International Journal of Business Innovation and Research

ISSN online: 1751-0260 - ISSN print: 1751-0252
https://www.inderscience.com/ijbir

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DOI: 10.1504/IJBIR.2022.10045199

Article History:

Received:	29 January 2021
Accepted:	05 January 2022
Published online:	15 January 2025

ARIMA modelling of weighted average lending rates of Indian scheduled commercial banks and estimation of VaR: implications on asset-liability management

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Abstract: Weighted average lending rates (WALRs) as introduced by Reserve Bank of India (RBI) to compute effective lending rates on outstanding rupee loans, play a significant role on value at risk (VaR) and asset-liability management of Indian banks. This study aims to predict WALR of scheduled commercial banks on outstanding Rupee loans in India by taking monthly data from February 2012 to November 2020 from 'rbi.org.in'. Using Box-Jenkins methodology, AR(16)MA(11) model is modified to have adjusted ARIMA (16,19,11) or AR(16) AR(19) AR(11) model, thereby optimising the model for efficient forecasting of WALR. Forecasted values are further used to estimate value at risk (VaR) on outstanding loans. Data does not exhibit any significant volatility for GARCH adjustments. The proposed model has substantial implications on asset-liability management (ALM) and risk shifting strategies of banks to hedge themselves against VaR limits at 99% confidence, leading to an efficient risk management.

Keywords: lending rates; interest rates; commercial banks; ARIMA; forecasting; liquidity and asset-liability management; ALM; risk management; VaR; risk management.

Reference to this paper should be made as follows: Shukla, U.N., Kushwaha, R., Mohan, H. and Medhavi, S. (2025) 'ARIMA modelling of weighted average lending rates of Indian scheduled commercial banks and estimation of VaR: implications on asset-liability management', *Int. J. Business Innovation and Research*, Vol. 36, No. 1, pp.19–41.

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1 Introduction

Issue of frequent changes in demand-based interest rates, in competitive Indian money market, disrupts financial market participants, while strategising their business activities. This is a matter of great concern of policymakers as well, to choose an appropriate monetary and fiscal policy under somewhat predictable future interest rates.

In the growing economy like India where the banking system is pivotal for providing sustainable funding to upcoming start-ups and industries, it is most important to have efficient forecasting intelligence about 'weighted average lending rate (WALR)' to achieve the eventual objectives of economic policy post COVID-19 disruptions. However, transmission to banks' lending rates in India is hindered by a variety of factors, the most important being the long maturity profile of lending/borrowings primarily at fixed interest rates. Diffusion to money market and long-term rates has been swift and becomes significant to be paid attention after the liquidity crisis during COVID-19 (RBI Bulletin, 2020). However, lending rates would no longer be reliant upon adjustment in deposit interest rates only, instead changes in lending rates will induce changes in deposit interest rates establishing the significance of volatility in WALR. The nominal WALR for scheduled commercial banks (SCBs) is computed based on the amount outstanding taken as weight for calculating average lending rates. The formula for computing WALR is

$$WALR^* = \sum_{j=1}^{m} \left(i_j c_j\right) \div \sum_{j=1}^{m} \left(c_j\right)$$

*i_j is lending rate and c_j is amount outstanding of rupee loan at period j and m is positive integer indicating time period.

Equity market in India has observed a series of reforms which were intended to boost lending rate (WALR) improving efficiency of credit markets to further develop domestic financial markets with steady deregulation of interest rates. Monetary policy operating procedure in India has evolved towards greater reliance on interest rates to indicate the stance of monetary policy in the recent years (Mohanty, 2012). The transmission from the policy repo-rate to bank-lending rates, which is the dominant transmission channel in India, has been a matter of concern. With the recent specific objective of price stability directed by the legislature, the issue of smooth monetary transmission has gained an added significance. Consequently, WALR and its efficient prediction is greatly helpful in managing the better liquidity at banks and financial institutions in an efficient manner (Acharya, 2017). Considering the rising demand of funds for industry and agriculture in India low and feasible interest rates are required in growing economies for better availability of funds. But unique fluctuations in interest rates would have long-term repercussions on Indian banks in terms of stressed borrowings at fixed rates with higher interest payment liability, creating liquidity risk for the banks. Therefore, predictability of lending rates and corresponding risk is much anticipated for sound financial health of Indian banks (Chaudron, 2018).

During volatile WALR, asset-liability management (ALM) would be the key to manage them in efficient manner. One of the important factors in ALM model is – less risky liquid assets ratio (LRLATA) which influences liquidity coverage ratio (LCR) and loan to deposit ratio (LDR) affecting net interest margin and return on equity (ROE) of banks. All these components are well connected to lending rates of banks affecting availability of funds at low cost of capital according to demand. In such a state lending rate would be pivotal to manage asset-liability of any bank, in volatile money market due to fast moving business trends at both national and international fronts (Anggono, 2017). Considering this, predictor model of lending rates of commercial banks is of utmost importance to manage risk and asset-liability of banks in long run-in emerging economies. Predictions of lending rates by extending the dataset in terms of frequency and size as per future needs, is found to be of great help in managing the risk and uncertainty in financial institutions. In emerging economies reference rates may fluctuate and may turn negative as well, hence a framework to study market interest rates using autoregressive model, would have great implications to handle asset and liability and related risk in financial institutions for long-term sustainability (Orlando et al., 2020). In this context availability of funds at predictable rates are much required in India as innovation-based start-ups, founded on business process management for faster economic growth, seek plenty of reasonable funding opportunities from banks. To finance such enterprises at higher credit risk forecasting of lending rates would help the banks to plan their asset and liability more effectively with minimal possible credit risk (Pereira et al., 2021). Immense funding opportunities to innovation based potential start-ups and micro, small and medium enterprises (MSMEs), would fetch more value to banks in terms of revenue and sustainable growth. On the other hand, start-ups/MSMEs are getting encouraged at mass media to have reasonable funding from commercial banks to induce business innovation for long-term growth of economy. Such enhanced funding to

MSMEs may augment the interest rate and credit risk of banks, which can be minimised by efficient risk estimation system based on overseen lending rates (Singh and Agrawal, 2017).

While funding innovative start-ups, efficient risk, and ALM system maintaining quality of assets of banks in India would improve efficiency of money markets by minimising capital depletion, to have sound capital adequacy and solvency ratio. *In this scenario inflation and enhanced credit risk would adversely affect* lending rates leading higher cost of funds. In such a situation to have better control over enhanced credit risk assets-liabilities management system of banks should be based on optimal future lending rates Singh (2021). Furthermore, international reserves and money market disequilibrium would result in market uncertainty, affecting the risk planning of financial institutions adversely. To manage the efficiency of financial institutions, proper deliberations on lending rates are much required, to control value at risk (VaR) in volatile and dynamic financial and money markets of India. Fluctuations in lending rates are likely to create asset liability mismatch on fixed rated lending and borrowing of banks. Hence, for efficient risk management, predictability of lending rates by minimising VaR is vital, for sound financial health of banks (Nayak and Baig, 2019).

2 Objective of the study

In reference to above mentioned background the importance of WALR and its probable movements, are found to be as one of the most significant elements to be taken care of in the growing economy like India. The initiatives like 'Make in India' have raised the level of fixed rate borrowing by innovation-based Start-ups and MSMEs, resulting in more risk exposure of banks on outstanding borrowings and lending. Current study attempts to understand the changed behaviour of WALR for commercial banks to provide better decision making for financial risk management with minimum VaR to ensure relatively sound asset and liability management system at Indian banks.

1. To understand the trend of WALR on outstanding Rupee loans for commercial Indian banks by integrated ARIMA model.
2. To develop a forecasting-model of WALR.
3. Estimation of VaR on outstanding rupee loan portfolio of Rs-1 billion.

Availability of limited secondary information remains to the primary constraints of the study. Study would be of great use for existing scheduled Indian commercial banks, NBFCs and central bank, to add value to effective management of asset and liability by minimising interest rate risk. Study may further be extended to examine the effect of COVID lockdown and crude-oil prices, on interest rate movements.

3 Review of literature

To understand the research question on implications of falling WALR on Indian commercial banks extensive review of literature is conducted which is organised in four parts. First part deals with autoregressive models and assessment of interest rates. In next part, interest rate uncertainty is explored with WALR, and VaR. Thereafter, interest rate uncertainty in Islamic banking is studied followed by international experience on interest rate uncertainty and risk management to develop a sound conceptual framework of study.

3.1 Autoregressive models and forecasting assessment of interest rates

Autoregressive integrated moving-average forecasting of the inflation rate with ordinary least-square (OLS) using quarterly data in Malaysian financial market is found to be significant in understanding interest rates trends to have preventive measures against any future liquidity issue to maintain sound asset liability mismatch in competitive market (Ahmad and Abd Karim, 2011). Risk-based audit plan and performance analysis can help to perform risk assessments across different key aspects in banking, investments, product/process innovations, etc. Dynamic tools like autoregressive forecasting can help to minimise VaR of an enterprise by way of developing a proactive intelligence for efficient management of business assets for long-term growth in competitive environment (Wonglimpiyarat, 2018). Box-Jenkins methodology and VaR simulations are successfully used for modelling interest rates in banks and financial institutions. Interest rates variations are very significant for availability of capital in growing economies. Short-term variations in interest rates are also substantial for overall business climate of any country. Hence such predictions of interest rates using financial analytics provide a right direction to policy makers and investors to work together for inclusive growth (Pejović and Karadžić, 2020). ARDL approach exhibits that there is no fixed long-run impact of the foreign interest rates and net foreign assets etc. on domestic interest rates in predicting short-term lending rates. Hence, autoregressive forecasting is found to be the best solution to address interest rate volatility in emerging economies to ensure long-term supply of funds by banks to potential enterprises with higher business risk for inclusive economic growth (Peiris and Jayasinghe, 2014). Impact of monetary and fiscal factors on interest rate variations in Sri Lanka, under its deregulated regime of interest rates, is found to be significant. Information of nominal interest rates and money growth are auto regressed using augmented-Dickey-Fuller and the Phillips-Perron-unit-root tests to understand capital adequacy more scientifically. It is found that any change in money growth swiftly changes the interest rates, hence autoregressive models are fit to predict interest rates and volatility to manage asset and liability at minimum risk (Maitra 2017). In Pakistan, Karachi Inter Bank Offer Rates (KIBOR) is the average interest rate at which banks want to lend money to other banks. Forecasting of KIBOR rates by ARMA (Box-Jenkins method) model is very beneficial for proactive intelligence. The results extracted from this model are trustworthy for making any forecasting which is very advantageous for policy makers for enhancing asset quality at banks for sound financial health in long run (Ahmed et al., 2017).

3.2 Interest rate uncertainty: ALM, capital adequacy, and VaR

Banks contribute about 7.7% of total GDP in India making banking companies being the backbone of Indian economy. Banks are primarily involved into lending activity playing an important role by providing reasonable capital to business firms, thereby contributing towards constructive capital formation. Performance of banking companies using TOPOSIS method based on financial ratios of banks revealed the financial trustworthiness of Indian banks. Effective management of capital adequacy, liquidity and interest rates is pivotal for banks to maintain their financial soundness in long run by managing their asset and liability more proactively (Yadav and Dharani, 2019). Ongoing digitalisation in Indian banking sector has boosted up efficient banking practises in India with increased use of cashless payments and mobile applications of modern banking systems. Digital transactions have increased the leading efficiency to ensure better capital adequacy of banks. However, to minimise the risk of enhanced rural unsecured lending for inclusive financial and economic growth, forecasting intelligence of lending rates is obligatory to stipulate farsightedness for rural lending and ALM for long run productivity of banks (Shukla, 2019). Thus, innovation-based business planning would strengthen business-organisations and banks in new competitive and complex business environment functioning both in profit and non-profit sectors including different rural banks, co-operative banks, and non-profit NGOs. Innovation tools and forecasting intelligence would fetch competitive advantage for better management of business assets with improved farsightedness. Thus, for pre-emptive approach to manage asset and liability would help in enhancing capital adequacy for sustainability at the level of rural and cooperative banks as well (Klassen et al., 2020). Enhanced rural lending due to augmented use of digital payment systems would facilitate rural lending by Indian banks leading to more credit risk while serving Indian rural market which is largely unsecured. To manage this enhanced credit risk on unsecured lending, forecasting intelligence based on the past lags would help Indian banks to minimise rural credit risk by way of enhancing the quality of lending assets and capital adequacy in terms of tear-1 capital (Shukla, 2017). Capital adequacy is also used to measure the future solvency level of the banks forced by capital depletion. Macroeconomic indicator economic growth and inflation are significant while strengthening capital adequacy of Indian banks which is positively associated with credit risk. Therefore, to minimise credit risk the effective mechanism to measure the interest rate and credit risk must be established to ensure lesser VaR in terms of Tier 1 capital of commercial banks (Singh, 2021). Efficient rating system about lending rate, is an indicator of financial soundness of banks, which is correlated with liquidity position of banks both in long and short run. Healthier management of capital-adequacy, operational-efficiency, and earning-ability, positively affect the balance sheet components pertaining to liquidity, minimising any mismatch of assets and liabilities of banks (Sahyouni et al., 2021). Macro factors affecting the liquidity of SCBs in India confirm that, lending rates are significant to both dynamic micro and macro factors affecting the quality of financial assets in long run. Therefore, to manage asset and liability fairly, intelligent management of lending rates is required to minimise VaR to ensure the financial efficacy of banks in India (Grover and Sinha, 2021) Behaviour of lending rates reveals that the cycle of lending rate may peak at different time lags. This expected behaviour in lending rates of commercial banks is primarily due to the assimilation of the domestic economy with the worldwide money and financial market. Thus, modelling of lending rates of banks for efficient management of asset and liability is obligatory for sound financial health of banks and financial institutions (Bhattacharya et al., 2008). In addition to it, rising income and variations in call money would initiate significant upsurge in lending rates leading to higher cost of bank borrowings and cost of capital thereby making asset financing more costly in short run. This would lead to liquidity crunch in banks with mismatch of asset and liabilities. Hence, to have better understanding of future trends of bank prior estimation of WALR is very significant for Indian banks (Maitra, 2018).

Under Basel III norms, measuring, managing, mitigating, and forecasting interest rate risk has been given utmost importance in highly competitive modern volatility, uncertainty, complexity and ambiguity (VUCA) world. By examining the stress of financial assets in banks it is observed that although Indian economy has revealed relatively less volatility in interest rates after second quarter of 2018, but such consistent volatility of interest rates has shown significant repercussions on money supply. Therefore, WALR needs to be administered properly for inclusive and equitable growth of economy (Mallick and Mishra, 2019). In larger banks' due to financial leverage, they are more responsive to lending rate changes, while smaller banks strengthen the potency of such transmission by maintaining better liquidity. Therefore, it is concluded that managed interest rates induce a positive strategic impact on the net stable funding ratio (NSFR) of both large and small banks under Basel-III norms to ensure less credit risk with better ALM. Thus, banks must develop intelligence of understanding lending rates to manage composition of liabilities against availability of funding sources, to minimise VaR of banks (Dang and Nguyen, 2020).

3.3 Interest rate uncertainty and Islamic banking

Comparative analysis of dual banking systems for ALM, in Islamic Commercial Banks (ICBs) and Conventional Commercial Banks (CCBs) also describes that ICBs have got more variations in their mean duration gap as compared to the CCBs. Thus, Islamic Commercial banks have more exposure to interest rate risk due to demand supply forces in competitive market. This gap is found to be more prominent with the change of geographical pattern which adversely affects the asset liability framework and VaR of these banks as well (Chattha et al., 2020). Islamic banks represent a significant share of the market for financial services. Islamic financing allows for periodic adjustments of the profit rate or lease rental, resulting in a significant impediment in the functioning of banks at competitive marketplace. Such heterogeneous periodic adjustments would result in asset liability mismatch, leading to interest rate risk, liquidity risk, inducing imbalance in risk profile of such banks (Archer and Abdel Karim, 2019). On more issue is associated with quality of services provided by these banks, as Islamic banks in Indonesia require innovation in service delivery based on customer's perspective to reduce the operational risk. With increased operational risk VaR is enhanced due to imbalances in asset and liability management. Digitisation and service innovations are required to improve their farsightedness and better response to competitive macro environment. Such service innovation would reduce operational risk with better ALM (Azis and Kamal, 2019).

3.4 International experience on interest rate uncertainty and risk for asset and liability management

International familiarity about the concept is observed primarily in the studies on business innovation and forecasting based on financial-intelligence.

Internationalisation of financial services and Interest rate liberalisation has a nonlinear impact on liquidity of banks, and the relationship between them is in the shape of inverted U. Thus, as interest rate liberalisation evolves, first liquidity of bank increases and then it drops subsequently hampering their risk-taking ability. Thus, frequent fluctuations in interest rates affect bank's risk-taking ability hampering the ALM. Therefore, to manage the uncertainty of lending rates fluctuations, autoregressive forecasting of lending rates would provide financial intelligence for suitability (Zhang and Deng, 2020). Interest rate has a significant impact on bank loans, leading to effectiveness of overall lending mechanism. Different bank level variables, like-liquidity, assets and liability have been found to be significantly affecting the lending ability of the banks in Egypt as well (Shokr, 2020). In an analysis of risk management practices in Japan and USA on investigating the pattern of product risk management utilised by firms, it is found that US firms uses both project and quality management to manage and forecast risk by emphasising the significance of farsightedness in business. Therefore, it becomes more important for banks and financial institutions over there to equip themselves with efficient forecast mechanism of lending rate uncertainty to manage critical liquidity crisis in dynamic business environment (Shimizu et al., 2020). In a primary study of post offices in Malaysia, it is found the service innovation has a direct positive effect on service loyalty and service quality of financial institutions as well. Therefore, to ensure sound service quality financial health of banks is a prerequisite. Primary service innovation is to be based on efficient lending rate management in dynamic environment to minimise both liquidity risk and poor quality of financial assets (Kiumarsi et al., 2020).

Emerging financial technologies with the potential to disrupt various industries even in Thailand, are bringing significant service innovations and business intelligence in crowd funding and peer to peer lending by maintaining their assets in accordance with liability using dynamic tools of financial analytics providing forecasting intelligence as well for minimising the value of business at risk (Harris and Wonglimpiyarat, 2020). Long-run equilibrium relationship between the average lending rate of commercial banks with their determining factors is found to be predominant in highly dynamic international financial markets. In long run, bank lending rates in Ghana are found to be positively influenced by nominal exchange rate and monetary policy. This leads to the significance of forecasting of WALR using econometric analytics to have correct anticipation of movement of interest rate in future to have better management of quality of financial assets (Asamoah and Adu, 2016). Influence of arbitrage trading between index returns of developed US marketplaces and their financial performance in two emergent markets viz., India and China by applying VaR-SURE model it is found that model of VaR provides a strong platform for efficient strategy formulation against different adverse financial movement in highly competitive and volatile global financial markets (Lakshmi and Visalakshmi, 2016).

Based on above mentioned review of literature it is established that ARIMA-based forecasting model with volatility adjustments, by GARCH model are of crucial importance to understand the movement of interest rates. Based on the above-mentioned theoretical background the study would further add value to the existing knowledge by predicting WALR and VaR to provide financial farsightedness to Indian commercial banks against volatility of interest rate risk leading to lower interest income from outstanding long-term rupee loan. This would provide a platform to Indian banks to manage their spread within prime lending rates and base rates to optimise their asset and liability spectrum.

4 Research methodology and conceptual framework

This study aims to predict WALR of SCBs on outstanding rupee loans in India by taking a monthly data from Feb'2012 to November'2020 from the data available at 'rbi.org.in' which is the repository of data by Reserve Bank of India (RBI).

Box-Jenkins methodology (Makridakis and Hibon, 1997) is used to identify and estimate the suitable auto regressive model. Jenkins methodology is further extended to diagnose and forecast the adjusted and integrated ARIMA model, for commercial banks, to manage their assets and liabilities (Singh, 2021). Data of Feb'2012 to November'2020 was found to be non-stationary at level. Jarque-Bera test (Thadewald and Büning, 2007; Gel and Gastwirth, 2008) is used to test the normality of WALR data. At first difference data got stationary as conformed by augmented Dickey-Fuller test (ADF test) (Paparoditis and Politis, 2018).

Autocorrelation and partial autocorrelation (Gel and Gastwirth, 2008) are considered to study the significant lags for identifying best suitable ARIMA model. Significant auto regressive lags along with moving average (MA) lags are identified effecting the WALR using autocorrelation and partial autocorrelation. Identified model is validated using residual diagnostics. Using principal of parsimony different combinations of the models were tested at the difference series of WALR to find the suitable integrated model of ARMA (p, q, r). Further under diagnostic test as per box Jenkins (Tang et al., 1991). Lag significance is tested, followed by residual autocorrelation and heteroskedasticity test, to validate the model. Forecasting is done using validated ARMA (p, q, r) for the year 2021 and estimation of VaR limits is done at three sigma level with 99% confidence.

4.1 Structuring ARIMA model

Auto-regressive (AR) model is considered for the study where number of past values of the variable WALR are included is denoted by AR(p).

Generalised AR(p) model taken is

$$Y_t = a_0 + b_1 Y_{t-1} + \ldots\ldots + b_p Y_{t-p} + e_t \ldots\ldots\ AR(p), b < 1$$

where Y_t is forecasted value of WALR, Y_{t-1} to Y_{t-p} are past value monthly values of lending rates, coefficient b is less than one.

Similarly generalised MA where number of present and past error terms of WALR are included to make forecast, which is denoted by MA(q),

$$Y_t = a_0 + \delta_1 e_{t-1} + \ldots\ldots + \delta_q e_{t-q} + e_t \ldots\ldots\ldots\ldots\ MA(q), \delta_{q<1}$$

where Y_t is forecasted value of WALR, e_{t-1} to e_{t-q} are past values of error term (error lag) with reference to the monthly forecasted value and actual value, coefficient δ_q is less than one.

Combined ARMA(1, 1) model is obtained by combining Y_t with Y_{t-1} and e_{t-1}. Thus, Y_t will be forecasted using its own past values and error terms.

$$Y_t = a_0 + b_1 Y_{t-1} + \delta_1 e_{t-1} + e_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots ARMA(1,\ 1)$$

Generalised ARMA(p, q) model considered for the study on WALR is

$$Y_t(WALR) = a_0 + b_1 Y_{t-1} + \delta_1 e_{t-1} + \ldots\ldots\ldots\ldots + b_p Y_{t-p} + \delta_q e_{t-q} + e_t \ldots ARMA(p,\ q).$$

In order to explore optimum ARMA model with integration (ARIMA) model is generalised to it is p^{th} and q^{th} lag of error term and Y_t.

Once the optimum ARIMA model is estimated determination of VaR is estimated based on three sigma limits at 99% confidence level to estimate the probable loss to banks with decrease in WALR due to higher payment liability on a portfolio of loans/borrowings carried by banks at fixed rates.

4.2 Determination of VaR

At three sigma level and 99% confidence level the computation of 99% VaR is (Hull, 2018)

$$VaR = \mu - \sigma N - 1(X),$$

where μ = mean = $\sum fx_i / \sum f$, and $\sigma N - 1(X)$ at 99% confidence level is 2.326348.

Standard deviation of WALR (from Nov'20 to Nov'21) $\sigma = \sqrt{\sum fx^2 / \sum f - \left(\sum fx / \sum f\right)^2}$.

$VaR = \mu - \sigma N - 1(X)$. Only worst case is considered with negative sign as falling interest rates would form distribution of losses on the borrowings of banks for fixed rates loans. Therefore, VaR thus estimated would provide the Rupee values of outstanding payments fixed rate borrowing by banks in long run for proactive management of asset and liability of Indian banks.

5 Analysis and discussion

5.1 Data description

This study aims to predict WALR of SCBs on outstanding Rupee loans in India by taking a monthly data from Feb'2012 to November'2020 from the data available at 'https://www.rbi.org.in/scripts/Statistics.aspx'. Subsequently ARIMA model is developed for forecasting the WALR of SCBs on outstanding Rupee Loans for next 12 months.

5.2 Test of stationarity and normality of data

Stationarity of data is tested as following:

Graph is plotted using E-views 10 as per Figure 1, which reflects that data is not mean reverting and is nonstationary in nature.

Further, Test of normality is performed using Jarque-Bera test as per following Figure 2, where Jarque-Bera test is applied to understand the normal behaviour of data as well.

Ho Data is normally distributed.

H1 Data is not normal distributed.

At 5% significance value = 0.05 P, P < significance value 0.015276 (p value in Figure 2) <0.05, therefore null hypothesis (Ho) is rejected and thus data is not found to be normally distributed.

Figure 1 WALR on outstanding rupee loans (see online version for colours)

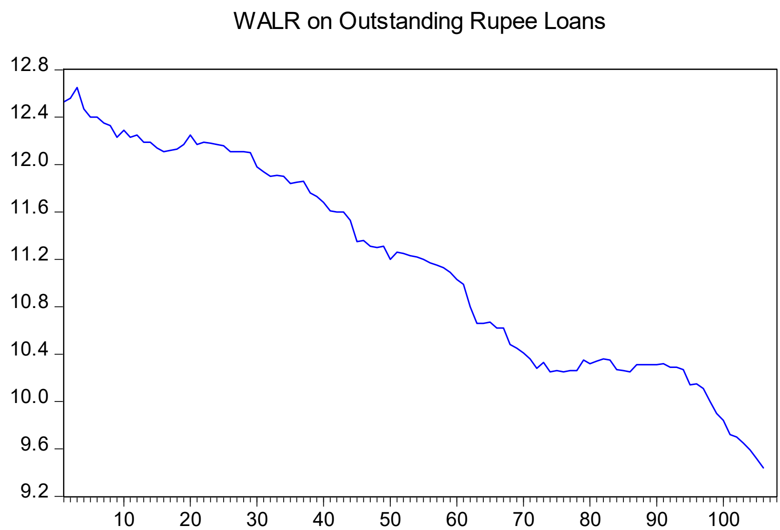
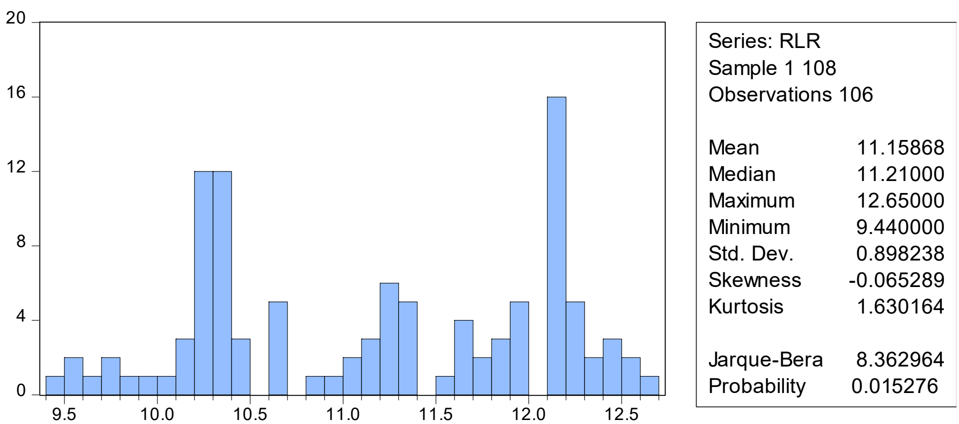


Figure 2 Test of normality: Jarque-Bera test (see online version for colours)



5.3 Test of stationarity of data at first difference

As the data is neither stationary at level nor normally distributed, hence first difference of the WALR series is considered to make the data stationary for further study. Trend movement of the difference series of WALR represented by 'DRLR' is plotted as per Figure 3.

Figure 3 Trend movement of the difference series (DRLR) of WALR (see online version for colours)

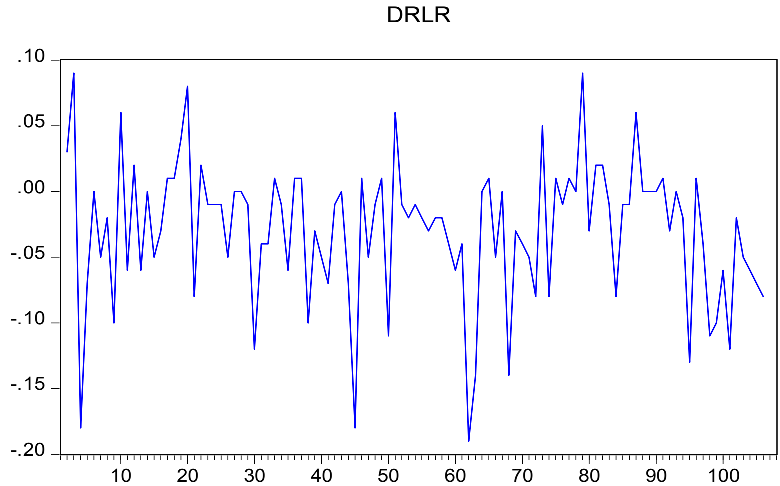


Figure 3 represents that transformed data has got a mean reverting tendency of stationary data. To confirm the stationarity augmented Dickey-Fuller test statistic is used as per Table 1.

Table 1 Augmented Dickey-Fuller test statistic

*Null hypothesis: DRLR has a unit root				
Exogenous: None				
Lag Length: 2 (Automatic – based on SIC, maxlag = 12)				
		t-statistic		*Prob.**
Augmented Dickey-Fuller test statistic		–3.1736		0.0018
Test critical values:	1% level	–2.5878		
	5% level	–1.944		
	10% level	–1.6147		
*MacKinnon (1996) one-sided p-values.				
Included observations: 102 after adjustments				
Variable	*Coefficient*	*Std. error*	*t-statistic*	*Prob.*
DRLR(-1)	–0.3901	0.12291	–3.1736	0.002
D(DRLR(-1))	–0.4447	0.11766	–3.7795	0.0003
D(DRLR(-2))	–0.202	0.09202	–2.1957	0.0304

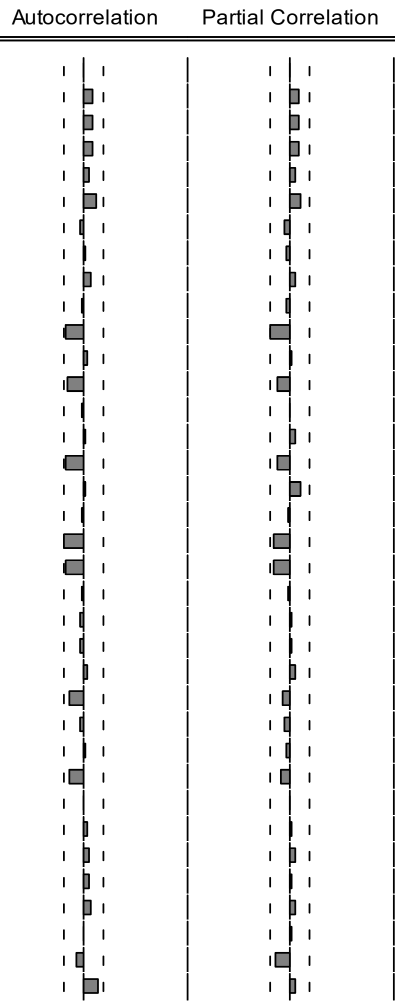
In Table 1, as the p (0.0018) < 0.05, hence, *Null hypothesis gets rejected. Therefore, difference series (DRLR) has no unit root, and data gets stationary.

5.4 Autocorrelation and partial correlation

Difference series (DRLR) is tested for autocorrelation (AC) and partial correlation (PAC) where no significant spikes are damping out of the standard error bounce. AC and PAC are plotted as per following Figure 4 for justification.

Figure 4 Autocorrelation and partial correlation: correlograms

Date: 01/16/21 Time: 08:11
Sample: 1 108
Included observations: 105



	AC	PAC	Q-Stat	Prob
1	0.006	0.006	0.0037	0.951
2	0.085	0.085	0.7978	0.671
3	0.098	0.097	1.8458	0.605
4	0.096	0.090	2.8662	0.580
5	0.061	0.047	3.2909	0.655
6	0.130	0.110	5.2092	0.517
7	-0.035	-0.059	5.3492	0.617
8	0.009	-0.029	5.3595	0.719
9	0.073	0.050	5.9868	0.741
10	-0.015	-0.029	6.0138	0.814
11	-0.182	-0.203	9.9661	0.533
12	0.036	0.017	10.123	0.605
13	-0.162	-0.139	13.322	0.423
14	-0.024	-0.006	13.392	0.496
15	0.013	0.053	13.412	0.571
16	-0.177	-0.134	17.362	0.363
17	0.025	0.099	17.439	0.425
18	-0.024	-0.012	17.510	0.488
19	-0.191	-0.162	22.269	0.271
20	-0.184	-0.166	26.736	0.143
21	-0.016	-0.010	26.771	0.179
22	-0.040	0.023	26.982	0.212
23	-0.031	0.011	27.117	0.251
24	0.034	0.042	27.279	0.292
25	-0.148	-0.075	30.350	0.211
26	-0.048	-0.051	30.671	0.241
27	0.023	-0.039	30.745	0.282
28	-0.141	-0.088	33.637	0.213
29	0.007	-0.007	33.643	0.253
30	0.035	0.022	33.830	0.288
31	0.043	0.051	34.110	0.320
32	0.060	0.021	34.657	0.342
33	0.072	0.047	35.468	0.353
34	-0.002	0.018	35.468	0.399
35	-0.077	-0.155	36.425	0.402
36	0.147	0.063	39.955	0.299

5.5 Box-Jenkins's decision tree

Box-Jenkins's decision tree is used for ARIMA forecasting, to understand seasonal trends as per the theory of modern econometric analysis, under the following steps:

1 model identification
2 estimation of parameters
3 diagnostic checking and revision in model
4 forecasting.

5.5.1 Model identification

Model is identified as per the spikes in Figure 4 of autocorrelation and partial correlation-correlograms, and different models are tested to get the best possible model.

Model estimation

Based on the AC and PAC correlograms (Figure 4) different combination of models are tested to get the best possible model.

AR(11) MA(11), AR(16) MA(11), AR(16)AR(19)MA(11) models are tested to find the best suitable model.

AR(11) MA(11) model

Model statistics is as under:

Table 2 Model estimation AR(11) MA(11)

Dependent variable: DRLR				
Method: ARMA maximum likelihood (OPG-BHHH)				
Variable	*Coefficient*	*Std. error*	*t-statistic*	*Prob.*
C	–0.028939	0.004513	–6.412566	0
AR(11)	0.048348	0.5453	0.088663	0.9295
MA(11)	–0.291718	0.531107	–0.549264	0.584
SIGMASQ	0.002732	0.000405	6.74598	0
R-squared	0.052	Mean dependent var		–0.029429
Adjusted R-squared	0.023842	S.D. dependent var		0.053938
S.E. of regression	0.053291	Akaike info criterion		–2.982164
Sum squared residues	0.286832	Schwarz criterion		–2.881061
Log likelihood	160.5636	Hannan-Quinn criterion.		–2.941195
F-statistic	1.846711	Durbin-Watson stat		1.939596
Prob(F-statistic)	0.143503			

To estimate best model other probable models are tested as following: AR(16) MA(11) model statistics is as shown in Table 3.

To estimate the best model other probable models are tested as following: AR(16)AR(19)MA(11) Model statistics is as shown in Table 4.

Models AR(11) MA(11), AR(16) MA(11), AR(16) AR(19) MA(11) and other significant models are compared to find the best suitable model, as following.

Table 3 Model estimation AR(16) MA(11)

Coefficient covariance computed using outer product of gradients				
Variable	*Coefficient*	*Std. error*	*t-statistic*	*Prob.*
C	–0.028594	0.003785	–7.55453	0
AR(16)	–0.220955	0.103933	–2.125932	0.0359
MA(11)	–0.240279	0.100583	–2.388869	0.0188
SIGMASQ	0.002607	0.00039	6.677672	0
R-squared	0.095353	Mean dependent var		–0.029429
Adjusted R-squared	0.068482	S.D. dependent var		0.053938
S.E. of regression	0.052058	Akaike info criterion		–3.021703
Sum squared residue	0.273715	Schwarz criterion		–2.9206
Log likelihood	162.6394	Hannan-Quinn criterion.		–2.980734
F-statistic	3.548584	Durbin-Watson stat		1.918241
Prob(F-statistic)	0.017169			

Table 4 Model estimation AR(16) AR (19) MA(11)

Coefficient covariance computed using outer product of gradients				
Variable	*Coefficient*	*Std. error*	*t-statistic*	*Prob.*
C	–0.02882	0.00324	–8.895052	0
AR(16)*	–0.206114	0.106204	–1.94073	0.0551
AR(19)*	–0.247543	0.128758	–1.922545	0.0574
MA(11)*	–0.255101	0.103597	–2.462436	0.0155
SIGMASQ#	0.002449	0.00035	6.990367	0
R-squared	0.149949	Mean dependent var		–0.029429
Adjusted R-squared	0.115947	S.D. dependent var		0.053938
S.E. of regression	0.050715	Akaike info criterion		–3.052626
Sum squared residue	0.257196	Schwarz criterion		–2.926247
Log likelihood	165.2629	Hannan-Quinn criterion.		–3.001415
F-statistic	4.409987	Durbin-Watson stat		2.03164
Prob(F-statistic)	0.002521			

Table 5 Model parameters AR(16) AR (19) MA(11)

Variable	*Coefficient*	*Std. error*	*t-statistic*	*Prob.*
C	–0.028820	0.003240	–8.895052	0.0000
AR(16)	–0.206114	0.106204	–1.940730	0.0551
AR(19)	–0.247543	0.128758	–1.922545	0.0574
MA(11)	–0.255101	0.103597	–2.462436	0.0155

Model confirmation and estimation of parameters

It is explored on comparing Tables 2, 3 and 4, that adjusted and integrated ARIMA model as AR(16) AR(19) MA(11) or ARIMA (16, 19, 11) is found to be best suitable as all the parameters are significant* with least value of SIGMASQ#, maximum value of adjusted R square, least values of Akaike info criterion and Schwarz criterion. Parameters for the model AR(16) AR(19) MA(11) are summarised in Table 5.

$$Model: \; Y_t = -0.028820 - 0.206114 Y_{t-16} - 0.247543 Y_{t-19} - 0.255101 \, e_{t-11} + e_t$$

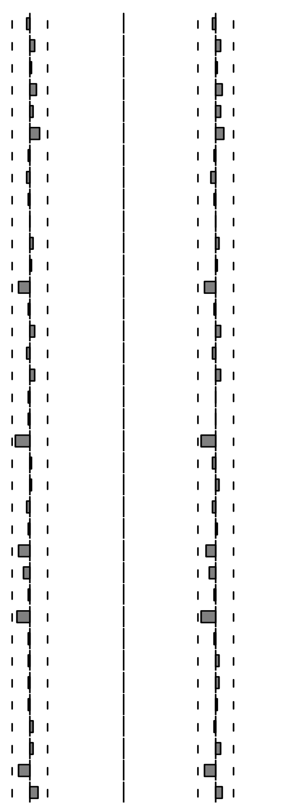
ARIMA(16, 19, 11), as exhibited in table above satisfies all the characteristics of a model to be a good fit.

5.5.2 *Diagnostic checking and revision in model-*

Lag significance of the proposed AR(16) AR(19) AR(11) model is examined as per correlogram in Figure 5, and it is found that all the lags are with in defined error bounce and no lag is significant.

Figure 5 Lag significance of the proposed AR(16) AR(19) AR(11) model

Date: 01/16/21 Time: 08:23
Sample: 1 108
Included observations: 105
Q-statistic probabilities adjusted for 3 ARMA terms

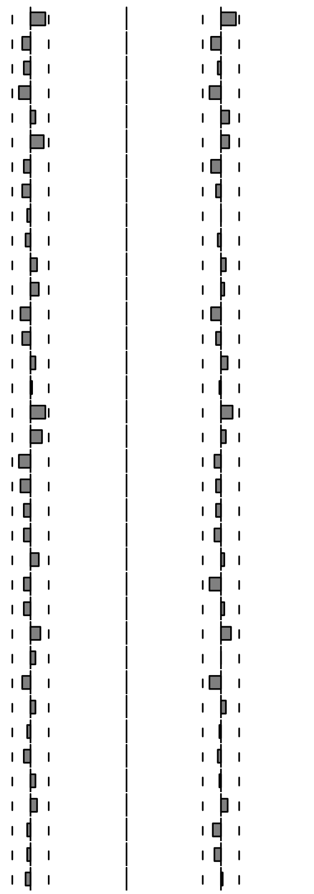


Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.026	-0.026	0.0721	
		2	0.064	0.063	0.5205	
		3	0.011	0.014	0.5331	
		4	0.074	0.071	1.1482	0.284
		5	0.040	0.042	1.3250	0.516
		6	0.102	0.097	2.5156	0.472
		7	-0.020	-0.021	2.5605	0.634
		8	-0.037	-0.057	2.7196	0.743
		9	-0.013	-0.023	2.7397	0.841
		10	0.005	-0.007	2.7421	0.908
		11	0.031	0.029	2.8567	0.943
		12	0.016	0.018	2.8892	0.969
		13	-0.131	-0.126	4.9972	0.891
		14	-0.021	-0.022	5.0503	0.929
		15	0.042	0.055	5.2695	0.948
		16	-0.026	-0.025	5.3577	0.966
		17	0.059	0.065	5.8083	0.971
		18	-0.019	-0.002	5.8558	0.982
		19	-0.018	-0.003	5.8976	0.989
		20	-0.161	-0.168	9.3102	0.930
		21	0.013	-0.025	9.3335	0.952
		22	0.010	0.030	9.3481	0.967
		23	-0.027	-0.028	9.4473	0.977
		24	-0.011	0.023	9.4640	0.985
		25	-0.120	-0.099	11.470	0.967
		26	-0.067	-0.071	12.110	0.969
		27	-0.022	-0.024	12.178	0.978
		28	-0.153	-0.163	15.592	0.926
		29	-0.017	-0.011	15.636	0.945
		30	-0.020	0.034	15.694	0.959
		31	-0.022	0.026	15.766	0.969
		32	-0.010	0.016	15.782	0.978
		33	0.031	-0.010	15.936	0.983
		34	0.032	0.050	16.100	0.987
		35	-0.118	-0.120	18.320	0.975
		36	0.092	0.066	19.708	0.967

Further residual autocorrelation is tested as per following Figure 6 by using correlogram of residual squired.

Figure 6 Residual autocorrelation of the proposed AR(16) AR(19) AR(11) model

Date: 01/16/21 Time: 08:24
Sample: 1 108
Included observations: 105



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.162	0.162	2.8421	0.092
		2	-0.083	-0.112	3.5906	0.166
		3	-0.071	-0.040	4.1505	0.246
		4	-0.129	-0.124	6.0091	0.198
		5	0.060	0.098	6.4158	0.268
		6	0.142	0.094	8.7082	0.191
		7	-0.067	-0.112	9.2205	0.237
		8	-0.091	-0.053	10.187	0.252
		9	-0.034	0.004	10.325	0.325
		10	-0.051	-0.040	10.633	0.387
		11	0.070	0.043	11.226	0.425
		12	0.085	0.037	12.098	0.438
		13	-0.106	-0.104	13.469	0.412
		14	-0.097	-0.053	14.628	0.404
		15	0.047	0.080	14.902	0.458
		16	0.014	-0.013	14.927	0.530
		17	0.166	0.127	18.439	0.362
		18	0.122	0.065	20.364	0.313
		19	-0.115	-0.076	22.087	0.280
		20	-0.105	-0.058	23.558	0.262
		21	-0.071	-0.053	24.230	0.282
		22	-0.075	-0.070	24.991	0.298
		23	0.087	0.034	26.019	0.300
		24	-0.078	-0.135	26.866	0.311
		25	-0.078	0.030	27.714	0.321
		26	0.098	0.113	29.093	0.307
		27	0.046	0.005	29.392	0.342
		28	-0.088	-0.134	30.514	0.339
		29	0.042	0.053	30.778	0.376
		30	-0.041	-0.016	31.023	0.414
		31	-0.072	-0.038	31.808	0.426
		32	0.047	-0.012	32.151	0.459
		33	0.068	0.072	32.873	0.473
		34	-0.044	-0.089	33.183	0.508
		35	-0.036	-0.078	33.385	0.546
		36	-0.052	0.018	33.830	0.572

All the lags are within the error bounce limits. P values are more than 0.05 but it is found that none of the lags added any improvement in the proposed model AR(16) AR(19) AR(11) model hence lags of squired residuals are found spurious, therefore, diagnostic checks on residual autocorrelation (refer Figures 5 and 6) are satisfied. Further, test of heteroskedasticity is performed to further diagnose the model – AR(16) AR(19) AR(11) as a good fit and suitable for forecasting.

ARIMA (16, 19, 11) model: suggested model equation is as following:

$$Y_t = a_0 + b_{t-16}Y_{t-16} + c_{t-19}Y_{t-19} + \delta_{11}e_{t-11} + e_t$$

$$Y_t = -0.028820 - 0.206114Y_{t-16} - 0.247543Y_{t-19} - 0.255101e_{t-11} + e_t$$

Table 6 Heteroskedasticity test: ARCH

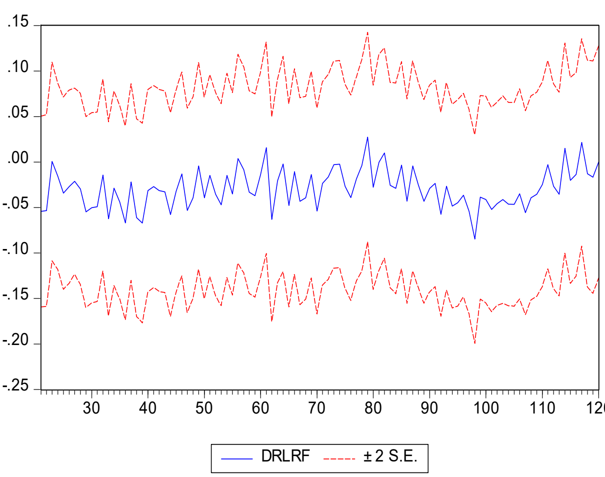
Heteroskedasticity test: ARCH				
F-statistic	2.75674	Prob. F(1,102)		0.0999
R-squared	2.736826	Prob. Chi-square(1)		0.0981
Variable	*Coefficient*	*Std. error*	*t-statistic*	*Prob.*
C	0.002047	0.000447	4.580448	0
*RESID^2(–1)	0.16222	0.097703	1.660343	0.1999
R-squared	0.026316	Mean dependent var		0.002445
Adjusted R-squared	0.01677	S.D. dependent var		0.00388
S.E. of regression	0.003847	Akaike info criterion		–8.264082
Sum squared residue	0.001509	Schwarz criterion		–8.213228
Log likelihood	431.7323	Hannan-Quinn criterion.		–8.24348
F-statistic	2.75674	Durbin-Watson stat		1.912048
Prob (F-statistic)	0.099917			

Notes: *As the p value (0.1999) for variance RESID^2(–1) is > 0.05 hence heteroscedasticity is not found to be significant at 95% confidence level. Null hypothesis is rejected therefore, no arch effect is found. Therefore, data is homoscedastic. Hence, as per Box-Jenkins's decision tree, proposed ARIMA(16, 19, 11) model is the most suitable model for forecasting with seasonal adjustments in WALR.

5.5.3 Forecasting

Developed model ARIMA (16, 19, 11) is extended to 120 observations from 106 to forecast the WALR for SCBs on outstanding loans for the year 2021, please refer to the Figure 8 and Table 7.

Figure 7 Forecasting of WALR of outstanding Rupee loan (see online version for colours)



Forecast: DRLRF	
Actual: DRLR	
Forecast sample: 1 120	
Adjusted sample: 21 120	
Included observations: 100	
Root Mean Squared Error	0.046270
Mean Absolute Error	0.036446
Mean Abs. Percent Error	NA
Theil Inequality Coefficient	0.473816
Bias Proportion	0.000942
Variance Proportion	0.416894
Covariance Proportion	0.582163
Theil U2 Coefficient	NA
Symmetric MAPE	116.6787

Figure 7 suggest that all the forecasted values are within the range of +_ 2SE limits, leading to appropriateness of forecasted results.

Table 7 Forecasting of WALR of outstanding Rupee loan

Months	*Time lag*	*Difference value*	**Forecasted values*
Nov-20			9.44 (actual value) = x
Dec-20	t + 1	–0.03545	9.404554
Jan-21	t + 2	–0.02465	9.379904
Feb-21	t + 3	–0.00293	9.376977
Mar-21	t + 4	–0.02665	9.350324
Apr-21	t + 5	–0.03531	9.31501
May-21	t + 6	0.015139	9.330148
Jun-21	t + 7	–0.02025	9.3099
Jul-21	t + 8	–0.01367	9.296229
Aug-21	t + 9	0.021535	9.317765
Sep-21	t + 10	–0.01302	9.304747
Oct-21	t + 11	–0.01674	9.288012
Nov-21	t + 12	0.000178	9.288189

Notes: *Fore casted values of WALR are exhibited to understand the implications of the ALM of commercial banks. Every fall in WALR on outstanding rupee loans would create lessor interest income to banks, due to floating interest rates on outstanding rupee loans which is in accordance with the study on bank's interest rate risk and profitability by Chaudron (2018) as well.

6 Determination of VaR

Based on the *forecasted values (Table 7), VaR is identified at 99% confidence level using normal distribution.

Mean value of WALR (from Nov'20 to Nov'21)

$$Mean(\mu) = \sum fx_i \Big/ \sum f = 9.3386.$$

Standard deviation (σ) of WALR (from Nov'20 to Nov'21) = $\sqrt{\sum fx^2 \Big/ \sum f - \left(\sum fx \Big/ \sum f\right)^2}$ = 0.048197173.Using the properties of normal distribution at three sigma level 99% VaR at three sigma level is– $VaR = \mu - \sigma N - 1(X)$, where at 99% confidence level N-1(X)is- 2.326348.

VaR= 9.3386 – 0.048197173 * 2.326348 = 9.2265%, Value in the worst scenario is expected to be 9.2265 % with a decrease of 0.112123% from the mean value. Hence, VaR of a portfolio of long-term outstanding loan of Rs 1 billion would be 1,000,000,000*0.112123 % = Rs. 1,121,230.00 at 99% confidence. Therefore, expected loss on interest income on the outstanding loan portfolio of Rs 1 billion is estimated to be- Rs. 1121230.00 at 99% confidence which further boosts the findings on Real interest rate and corresponding income of banks with minimised risk by Shokr (2020).

7 Model implications and conclusions

Derived mathematical ARIMA model as given below, exhibits the relationship of forecasted WALR with it is previous significant lags and lags of error term after integration of AR and MA models.

$$\begin{aligned} ARIMA(16,\ 19,\ 11): Y_t = & -0.028820 - 0.206114 Y_{t-16} \\ & -0.247543 Y_{t-19} - 0.255101 e_{t-11} + e_t \end{aligned}$$

Model suggests that previous values of 19th lag are most significant in determining the WALR followed by 16th lag. 11th error lag is also found significant while predicting WALR of SCBs. Therefore, the variations from 11th months till 19th months are significant to compute probable WALRs on outstanding loans of SCBs. As fall in WALR reduces the income of SCBs on the outstanding loans leading to increased VaR of the portfolio of total outstanding loans disbursed as per floating rates. VaR at 99% confidence level could rise significantly if due farsightedness is not adapted by incumbent banks and financial institutions as advocated by (Kiumarsi et al 2020) as well.

On one hand the income of the bank on the outstanding loans decreases due to decrease in WALR, on the other hand, the cost of the fund (liabilities) financing the above assets would remain high particularly if it is on fixed rates as a practice earlier, in such a situation asset liability imbalance would be induced. Such asset liability mismatch would lead to credit risk as well as liquidity risk affecting adversely the operational efficiency of commercial banks towards rural and crowd funding as demonstrated by Harris and Wonglimpiyarat (2020) also. To handle such a mismatch of asset and liability, probable movement of WALRs on outstanding loans is predicted to create a structured balance between the lending and borrowing rates. Long-term deposits and borrowings should be linked to base rates with greater spread window being maintained by the banks to fund maturities to have a good balance of asset and liability. Model suggested above would be helpful in deciding the spread of commercial banks for short- and long-term deposits and lending as suggested by Pereira et al (2021) as well while maximising Return of investment with proactive forecasting intelligence.

Based on computed VaR limits at 99% confidence, expected loss on interest income on the outstanding loan portfolio of Rs 1 billion is estimated to be – 1,121,230.00. Hence, to hedge themselves against this adverse scenario banks should either adopt appropriate provisioning of Rs. 1,121,230.00 or should go for short position in interest rate futures with SWAP deals to boost their asset-liability position efficiently, findings are in accordance with results of Maciel (2019) and Shukla (2019) as well.

In a country like India where banking system is extremely robust with presence of different type of banks providing funds to MSMEs and unorganised sector leading to more credit risk on outstanding rupee loan. Thus, scientific estimation of values of WALR would have a great value in policy making for managing asset liability of banks and financial institutions in both long and short run. Critical factors like – tier-1 capital, risk weighted asset and long-term stability funding ratio are required be managed more efficiently using suggested model by predicting the extended liability on outstanding borrowings. In India, significance of WALR for estimating credit risk of banks would be more relevant post-COVID to infuse liquidity in the Indian economy to gain momentum for economic growth. Farsightedness and predictability about WALR as suggested in this study, would boost the effectiveness of banks by minimising credit risk which is much required in Indian banks for sustainability in long run.

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