaken with a view of examining the behavior of CIC in Sri Lanka. Accordingly tests and models such as VECM, exponential smoothing and ARIMA were employed. It is found that depending on the VECM model, variables such as the deposit rate, inflation, GDP and dummy variables for New Year/ Christmas and election were significant in explaining changes in CIC. GDP has a positive impact on the demand for currency. Seasonally proxied by a dummy variable which recognizes April and December as special months (given that they are festive periods) is also significant. Elections also have positive impact on CIC. Movements in interest rates (AWDR) have a negative impact on CIC. The inflation was also found to have a positive impact on CIC as expected.

Both exponential smoothing an ARIMA models accurately matches the shape of the monthly behavior and capture the trend, seasonal and cyclical effects. As per Cassino et al (1997), ARIMA model may be more suitable for forecasting currency than the currency demand function as structural relationships of an error correction model will only have an impact on economy in the long run. However, it is noted that the CBSL cannot totally depend on forecasting models such as ARIMA to predict CIC to be used in liquidity management as CIC can be influenced by various other factors such as elections, festive seasons and long holidays. Therefore, the review market conditions daily and do necessary adjustments manually to make the assessment more realistic is also required.

There are several limitations of this study. Most of them are arising from the non-availability of relevant data. Absence of data on daily and monthly such as GDP, inflation forecast, financial innovations could not capture the real determinants of currency demand. There are several improvements to be made in this forecasting framework based on the experiences with this exercise. Especially this model has constructed on using quarterly and monthly data. But in order to capture real movements of CIC, need to forecast for daily data. Moreover, a variety of more advanced forecasting methods could be employed. On the other hand, there are other variables (autonomous factors), such as financial innovations, cash in commercial bank vaults and government deposits whose forecasts can be further improved using the methods described in this paper.

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Appendix 1: Summary of the Empirical Evidence. Authors	**Scope**	**Methodology**	**Key Findings**
Khatat (2018)	Variables used are GDP, inflation, interest rates and CIC for VAR estimation. Used the cases of Brazil, Kazakhstan, Morocco, New Zealand and Sudan.	Transformed currency demand function in a Vector Auto regression and applied ARIMA modelling to estimate CIC.	Higher interest rates do not decrease relative attractiveness of cash. Transmission of monetary policy shocks to the currency demand differ from country to country. An application of ARIMA models to the CIC in five countries provided good performances.
Nachane , D. M. Chakraborty, A . B. Mitra, A. K. and Sanjib Bordoloi (2013)	Annual data for 1989-90 to 2010-11 and quarterly data for 1996-97:Q1 to 2010-11:Q4 for the following variables - CIC in nominal terms - Inflation - Expected Inflation - GDP - Deposit rate	Johansen cointegration analysis was employed for modelling currency demand in India	Results show that output, inflation, interest rates directly affect the growth and composition of currency.
Ikoku, A. (2013)	Daily, weekly and monthly data of Nigiria from January 3, 2000 to September 30, 2010 for the following variables - CIC -Naira/US dollar Exchange rate - Interbank rate - Dummy variables for holidays and elections	ARIMA and Structural ARIMA models was used to forecast CIC in Nigiria. VECM employed for test long run relationship of CIC.	The results reveal that exchange rate, interbank rate, seasonality, holidays and elections were significant in explaining the demand for currency.
Sarwar, H. Sarwar, M. and Waqas, M. (2013)	Annual data for Pakistan economy was used comprising the time period of 1972-2007 for the following variables - M1, M2, and M3 - Real GDP - Inflation rate - Interest rate on time deposits - Financial innovation (Ratio of M2-CC/GDP	Johansen cointegration and VECM analysis is used to investigate the long-run real money demand relationship in Pakistan	M2 (broad money) was the proper aggregate for stable money demand function. GDP and financial innovation significant in explaining money demand function.
Balli, F. and Elsamadisy, E. (2010)	Daily and weekly data of Quarter from 1/1/2002-31/12/2006 for the following variables - CIC - Dummy variables for holidays	Seasonal ARIMA model was employed to forecast CIC	Seasonal ARIMA performs better in forecasting CIC in short term horizons.
Dheerasinghe, R. (2006)	Monthly, weekly and daily data of Sri Lanka for the period of 1 January 2000 to 31 August, 2005 for following variables -CIC - Dummy variables for new year, Christmas, holiday and election effects	ARMA model to forecast CIC	The model evidenced clear seasonality in new year and Christmas. Special holidays and general elections are significant in determining CIC

Source: Author’s Calculation

Appendix 2

Table 9: Results of ADF Tests of ARIMA Model

Null Hypothesis: D(DLNCIC) has a unit root
Exogenous: Constant
Lag Length: 10 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-27.29183	0.0000
Test critical values:	1% level	-3.465977	
	5% level	-2.877099	
	10% level	-2.575143	

*MacKinnon (1996) one-sided p-values.

Source: Author's Calculation

Table 10: Results of ARIMA Model

Dependent Variable: DLNCIC
Method: Least Squares
Date: 11/29/16 Time: 13:54
Sample (adjusted): 2001M 04 2016 M05
Included observations: 182 after adjustments
Convergence achieved after 25 iterations
MA Backcast: 2000M02 2001M03

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.007468	0.057584	-0.129697	0.8970
AR(1)	0.294028	0.032557	9.031148	0.0000
AR(2)	-0.881929	0.036797	-23.96737	0.0000
SAR(12)	1.004072	0.005441	184.5488	0.0000
MA(1)	-0.390999	0.016224	-24.09962	0.0000
MA(2)	0.980727	0.008928	109.8538	0.0000
SMA(12)	-0.903016	0.024066	-37.52234	0.0000

R-squared	0.928563	Mean dependent var	0.010773
Adjusted R-squared	0.926113	S.D. dependent var	0.043760
S.E. of regression	0.011895	Akaike info criterion	-5.987699
Sum squared resid	0.024761	Schwarz criterion	-5.864468
Log likelihood	551.8806	Hannan-Quinn criter.	-5.937743
F-statistic	379.1168	Durbin-Watson stat	1.809085
Prob(F-statistic)	0.000000		

Source: Author's Calculation