Credit Growth in India

A time series analysis

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Abstract

The financial sector stability is often considered a prerequisite to economic growth in a country. Some economists contest that an increasing credit growth is an indicator of a flourishing economy while some others argue that it is considered a sign of an expansionary monetary policy and highly flexible banking regulations. The Indian banking system was already struggling through low credit offtake in the past few years and the nationwide lockdown due to the COVID-19 pandemic has further worsened the situation. The paper aims to examine this interdependence between credit growth and other macroeconomic factors such as economic growth and condition of the banking system, in the past decade using techniques of time series analysis such as Vector Autoregressive (VAR) models. A univariate time series analysis of credit growth on a quarterly basis was also conducted using the ARIMA model. We conclude by forecasting for credit growth and giving relevant implications for the Indian economy.

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1 Introduction

The importance of credit in an economy and its role in driving economic growth and as a transmission mechanism for monetary policy has often been a subject of common debate amongst macroeconomists. While several studies have been conducted to study this relationship and different econometric techniques have implied causality in both directions, the results for these studies have been mixed.

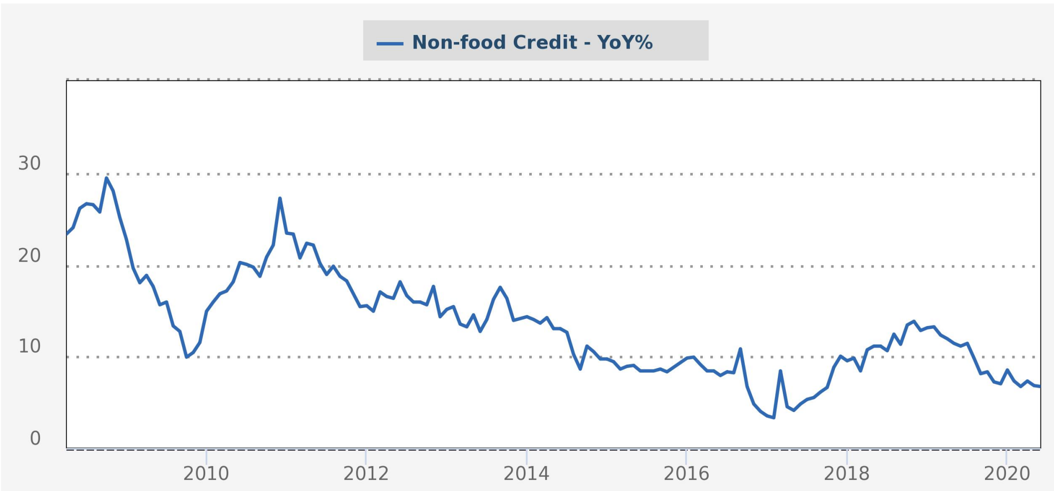
In India, the banking sector is dominated by the public sector banks. As of 31 March 2019, public sector banks had 63.1% of the deposits and private sector banks had a share of 28.7% while out of the total amount of loans given by Indian banks, public sector banks had a share of 58.8% and private sector banks had a share of 33.6%. These proportions have changed drastically over the years, in favour of the private sector banks which have captured a much larger portion of the Indian banking system.

Over the past few decades, India has witnessed a significant credit expansion. This is a result of various factors such as increased market access, corporate easing norms, entry of foreign banks and easing of monetary policy. However, in the past few years, the Indian banking system has been struggling with low credit offtake despite multiple rate cuts by the Reserve Bank of India (RBI).

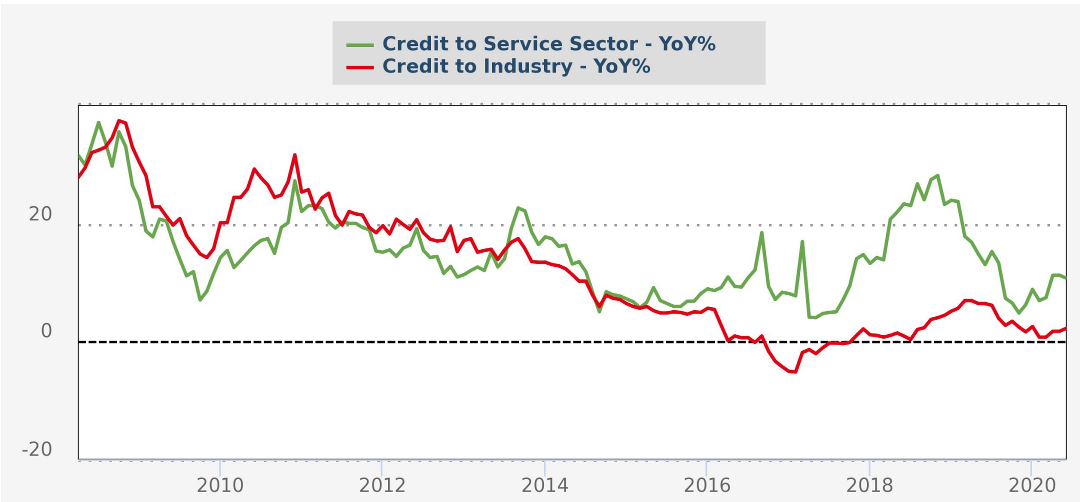
Credit growth to the industry has been slowing down since September 2016 contracting by 1.7% for the first time in October 2016. This fall can partly be attributed to a slowdown in credit demand post demonetisation. Some other possible reasons are risk aversion among banks due to rising non-performing assets (NPAs), economic slowdown, and lower working capital requirements. Credit growth to industry is an important factor while analysing the credit situation in a country as it is often seen as a substitute of economic growth in a country. Higher credit to industry indicates higher production of goods which translates to a higher Gross Domestic Product (GDP) and better economic growth. While credit growth towards personal loans and towards the service sector has risen over the years the overall credit growth has seen a declining trend.

This declining trend was further worsened in March 2020 when the country went into a nationwide lockdown due to the global pandemic of COVID-19.

With the economic activity completely shut down for more than a month, banks in India were faced with new challenges in disbursing credit. They became more risk averse which was prevalent in the data as outstanding loans to many sectors remained flat. Credit growth for Scheduled Commercial Banks (SCBs) which had considerably weakened during the first half of 2019-20 slid down even further in the first quarter of 2020-21. The pandemic, could amplify financial vulnerabilities, including corporate and household debt burdens. This could further increase the risk aversion shown by banks. Both, discretionary spending by consumers and capital expenditure by corporates has been adversely affected. Thus, the demand for credit and the supply of credit are both declining due to the virtual standstill in economic activity which is likely to worsen the lower credit offtake.



Source: RBI, IMA



Source: RBI, IMA

On March 27, 2020, in an attempt to support the slowing economy, RBI permitted all commercial banks (including regional rural banks, small finance banks and local area banks), co-operative banks, all-India Financial Institutions, and NBFCs (including housing finance companies and micro-finance institutions) to allow a moratorium of three months on payment of instalments in respect of all term loans outstanding as of March 1, 2020. This moratorium was further extended by another three months, i.e. till August 31, 2020. Accordingly, the repayment schedule and all subsequent due dates, as also the tenor for such loans, was shifted across the board by another three months. While the move brought much relief to borrowers, it may have a long term negative impact on the banking sector as it will clearly push the payment timeline back by the same time. .

Table 1.4: Analysis of Loan Moratorium Availed as on April 30, 2020.

Sector	Corporate		MSME		Individual		Others		Total	
	% of total customers	% of total outstanding	% of total customers	% of total outstanding	% of total customers	% of total outstanding	% of total customers	% of total outstanding	% of total customers	% of total outstanding
PSBs	28.8	58	73.9	81.5	80.3	80	48.8	63.7	66.6	67.9
PVBs	21.6	19.6	20.9	42.5	41.8	33.6	39.1	40.9	49.2	31.1
FBs	32.6	7.7	73.3	50.4	8.4	21.1	75.8	4.8	21.4	11.5
SFBs	78.8	43.7	90.5	52.3	90.9	73.2	64.6	12.3	84.7	62.6
UCBs	63.4	69.3	66.5	65.5	56.8	62	35.6	59.2	56.5	64.5
NBFCs	39.7	56.2	60.7	61.1	32.5	45.9	37.3	41.4	29	49
SCBs	24.7	39.1	43.1	65.3	52.1	56.2	45.7	55.7	55.1	50
System	30.8	41.9	45.8	65	50.4	55.3	45.7	54.6	**48.6**	**50.1**

Source: RBI Supervisory Returns.

The future of credit growth in India after the crisis will be determined by how the financial system responds to the monetary policy and the new RBI regulations as well as how long the economy takes to come back to its former growth rate.

2 Literature Review

The financial system, especially banking is believed to be an effective mechanism that facilitates efficient allocation of resources from savers to borrowers. This in turn is said to sets a series of events that boost productivity, provide investment opportunity, generate employment and trigger demand thereby, leading to economic growth and better standards of living. The study of credit and GDP and the interdependence between them has been of significant interest in the past. Some economists argue that output will lead to finance and thus implies that the financial system does not play the leading role in economic growth. Others believe that financial systems by effectively transferring the resources and stimulating entrepreneurial response might be more development-inducing.

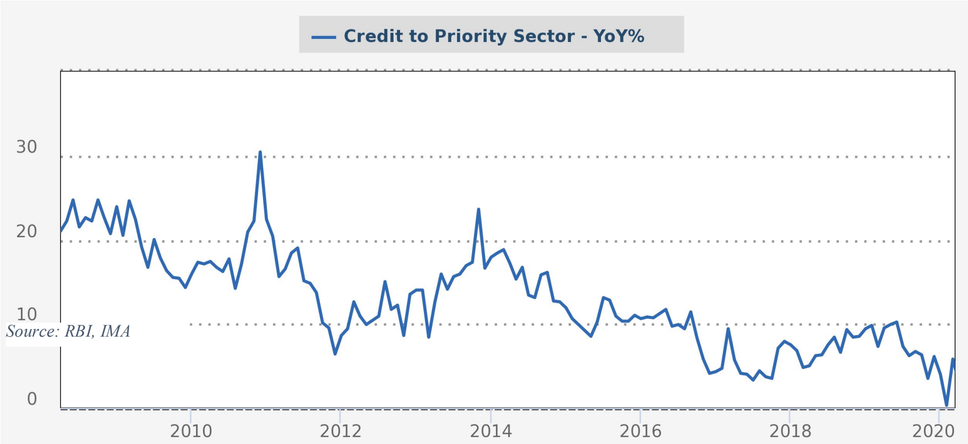
As discussed in (Patrick, 1966), the nature of the demand for financial services depends upon the growth of real output and upon the commercialization and monetization of agriculture and other traditional subsistence sectors. The more rapid the growth of real income, the greater will be the demand for external funds since in most situations, the firm may not be able to generate funds from internal sources. As a consequence of real economic growth, financial markets develop, widen and become more perfect, thus increasing the capacities of the entrepreneur towards risk mitigation which in turn becomes a catalyst to economic growth. Bank credit may initially play a leading role when the economy is in its nascent phase as it may be able to induce innovation type investment. However once, the economy picks up, it will only be the demand for credit that will eventually drive the financial system. (Jung, 1986) studied the relationship using Granger causality tests and inferred that while in lesser developed countries, the financial sector leads economic growth, more developed countries see a reverse causation. In the Indian context, the relationship between the development of the financial system and economic growth have been studied from multiple perspectives using different proxies for both. However, the results of these studies in terms of direction of causality have been mixed. In essence, it may be postulated that the financial system and economic growth run in a simultaneous system and eventually, none can sustain without the other.

The Central Bank (RBI) attempts to ensure price stability, macroeconomic management and growth via monetary policy. The conduct of monetary policy has evolved over time on the front of the policy framework and operating procedure. Back in the 1980s, when the economy was plagued by high inflation fuelled by excessive money supply in the form of RBI credit to government, price stability became utmost important. As discussed in (Charles Abuka, 2019) monetary policy tightening is likely to reduce credit supply in the economy. It is often observed that monetary policy is ineffective in developing economies mainly because of underdeveloped institutions, financial markets and banking systems. In India, RBI has attempted to control a high level of credit growth via rate cuts. This occurs when there is a high level of inflation in the economy or when it is observed that banks may be easily disbursing credit with ease, thereby increasing the risk of default by borrowers, leading to higher Non-Performing Assets (NPAs). An alternative approach to monetary policy and its effect on the system was discussed in (Bernanke, 1988) that in the process of creating money, banks extend credit and their willingness to do so has its own effect on aggregate spending i.e. the banks' decision about how to manage their asset portfolios determine whether the monetary policy's impact will fall primarily on open-market interest rates or on effective bank loans.

The willingness of a bank to disburse credit will depend on its capital base (Verma, 2019). A bank with a weak capital base may try to conserve its capital and any capital in excess of minimum regulatory requirement may be either used to finance retail loans, which typically have lower NPAs or may be invested, possibly in government bonds. Bank lending is typically determined by a combination of bank specific variables such as Capital to Risk Weighted Assets (CRAR), Gross Non Performing ratios (GNPAs) and other factors such as net interest income, etc. If banks are well capitalised as reflected in higher CRAR, it leads to higher credit growth. Also, if banks are well capitalised they are better able to withstand output shocks and they have to less adjust their lending during economic downturns in order to avoid regulatory capital shortfalls (Gambacorta and Mistrulli, 2004). The CRAR is also a variable that is expected to reflect the impact of regulatory norms on the bank's lending behaviour as a minimal CRAR is required as per Basel Norms. As per the current norms, Indian scheduled commercial banks are required to maintain a CRAR of 9%. On the other hand, an increase in the GNPA ratios is likely to have a negative impact on credit growth as banks become more risk averse and are unwilling to disburse credit with ease. In addition to this, in India, aggregate deposits form the largest amount of funds mobilised by commercial banks. Therefore, deposit growth essentially forms a binding constraint on a bank's ability to extend loans to its borrowers. Thus, these factors can be observed as important determinants for the supply side of credit growth (Das, 2002).

3 Credit in India – An Overview

In India, credit control is an important monetary policy used by the Reserve Bank of India in order to ensure 'Economic Development with Stability'. This would allow banks to influence inflationary trends and allow an inclusive growth in the economy. Banks in India have been the main source of credit in the past few decades and their lending operations have evolved as per the requirements of the economy. In fact, as per RBI's regulations, 40 per cent of adjusted net bank credit must be given to the priority sector.



The priority sectors in India include agriculture, MSME, export credit, education, housing, social infrastructure, renewable energy. The recent schemes of financial inclusion that aim to make the rural areas a part of the financial system have also contributed to the overall credit expansion in the economy.

4 Methodology

Time Series Analysis

A time series is a series of observations indexed in time order i.e. the value of a variable recorded at different time points. Most commonly, a time series is a sequence taken at equally spaced intervals. Thus it is a sequence of discrete-time data. Time series models are an attempt to capture empirically relevant features of the observed data that may have arisen from a variety of different structural models. Let us define some basic concepts as discussed in (Brooks, 2014) and used for time series analysis in this paper.

Autocorrelation

A time series is likely to have autocorrelation. Autocorrelation is basically a mathematical representation of the degree of similarity of a variable with its own lagged values. It calculates the correlation using the same time series twice, one its original form and once lagged as per order specified. The Breusch-Godfrey LM-statistic was used to test the data for autocorrelation. It is based on the following auxiliary regression:

$$\varepsilon_t = \nu + A_1 y_{t-1} + \cdots + A_k y_{t-L} + \rho_1 \varepsilon_{t-1} + \cdots + \rho_s \varepsilon_{t-s} + u_t$$

where u_t is an error term which is assumed to be white noise. The null hypothesis of no multivariate autocorrelation of degree s is $H_{0:}\,\rho_1 = \rho_2 = \cdots \rho_s = 0$. The alternative hypothesis is given by $H_{1:}\,\rho_1 \neq \rho_2 \neq \cdots \rho_s \neq 0$ which indicates presence of autocorrelation in the model.

The diagnostic portmanteau test for the adequacy of fitted ARMA models was introduced by Box and Pierce (1970) based on the asymptotic distribution of the residual autocorrelations, $\widehat{r_1}, \widehat{r_2}, \ldots, \widehat{r_m}$, where $m \leq n - 1$ is the largest selected lag (Mahdi, 2016). Their test statistic is:

$$Q_m = n \sum_{l=1}^{m} \widehat{r_l^2} \sim \chi^2_{m-p-q}$$

The null hypothesis of no multivariate autocorrelation of degree s is $H_{0:}\,\rho_1 = \rho_2 = \cdots \rho_s = 0$. The alternative hypothesis is given by $H_{1:}\,\rho_1 \neq \rho_2 \neq \cdots \rho_s \neq 0$ which indicates presence of autocorrelation in the model.

Stationarity

A stationary time series will have no predictable pattern in the long term as it gets rid of the seasonality and trend component. It is important to determine whether a time series is stationary or not as it will strongly influence its behaviour and properties. For a stationary series, 'shocks' to the system will gradually die away. A stationary series can be defined as one with a *constant mean*, *constant variance* and *constant autocovariances* for each given lag. This relates to the concept of 'weak stationarity'. A series is strictly stationary if the distribution of its values remains the same as time progresses, implying that the probability that *y* falls within a particular interval is the same now as at any time in the past or the future. Our data deals with weak stationarity. A series is said to be weakly stationary for $t = 1,2,3..\infty$ if it satisfies the following conditions:

i)	$E(\gamma_t) = \mu$	(Constant Mean)
ii)	$E(\gamma_t - \mu)(\gamma_t - \mu) = \sigma^2 < \infty$	(Constant Variance)
iii)	$E(\gamma_{t_1} - \mu)(\gamma_{t_2} - \mu) = \Upsilon_{t_2 - t_1} \forall\, t_1, t_2$	(Constant Autocovariance)

In order to test for stationarity we use the Augmented Dickey Fuller Test (ADF) and the KPSS test. The ADF test checks for stationarity by detecting the presence of unit roots whereas the KPSS test checks for stationarity by detecting the presence of a trend in the series. Such a joint use of stationarity and unit root is known as confirmatory data analysis. In order to ensure stationarity, both tests must conclude the same.

There are various methods to make the data stationary such as log transformations, differencing, etc. In our data, we have used second order differencing. This can be interpreted as a 'change in the changes' of the original data. (Hyndman, 2018) Second order differencing will give $T - 2$ values. The stationary series values for second order differencing will be given as follows:

$$
\begin{aligned}
y_t'' &= y_t' - y_{t-1}' \\
&= (y_t - y_{t-1}) - (y_{t-1} - y_{t-2}) \\
&= (y_t - 2y_{t-1} + y_{t-2})
\end{aligned}
$$

A white noise series is stationary. It does not matter when you observe it, it should look much the same at any point in time.

ARIMA Model

ARIMA is an acronym for Auto Regressive Integrated Moving Average. These models are a combination of Autoregressive models and Moving Average models. Such a model states that the current values of some series γ depends linearly on its own previous values, plus a combination of current and previous values of a white noise error term (Brooks, 2014). The full model can be written as

$$y_t' = c + \phi_1 y_{t-1}' + \cdots + \phi_p y_{t-p}' + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t$$

where y_t' is the differenced series. The predictors on the right hand side include both lagged values of y_t and lagged errors. The ARIMA model is denoted by ARIMA (p, d, q) where p is the order of autoregression, d is the degree of differencing involved and q is the order of moving average part. These models are used on a univariate time series.

VAR Model

VAR is the acronym for Vector Autoregressive Model. These are commonly used on a multivariate time series as it allows for feedback relationships. A limitation of ARIMA models was that they only impose a unidirectional relationship. However, in macroeconomics and finance, it is common to observe bidirectional causation. This is simply because none of the economic factors exist in isolation. Thus, VAR allows a simultaneous equations setup where all variables are treated simultaneously. In this framework, all variables are treated as 'endogenous'. The VAR model gives one equation per variable. The right hand side of each equation includes a constant and lags of all variables in the system. Example, considering 2 variables with 1 lag. A 2-dimensional VAR(1) will be written as:

$$y_{1,t} = c_1 + \phi_{11,1}y_{1,t-1} + \phi_{12,1}y_{2,t-1} + e_{1,t}$$
$$y_{2,t} = c_2 + \phi_{21,1}y_{1,t-1} + \phi_{22,1}y_{2,t-1} + e_{2,t}$$

Where $e_{1,t}$ and $e_{2,t}$ are white noise processes. The coefficient $\phi_{ii,l}$ captures the influence of the l^{th} lag variable of y_i on itself while the coefficient $\phi_{ij,l}$ captures the influence of the l^{th} lag variable of the variable y_j on the variable y_i.

Every variable must be made stationary before implementing VAR on the model. There are two parameters that one has to decide when using a VAR to forecast, namely how many variables (K) and how many lags (p) should be included in the system. The number of coefficients to be estimated in a VAR is equal to $K + pK^2$ (or $1 + pK$ per equation) (Hyndman, 2018). In practice, since VAR models are a-theoretical in nature, the number of variables is usually kept small and a collection of related variables where no explicit interpretation is required. The number of lags is selected by using Information criteria such as AIC, BIC, SC or HQ. For VAR models, we prefer to use the BIC criteria.

Granger Causality

Granger causality really means a correlation between the *current* value of one variable and the *past* values of others and it does not mean that movements of one variable cause movements of another as per common misinterpretations. The argument follows that if $y_1$causes y_2, lags of y_1 should be significant in the equation for y_2. If this is the case and not vice versa, it would be said that y_1 'Granger-causes' y_2 or that there exists unidirectional causality from y_1 to y_2. On the other hand, if y_2 causes y_1, lags of y_2 should be significant in the equation for y_1. If both sets of lags were significant, it would be said that there was 'bi-directional causality' or 'bi-directional feedback'. If $y_1$is found to Granger-cause y_2, but not vice versa, it would be said that variable $y_1$is strongly exogenous (in the equation for y_2). If neither set of lags are statistically significant in the equation for the other variable, it would be said that y_1 and y_2 are independent. (Brooks, 2014)

Theil's U -statistic

The Theil's U statistic is a metric to evaluate forecasts, where the mean squared error of the forecasts from the model under study is divided by the mean squared error of the fore- casts from a benchmark model. A U-statistic of less than one implies that the model is superior to the benchmark. The statistic is given as:

$$U = \frac{\sqrt{\sum_{t=T_1}^{T} \left(\frac{y_{t+s} - f_{t,s}}{y_{t+s}}\right)^2}}{\sqrt{\sum_{t=T_1}^{T} \left(\frac{y_{t+s} - fb_{t,s}}{y_{t+s}}\right)^2}}$$

A U statistic of 1 implies that the model under consideration and the benchmark model are equally accurate, while a value of less than one implies that the model is superior to the benchmark, and vice versa for $U > 1$ (Brooks, 2014).

5 Data Exploration

As per economic implications and the literature survey, six variables were chosen to carry out an analysis to determine what causes credit growth in the Indian economy. The data is in the context of Scheduled Commercial Banks (SCBs) in India. Scheduled Commercial Banks are those banks which are included in the second schedule of RBI Act, 1934 and carry out usual banking operations and services.

Credit Growth

The bank credit in India mainly refers to credit lending by various SCBs to various sectors of the economy. Bank credit is categorised into Food Credit and Non-Food Credit. Food credit refers to the lending made by banks to the Food Corporation of India (FCI) mainly for procuring food grains and comprises less than 1% of the total bank credit. Thus, as a substitute, we have chosen Non-Food Credit as our main variable. Instead of taking the level data, we have taken the growth rate on a quarterly basis (YoY%). This allows us to remove the seasonality from the data as level figures may cause the same and also allows us to make better year-wise comparisons.

Capital to Risk (Weighted) Assets Ratio (CRAR)

Also known as Capital Adequacy Ratio, the CRAR is a measure of how well the bank can absorb a reasonable amount of loss. In India, a minimum level of CRAR is decided by the RBI which must be in line with Basel Norms. SCBs are required to maintain this ratio at 9%. Here, capital comprises primarily of common stock and disclosed reserves (or retained earnings), but may also include non-redeemable non-cumulative preferred stock and other reserves and provisions. CRAR is an indicator of bank soundness and is an important determinant of supply of credit by a bank.

Repo Rate

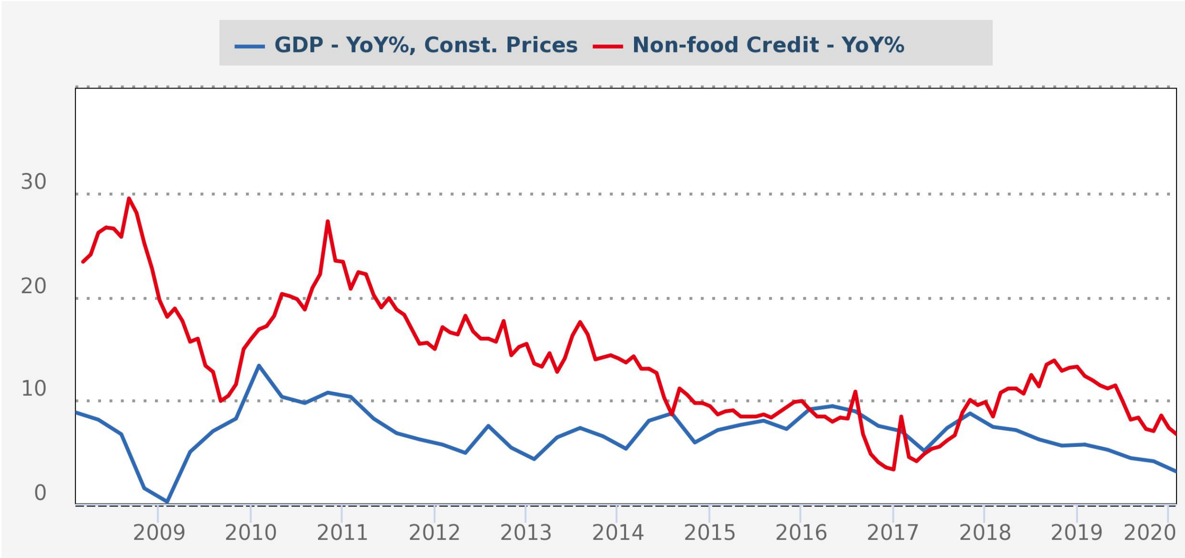
Repo rate is the rate at which the RBI lends money to commercial banks in the event of any shortfall of funds. Repo rate is used by monetary authorities to control inflation. Repo rates form a part of the liquidity adjustment facility. It has been used as a substitute of monetary policy.

Gross Non-Performing Assets (GNPA) Ratio

An asset becomes an NPA when it ceases to generate income for the bank. Gross NPA Ratio is the ratio of total gross NPA to total advances (loans) of the bank. It is used as a measure to evaluate the overall quality of the bank's loan book. When NPA ratios rise above a certain threshold, they have a negative impact on banks' willingness to lend indicative of nonlinearities and reverse causality also at work (Tracey, 2011), (Cucinelli, 2015). It is observed in the Indian banking system that while credit growth on the aggregate positively affects the NPA ratio in the Indian economy (Chavan, 2016), there are bi-directional effects as well which is further discussed ahead.

Gross Domestic Product (GDP) Growth

GDP is the total value of goods and services in a country. It is an macroeconomic indicator that shows the economic health of a country. Nominal GDP figures are avoided as it curtails the inflationary impact and gives a clear analysis of credit growth on real economic activity. For low-income or middle-income countries, high year-on-year GDP growth is essential to meet the growing needs of the population. Thus, we have taken the real GDP growth the growth rate on a quarterly basis (YoY%) as an indicator of the country's economic development and progress.



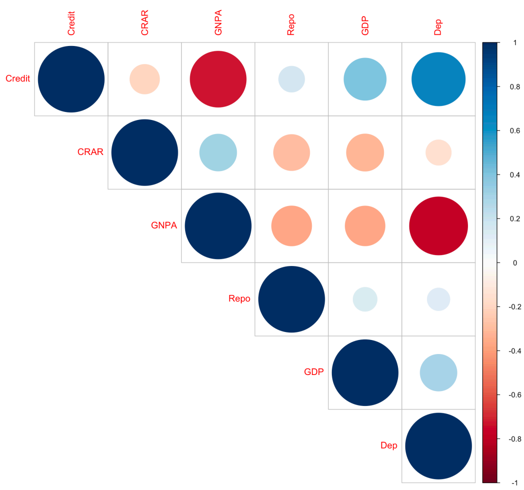
Source: RBI, IMA

Total Deposits in Banks

Total deposits refers to a cumulative of all kinds of deposits done in SCBs, such as Demands Deposits, Term Deposits, and Interest and Non-Interest bearing deposits. Again, we have taken the growth rate on a quarterly basis (YoY%) for this variable as well, to avoid seasonality in data and to make better comparisons.

Correlation

One of the factors about VAR modelling is that it is an a-theoretical model and thus, it is important for the variables to have some inter-relation in order to give results that can be easily interpreted. In addition to the literature already established on the same, we visualise the correlation matrix of the variables in discussion to know our data better and understand the underlying relationships.

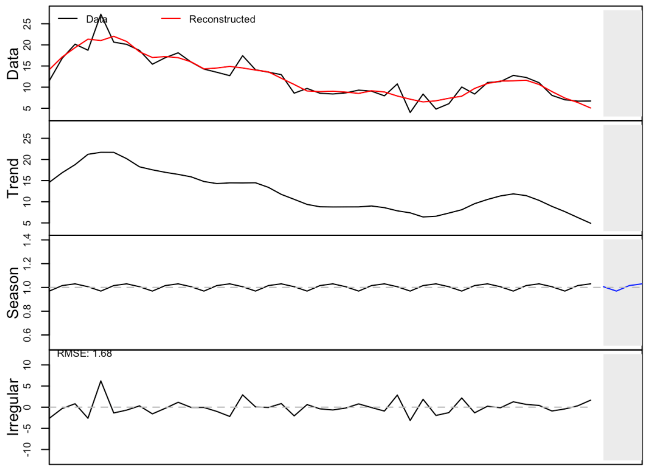


6 Data Modelling

Our original data is on a quarterly basis from the year October 2009 onwards till June 2020. After differencing on order 2, we were left with observations from June 2010 till June 2020. In order to forecast our data and check its accuracy, we divide our data into Training and Test (Validation Set) Data. The training data consists of observations till the final quarter of 2018 while the remaining observations form the test data set.

As discussed earlier, we convert all variables in to time series in R and make each variable stationary by second order differencing. The order of differencing was decided as per simultaneous results from the ADF test and the KPSS tests. It was found that some variables became stationary at first order differencing while some became stationary at second order differencing. Since the data must be consistent and have the same number of observations for all variables, we do a second order differencing on all variables. The results for the 'credit growth' variable are highlighted here. The results of all other variables are given in the Appendix section of the report.

Plotting the original data for credit growth, we clearly find that there is a trend in the time series which is confirmed by the stationarity tests of ADF and KPSS.



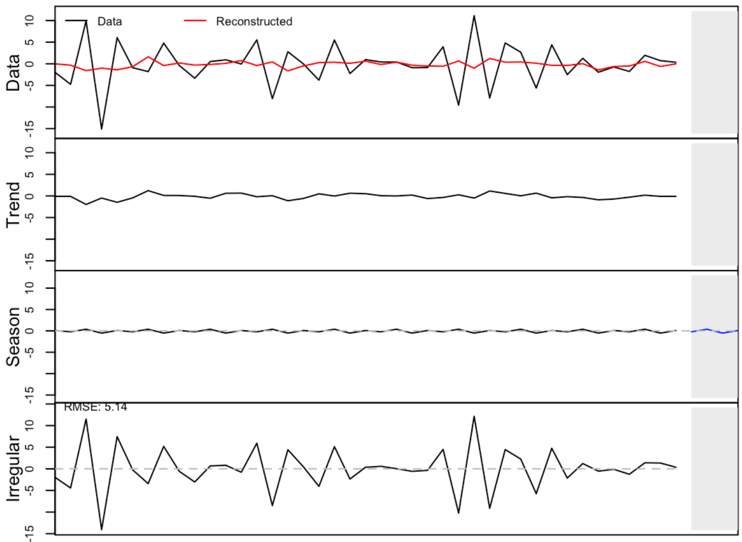
ADF Test (Before Differencing)

```
        Augmented Dickey-Fuller Test

data:  atscredit
Dickey-Fuller = -3.1004, Lag order = 3, p-value = 0.139
alternative hypothesis: stationary
```

KPSS Test (Before Differencing)

```
        KPSS Test for Level Stationarity

data:  atscredit
KPSS Level = 0.84067, Truncation lag parameter = 3, p-value = 0.01
```

After second order differencing, here is the credit growth data:



The data is now stationary as confirmed by the stationarity tests below.

ADF Test (After second order differencing)

```
        Augmented Dickey-Fuller Test

data:  afstcredit
Dickey-Fuller = -4.2628, Lag order = 3, p-value = 0.01
alternative hypothesis: stationary
```

KPSS Test (After second order differencing)

```
        KPSS Test for Level Stationarity

data:  afstcredit
KPSS Level = 0.078915, Truncation lag parameter = 3, p-value = 0.1
```

All the variables were made stationary and the results for the same can be seen in the Appendix.

7 Results and Findings

Model I ($K = 6, p = 3$)

VAR Modelling

After making our entire data stationary, the data is now ready for the VAR model. The number of lags for the VAR model is selected using BIC criteria (BIC is referred to as SC in R). The appropriate number of lags was 4.

```
> VARselect(aftrainingdata)
$selection
AIC(n)  HQ(n)  SC(n) FPE(n)
     4      4      4      5

$criteria
                1          2             3    4    5    6    7    8    9   10
AIC(n) -0.3177928 -2.2180931 -1.021172e+01 -Inf -Inf -Inf -Inf -Inf -Inf -Inf
HQ(n)   0.2501553 -1.1633323 -8.670142e+00 -Inf -Inf -Inf -Inf -Inf -Inf -Inf
SC(n)   1.7299186  1.5847995 -4.653641e+00 -Inf -Inf -Inf -Inf -Inf -Inf -Inf
FPE(n)  0.7980309  0.2139493  6.253906e-04  NaN    0    0    0    0    0    0
```

However, this result indicated presence of autocorrelation in the data as per the Portmanteau Test (asymptotic) for $p = 4$. Thus, we go on to the next p which minimises BIC (hereon referred to as SC) i.e. we perform the VAR model on $p = 3$. We tested the model (VAR(3)) for autocorrelation using the Portmanteau test.

```
        Portmanteau Test (asymptotic)

data:  Residuals of VAR object aftrainVAR
Chi-squared = 509.94, df = 468, p-value = 0.08792
```

We fail to reject the null hypothesis and thus, there is no autocorrelation in the model.

The results for the credit growth equation as per VAR(3) are as follows:

```
VAR Estimation Results:
=========================
Endogenous variables: afstcredit, afstcrar, afstgnpa, afstrepo, afstgdp, afstdep
Deterministic variables: const
Sample size: 32
Call:
```

```
VAR(y = aftrainingdata, type = "const", lag.max = 3, ic = "SC")


Estimation results for equation afstcredit:
==========================================
afstcredit = afstcredit.l1 + afstcrar.l1 + afstgnpa.l1 + afstrepo.l1 + afstgdp.l1
+ afstdep.l1 + afstcredit.l2 + afstcrar.l2 + afstgnpa.l2 + afstrepo.l2 +
afstgdp.l2 + afstdep.l2 + afstcredit.l3 + afstcrar.l3 + afstgnpa.l3 + afstrepo.l3
+ afstgdp.l3 + afstdep.l3 + const

              Estimate Std. Error t value Pr(>|t|)
afstcredit.l1 -0.81232    0.19398  -4.188 0.001064 **
afstcrar.l1   -5.95202    1.31668  -4.520 0.000575 ***
afstgnpa.l1    1.52507    0.86255   1.768 0.100488
afstrepo.l1   -1.91758    2.87186  -0.668 0.515995
afstgdp.l1    -0.15258    0.36793  -0.415 0.685129
afstdep.l1    -0.19894    0.16851  -1.181 0.258942
afstcredit.l2 -0.21803    0.26023  -0.838 0.417259
afstcrar.l2   -0.56481    0.33348  -1.694 0.114134
afstgnpa.l2   -2.03275    0.95222  -2.135 0.052394 .
afstrepo.l2    8.81057    2.89836   3.040 0.009484 **
afstgdp.l2     0.02446    0.31213   0.078 0.938724
afstdep.l2    -0.36541    0.20229  -1.806 0.094059 .
afstcredit.l3  0.46735    0.18177   2.571 0.023243 *
afstcrar.l3   -3.64838    0.82220  -4.437 0.000670 ***
afstgnpa.l3   -0.52067    0.78242  -0.665 0.517393
afstrepo.l3   -4.89720    2.02386  -2.420 0.030921 *
afstgdp.l3    -0.16736    0.30767  -0.544 0.595677
afstdep.l3    -0.44671    0.17882  -2.498 0.026686 *
const         -0.06891    0.36026  -0.191 0.851257
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Residual standard error: 1.99 on 13 degrees of freedom
Multiple R-Squared: 0.9388,      Adjusted R-squared: 0.8541
F-statistic: 11.08 on 18 and 13 DF,  p-value: 3.73e-05
```

Thus, for determining credit growth, we find that at 5% significance level, the main determinants are `afstcredit.l1` and `afstcredit.l3` i.e. its own second order differenced first and third lag, `afstcrar.l1` and `afstcrar.l3` i.e. the first and third lag of second order differenced CRAR, `afstrepo.l2` and `afstrepo.l3` i.e. the second lag of second order differenced repo rate and finally `afstdep.l3` i.e. the third lag of second order deposit growth rate. The model also gives us a good adjusted R^2 at 85.41%.

This indicates that the second order differenced credit growth is mainly influenced by its own previous lags and the previous lags of second order differenced CRAR, Repo rate and Deposits growth rate. GDP growth rate and GNPA come out to be insignificant at 5% significance level. This shows that economic growth will not play a huge role in the determination of credit growth and the quality of assets i.e. the GNPA ratio will not have a significant impact on credit growth. The results for all other variables are shown in the Appendix.

The equation for credit growth as per our VAR(3) model validates our previous discussion that past actions of monetary policy (here, repo rate) are important determinants of credit growth at the given time. Also, it reinforces the fact that the stability of the banking system (here, CRAR) and the trust of people in the banking system (here, deposit growth rate) play a role in the credit growth of an economy.

Granger Causality

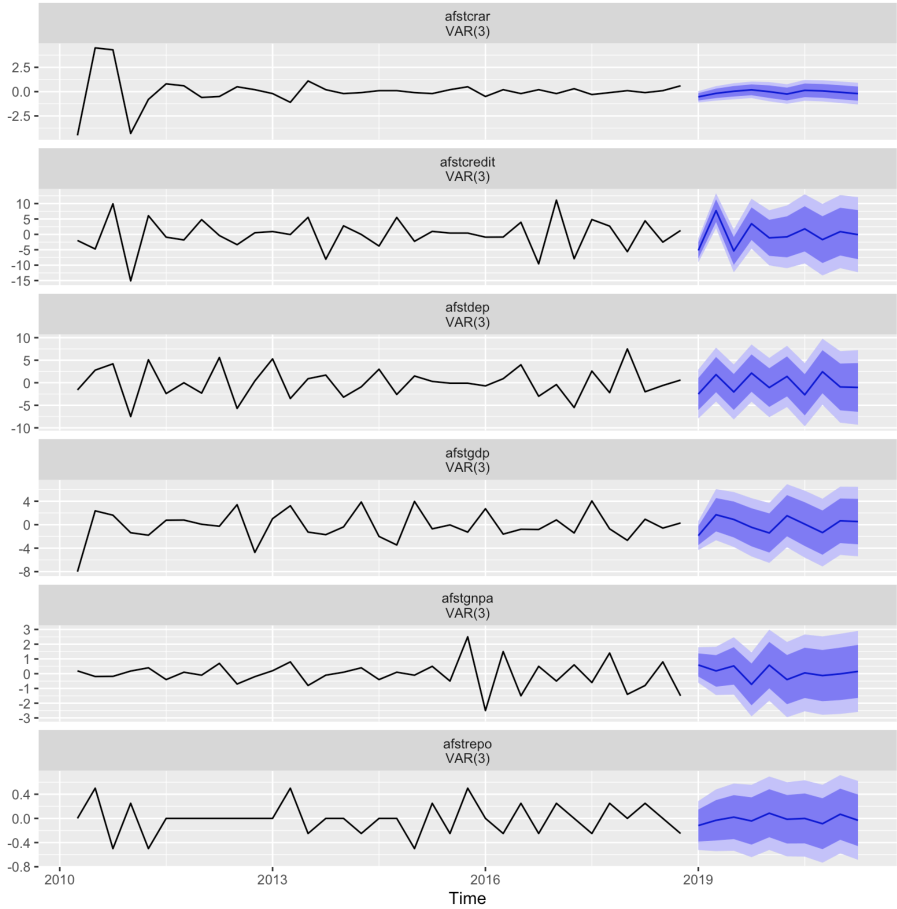
The null hypothesis for Granger tests says that x *does not granger cause* y. The optimal number of lags for each pair was decided as per the BIC criteria. On running pairwise Granger causality tests, we get the following results.

No.	Variables	Optimal lags as per BIC	p-value	Conclusion (at 5% significance level)	Conclusion (at 10% significance level)
1	CRAR → Credit	2	0.06381	No	Yes
	Credit → CRAR	2	0.06469	No	Yes
2	GNPA → Credit	2	0.3133	No	No
	Credit → GNPA	2	0.6399	No	No
3	Repo → Credit	2	0.5681	No	No
	Credit → Repo	2	0.6633	No	No
4	GDP → Credit	2	0.7011	No	No
	Credit → GDP	2	0.3745	No	No
5	Dep → Credit	5	0.6844	No	No
	Credit → Dep	5	0.006118	Yes	Yes

Therefore, we can conclude with 95% confidence, that second order difference of credit growth granger causes the second order difference of deposit growth and with 90% confidence that the second order difference of credit growth and CRAR has a bidirectional Granger causality.

Forecasting using VAR(3)

Using the `forecast` function in R, we forecasted the credit growth for the next 6 quarters i.e. from the first quarter of 2019, till the second quarter of 2020. The results are plotted as below:



However, on using the Theil's U statistic to check the accuracy of the model against the validation set, we get the following results:

	Theil's U statistic
afstcredit	2.5013038
afstcrar	0.6730327
afstgnpa	0
afstrepo	0.9407573
afstgdp	1.5943607

afstdep	0.9137631

This implies that while the model may forecast the second order difference of CRAR, Repo Rate, and Deposit growth well, it is unable to forecast GDP growth and credit growth very well. In fact, it is worse than the naïve forecasts. This brings us to the limitations of VAR modelling. Firstly, VAR models are a-theoretical and hence, it is important for the variables to be inter-related enough to make clear interpretations (as discussed earlier). Second, while VAR models are commonly considered to give better forecasts than other time series models, the number of variables (K) must be minimised to give better forecasts. The large number of variables reduces the importance of every variable in an equation thus, often giving poor results in terms of significant coefficients and determining practical implications.

Alternate Model ($K = 4,\ p = 1$)

Thus, we attempt an alternate model where we take only 3 variables to assess what causes (second difference) credit growth. These variables are GDP, Repo rate and CRAR.[2]

The number of lags for the VAR model is selected using BIC criteria. The appropriate number of lags was 1. We test the model for autocorrelation using the Portmanteau Test.

```
	Portmanteau Test (asymptotic)

data:  Residuals of VAR object crgtrainVAR
Chi-squared = 236.05, df = 240, p-value = 0.56
```

We fail to reject the null hypothesis and thus, there is no autocorrelation in the model.

[2] GDP is a substitute for economic growth while repo rate is a substitute for monetary policy, both of which are commonly believed to determine credit growth. Hence, the researcher gave a second attempt in finding causal relationships between the variables. The decision between CRAR, GNP and Deposit Growth, all of which are determinants of the soundness of the banking system, was taken after running the three models and the model which gave the best forecasts has been used in the final paper.

The results for the VAR(1) model

```
VAR Estimation Results:
=========================
Endogenous variables: crgstcredit, crgstcrar, crgstrepo, crgstgdp
Deterministic variables: const
Sample size: 34
Call:
VAR(y = crgtrainingdata, type = "const", lag.max = 1)


Estimation results for equation crgstcredit:
============================================
crgstcredit = crgstcredit.l1 + crgstcrar.l1 + crgstrepo.l1 + crgstgdp.l1 + const

               Estimate Std. Error t value Pr(>|t|)
crgstcredit.l1  -0.7619     0.1274  -5.980 1.68e-06 ***
crgstcrar.l1     0.2882     0.4617   0.624    0.537
crgstrepo.l1     1.6383     2.5478   0.643    0.525
crgstgdp.l1      0.2353     0.2782   0.846    0.405
const           -0.1278     0.6486  -0.197    0.845
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Residual standard error: 3.77 on 29 degrees of freedom
Multiple R-Squared: 0.5723,      Adjusted R-squared: 0.5134
F-statistic: 9.703 on 4 and 29 DF,  p-value: 4.162e-05
```

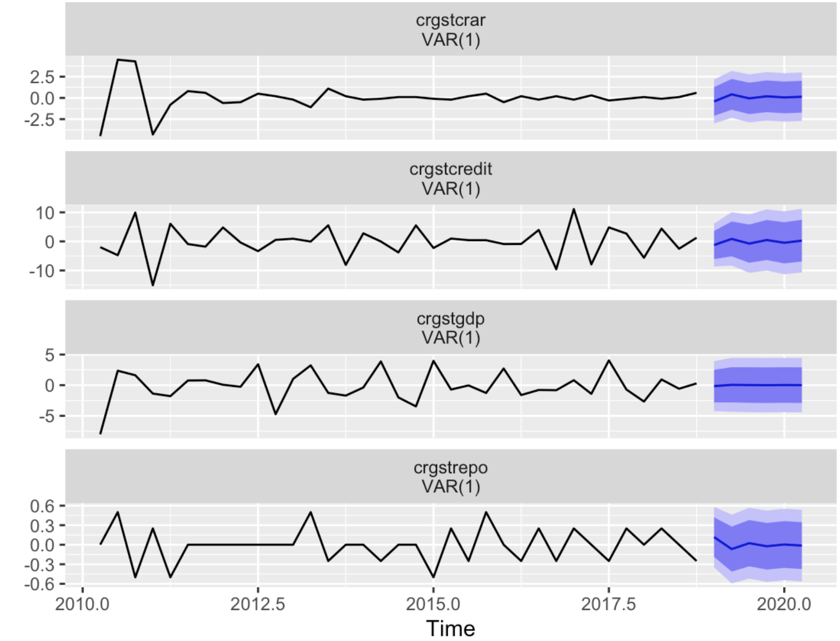
Thus, for determining credit growth, we find that at 5% significance level, the main determinant of credit is `crgstcredit.l1` i.e. its own second order differenced first lag. The model does not have a very good adjusted R^2 at 51.34% only.

The model indicates that (second differenced) credit growth is only influenced by its own previous lag and no other variable has a significant impact on the credit growth.

In fact, a multivariate Granger causality also indicated that no variable is Granger causing any other variable.

Forecasting using VAR (1)

Using the `forecast` function in R, we forecasted the credit growth for the next 6 quarters i.e. from the first quarter of 2019, till the second quarter of 2020. The results are plotted as below:



Using the Theil's U statistic to check the accuracy of the model against the validation set, we get the following results:

	Theil's U statistic
afstcredit	0.696867
afstcrar	0.803684
afstrepo	0.810996
afstgdp	0.6362155

The model gives us better forecast results than the previous model for all variables except CRAR. This implies that on using lesser variables and lags, generally VAR is likely to give better forecasts.

A common behavior in both the above models was that the (second order differenced) credit growth is certainly impacted by its own lag variables. As a result, we try out one final univariate ARIMA model and compare the forecasting accuracy of the three models.

ARIMA Model on Credit Growth

As done before, we split the (second differenced) credit growth variable in to training and validation data sets. The training data consists of observations till the final quarter of 2018 while the remaining observations form the test data set as before.

The `auto.arima()` function in R uses a combination of unit root tests, minimization of the AIC and MLE to obtain an ARIMA model. KPSS test is used to determine the number of differences (d) In Hyndman-Khandakar algorithm for automatic ARIMA modelling. The p, d , and q are then chosen by minimizing the AIC. The algorithm uses a stepwise search to traverse the model space to select the best model with smallest AIC (Chatterjee, 2018).

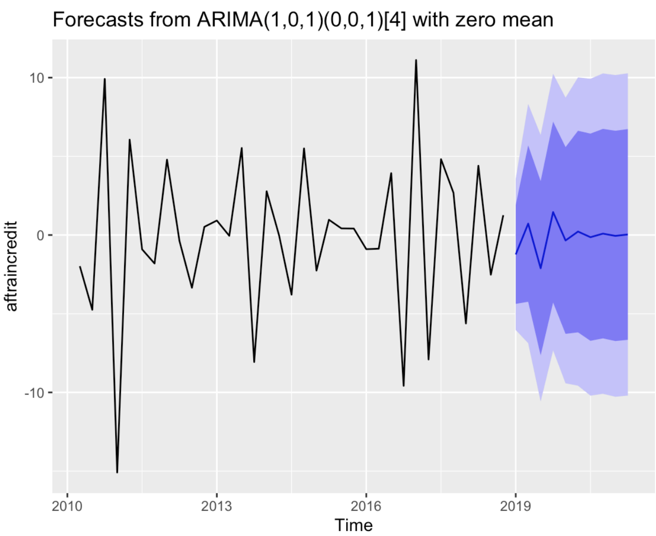
We use the `auto.arima` function in R which gives us the following results:

```
Series: aftraincredit
ARIMA(1,0,1)(0,0,1)[4] with zero mean

Coefficients:
          ar1      ma1     sma1
      -0.6341  -0.5935  -0.791
s.e.   0.1555   0.1975   0.209

sigma^2 estimated as 5.964:  log likelihood=-82.05
AIC=172.1   AICc=173.43   BIC=178.32
```

Thus, the model uses $p = 1$ and $q = 1$ to determine the best fit ARIMA model that minimises AIC. This implies that we need to take into account the credit growth value at 1 lag from a given time point t and the error term from 1 lagged value.

Forecasting using ARIMA

Using the `forecast` function in R, we forecasted the credit growth for the next 6 quarters i.e. from the first quarter of 2019, till the second quarter of 2021. The results are plotted as below:



The Theil's U statistic for this model is 0.3985441. Thus, ARIMA model clearly gave the best results as per forecasting accuracy.

Theil's U statistic	VAR(3)	VAR(1)	ARIMA
afstcredit	2.5013038	0.696867	0.3985441

Which is the best model?

The above results imply that the ARIMA model was the best model for forecasting credit growth as it had the least value of Theil's U statistic. Thus, we can infer that in order to forecast the credit growth, we should use its own lagged values.

However, forecast accuracy does not imply that the model is the best determinant of what causes credit growth. In fact, when we compare the AIC of the multivariate model and the univariate model, we find that the univariate model gives a much higher AIC and BIC. These information criterion estimate the relative amount of information lost by a given model: the less information a model loses, the higher the quality of that model. In estimating the amount of information lost by a model, the criterion deals with the trade-off between the goodness of fit of the model and the simplicity of the model. In other words, they deal with both the risk of overfitting and the risk of underfitting. The ARIMA model could be an example of underfitting and its much higher value of AIC and BIC indicates much more lost information as compared to the VAR models (which also ran a risk of overfitting).

8 Conclusion

The determinants of credit growth and its relationship with other macroeconomic variables has been of much debate with the existing literature giving mixed results about the same. In this paper, we have attempted to explain credit growth and these underlying relationships using Vector Autoregressive (VAR) models and Granger Causality by using the data from the past decade. It was observed that there exists a bidirectional Granger causality between Capital to Risk (Weighted) Assets Ratio (CRAR) which shows that the pertaining soundness of the banking system in the previous quarters has a correlation with the current credit growth and vice versa. Also, pertaining credit growth in the previous quarters impacts the current deposit growth.

We were also able to highlight the difference between the two time series techniques of analysis. While VAR clearly tells us more about credit growth, giving a better fit model with much lower BIC, ARIMA does not tell us much about the data and may be considered as an underfit model. VAR models can also be used to study the dynamic interrelationships between time series directly. At the same time, the measures used to evaluate forecasting performance in this study suggest that the univariate ARIMA model had a superior forecasting ability and outperformed the vector autoregression approach.

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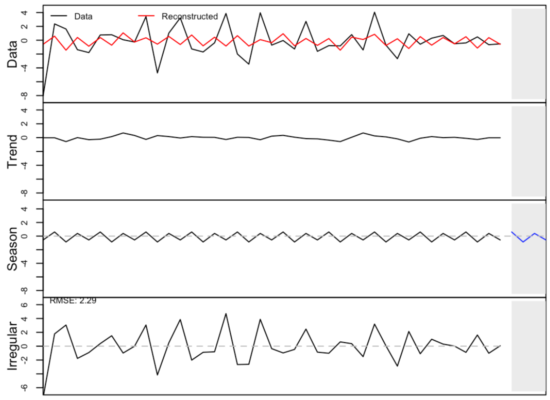
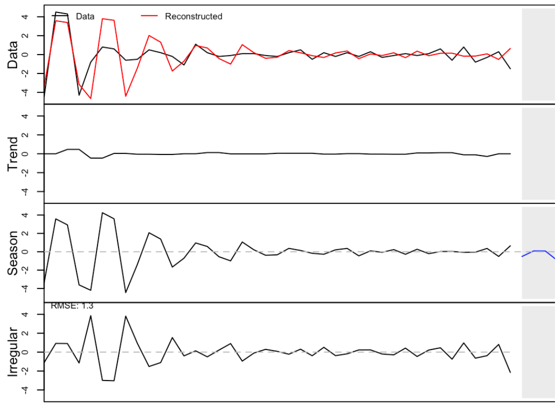
APPENDIX

A.1. Plots after second order differencing

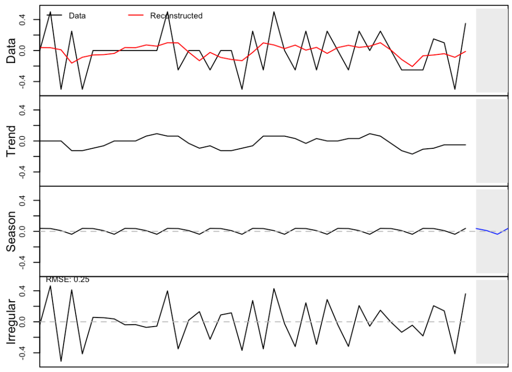
GDP



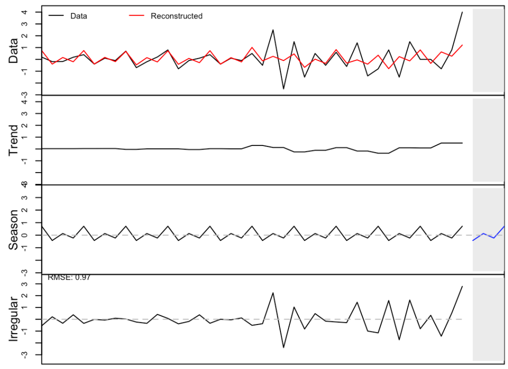
CRAR



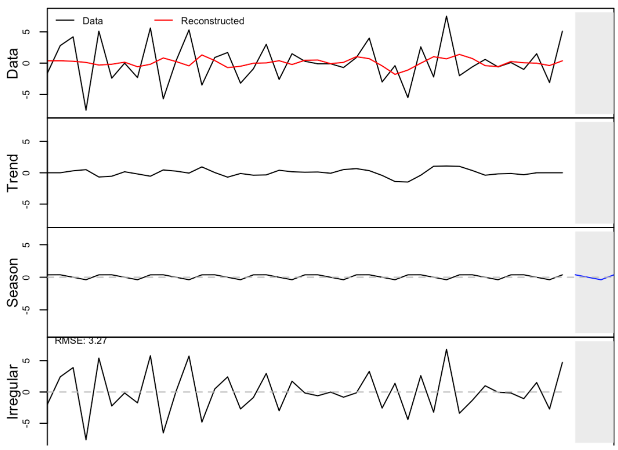
Repo



GNPA



Deposits



A.2.1 VAR(3) results for all other variables

```
Estimation results for equation afstcrar:
=========================================
afstcrar = afstcredit.l1 + afstcrar.l1 + afstgnpa.l1 + afstrepo.l1 + afstgdp.l1 + afstdep.l1
+ afstcredit.l2 + afstcrar.l2 + afstgnpa.l2 + afstrepo.l2 + afstgdp.l2 + afstdep.l2 +
afstcredit.l3 + afstcrar.l3 + afstgnpa.l3 + afstrepo.l3 + afstgdp.l3 + afstdep.l3 + const

              Estimate Std. Error t value Pr(>|t|)
afstcredit.l1  0.01334    0.02871   0.465  0.64986
afstcrar.l1   -0.68198    0.19490  -3.499  0.00392 **
afstgnpa.l1   -0.07732    0.12767  -0.606  0.55523
afstrepo.l1    0.29462    0.42509   0.693  0.50046
afstgdp.l1     0.03213    0.05446   0.590  0.56532
afstdep.l1    -0.02575    0.02494  -1.032  0.32076
afstcredit.l2  0.03113    0.03852   0.808  0.43348
afstcrar.l2   -0.58335    0.04936 -11.818 2.51e-08 ***
afstgnpa.l2   -0.13290    0.14095  -0.943  0.36294
afstrepo.l2    0.18046    0.42902   0.421  0.68090
afstgdp.l2     0.06977    0.04620   1.510  0.15495
afstdep.l2     0.02505    0.02994   0.837  0.41790
afstcredit.l3  0.02228    0.02691   0.828  0.42250
afstcrar.l3   -0.37112    0.12170  -3.049  0.00931 **
afstgnpa.l3   -0.11186    0.11581  -0.966  0.35174
afstrepo.l3    0.03040    0.29957   0.101  0.92073
afstgdp.l3     0.03930    0.04554   0.863  0.40375
afstdep.l3     0.05633    0.02647   2.128  0.05302 .
const         -0.03754    0.05333  -0.704  0.49385
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Residual standard error: 0.2945 on 13 degrees of freedom
Multiple R-Squared: 0.954,   Adjusted R-squared: 0.8903
F-statistic: 14.97 on 18 and 13 DF,  p-value: 6.537e-06


Estimation results for equation afstgnpa:
=========================================
afstgnpa = afstcredit.l1 + afstcrar.l1 + afstgnpa.l1 + afstrepo.l1 + afstgdp.l1 + afstdep.l1
+ afstcredit.l2 + afstcrar.l2 + afstgnpa.l2 + afstrepo.l2 + afstgdp.l2 + afstdep.l2 +
afstcredit.l3 + afstcrar.l3 + afstgnpa.l3 + afstrepo.l3 + afstgdp.l3 + afstdep.l3 + const

              Estimate Std. Error t value Pr(>|t|)
afstcredit.l1  0.03050    0.05965   0.511   0.6177
afstcrar.l1   -0.49230    0.40488  -1.216   0.2456
afstgnpa.l1   -0.64609    0.26523  -2.436   0.0300 *
afstrepo.l1   -0.85918    0.88310  -0.973   0.3484
afstgdp.l1     0.15383    0.11314   1.360   0.1971
afstdep.l1    -0.03261    0.05182  -0.629   0.5401
afstcredit.l2 -0.05624    0.08002  -0.703   0.4945
afstcrar.l2    0.26564    0.10254   2.590   0.0224 *
afstgnpa.l2   -0.39812    0.29281  -1.360   0.1971
afstrepo.l2   -0.04484    0.89125  -0.050   0.9606
afstgdp.l2     0.04315    0.09598   0.450   0.6604
afstdep.l2    -0.05216    0.06220  -0.839   0.4169
afstcredit.l3 -0.02254    0.05589  -0.403   0.6933
afstcrar.l3   -0.21893    0.25283  -0.866   0.4022
afstgnpa.l3   -0.02097    0.24060  -0.087   0.9319
afstrepo.l3   -1.32996    0.62234  -2.137   0.0522 .
```

```
afstgdp.l3     0.14306    0.09461   1.512   0.1544
afstdep.l3    -0.06258    0.05499  -1.138   0.2756
const         -0.08109    0.11078  -0.732   0.4772
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Residual standard error: 0.6118 on 13 degrees of freedom
Multiple R-Squared: 0.8333,  Adjusted R-squared: 0.6024
F-statistic: 3.609 on 18 and 13 DF,  p-value: 0.01134


Estimation results for equation afstrepo:
=========================================
afstrepo = afstcredit.l1 + afstcrar.l1 + afstgnpa.l1 + afstrepo.l1 + afstgdp.l1 + afstdep.l1
+ afstcredit.l2 + afstcrar.l2 + afstgnpa.l2 + afstrepo.l2 + afstgdp.l2 + afstdep.l2 +
afstcredit.l3 + afstcrar.l3 + afstgnpa.l3 + afstrepo.l3 + afstgdp.l3 + afstdep.l3 + const

               Estimate Std. Error t value Pr(>|t|)
afstcredit.l1 -0.023586   0.020111  -1.173   0.2619
afstcrar.l1    0.050282   0.136506   0.368   0.7185
afstgnpa.l1    0.034625   0.089424   0.387   0.7049
afstrepo.l1    0.011219   0.297739   0.038   0.9705
afstgdp.l1     0.098401   0.038145   2.580   0.0229 *
afstdep.l1     0.042438   0.017471   2.429   0.0304 *
afstcredit.l2 -0.032024   0.026979  -1.187   0.2565
afstcrar.l2    0.009409   0.034573   0.272   0.7898
afstgnpa.l2   -0.108323   0.098721  -1.097   0.2924
afstrepo.l2    0.083163   0.300487   0.277   0.7863
afstgdp.l2     0.040021   0.032361   1.237   0.2381
afstdep.l2     0.001427   0.020972   0.068   0.9468
afstcredit.l3 -0.019739   0.018845  -1.047   0.3140
afstcrar.l3   -0.035878   0.085241  -0.421   0.6807
afstgnpa.l3    0.034095   0.081117   0.420   0.6811
afstrepo.l3   -0.130954   0.209823  -0.624   0.5433
afstgdp.l3     0.071923   0.031897   2.255   0.0420 *
afstdep.l3     0.003112   0.018540   0.168   0.8693
const         -0.006234   0.037350  -0.167   0.8700
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Residual standard error: 0.2063 on 13 degrees of freedom
Multiple R-Squared: 0.6945,  Adjusted R-squared: 0.2714
F-statistic: 1.642 on 18 and 13 DF,  p-value: 0.1833


Estimation results for equation afstgdp:
========================================
afstgdp = afstcredit.l1 + afstcrar.l1 + afstgnpa.l1 + afstrepo.l1 + afstgdp.l1 + afstdep.l1 +
afstcredit.l2 + afstcrar.l2 + afstgnpa.l2 + afstrepo.l2 + afstgdp.l2 + afstdep.l2 +
afstcredit.l3 + afstcrar.l3 + afstgnpa.l3 + afstrepo.l3 + afstgdp.l3 + afstdep.l3 + const

              Estimate Std. Error t value Pr(>|t|)
afstcredit.l1  0.24711    0.12253   2.017 0.064876 .
afstcrar.l1   -1.76036    0.83171  -2.117 0.054158 .
afstgnpa.l1    1.19570    0.54484   2.195 0.046963 *
afstrepo.l1   -0.56163    1.81407  -0.310 0.761772
afstgdp.l1    -1.17149    0.23241  -5.041 0.000226 ***
afstdep.l1    -0.14710    0.10645  -1.382 0.190289
afstcredit.l2  0.32229    0.16438   1.961 0.071704 .
afstcrar.l2    0.25345    0.21065   1.203 0.250360
afstgnpa.l2    0.15000    0.60149   0.249 0.806963
afstrepo.l2    3.43619    1.83081   1.877 0.083159 .
```

```
afstgdp.l2    -1.09720    0.19717  -5.565 9.15e-05 ***
afstdep.l2    -0.32262    0.12778  -2.525 0.025374 *
afstcredit.l3  0.25002    0.11482   2.178 0.048455 *
afstcrar.l3   -0.85495    0.51936  -1.646 0.123679
afstgnpa.l3   -0.04182    0.49423  -0.085 0.933860
afstrepo.l3   -1.84968    1.27841  -1.447 0.171616
afstgdp.l3    -0.58112    0.19434  -2.990 0.010435 *
afstdep.l3    -0.29867    0.11296  -2.644 0.020237 *
const         -0.01328    0.22757  -0.058 0.954346
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Residual standard error: 1.257 on 13 degrees of freedom
Multiple R-Squared: 0.8578,  Adjusted R-squared: 0.661
F-statistic: 4.358 on 18 and 13 DF,  p-value: 0.004875


Estimation results for equation afstdep:
========================================
afstdep = afstcredit.l1 + afstcrar.l1 + afstgnpa.l1 + afstrepo.l1 + afstgdp.l1 + afstdep.l1 +
afstcredit.l2 + afstcrar.l2 + afstgnpa.l2 + afstrepo.l2 + afstgdp.l2 + afstdep.l2 +
afstcredit.l3 + afstcrar.l3 + afstgnpa.l3 + afstrepo.l3 + afstgdp.l3 + afstdep.l3 + const

               Estimate Std. Error t value Pr(>|t|)
afstcredit.l1  0.125823   0.269649   0.467   0.6485
afstcrar.l1   -1.225350   1.830272  -0.669   0.5149
afstgnpa.l1   -0.251307   1.198994  -0.210   0.8372
afstrepo.l1    0.104449   3.992068   0.026   0.9795
afstgdp.l1     0.132906   0.511445   0.260   0.7990
afstdep.l1    -0.488290   0.234247  -2.085   0.0574 .
afstcredit.l2  0.004016   0.361738   0.011   0.9913
afstcrar.l2   -0.207414   0.463556  -0.447   0.6619
afstgnpa.l2   -0.358851   1.323646  -0.271   0.7906
afstrepo.l2    1.835966   4.028911   0.456   0.6561
afstgdp.l2     0.658280   0.433888   1.517   0.1532
afstdep.l2    -0.200966   0.281197  -0.715   0.4874
afstcredit.l3 -0.219178   0.252668  -0.867   0.4014
afstcrar.l3   -0.058195   1.142908  -0.051   0.9602
afstgnpa.l3    0.832647   1.087619   0.766   0.4576
afstrepo.l3   -0.559368   2.813295  -0.199   0.8455
afstgdp.l3     0.320040   0.427679   0.748   0.4676
afstdep.l3    -0.059144   0.248577  -0.238   0.8156
const         -0.097497   0.500790  -0.195   0.8486
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Residual standard error: 2.766 on 13 degrees of freedom
Multiple R-Squared: 0.7234,  Adjusted R-squared: 0.3403
F-statistic: 1.888 on 18 and 13 DF,  p-value: 0.1235
```

A.2.2. Forecasting Results on Model 1 (VAR(3)

```
afstcredit
        Point Forecast     Lo 80      Hi 80      Lo 95     Hi 95
2019 Q1     -5.2124697 -7.762380 -2.6625591  -9.112222 -1.312718
2019 Q2      7.6960680  4.015820 11.3763159   2.067615 13.324521
2019 Q3     -5.3798375 -9.889519 -0.8701566 -12.276799  1.517124
2019 Q4      3.4665823 -1.810924  8.7440887  -4.604667 11.537832
2020 Q1     -1.1298244 -6.978232  4.7185828 -10.074191  7.814543
2020 Q2     -0.7995458 -7.455164  5.8560726 -10.978436  9.379344
```

```
afstcrar
        Point Forecast       Lo 80      Hi 80      Lo 95      Hi 95
2019 Q1   -0.536209540 -0.9136496 -0.1587695 -1.1134543 0.04103521
2019 Q2   -0.177990526 -0.6619233  0.3059422 -0.9181018 0.56212075
2019 Q3    0.039125689 -0.4988993  0.5771507 -0.7837126 0.86196395
2019 Q4    0.185807322 -0.3675837  0.7391983 -0.6605311 1.03214579
2020 Q1   -0.005716476 -0.6504340  0.6390010 -0.9917268 0.98029385
2020 Q2   -0.248253694 -0.9059209  0.4094136 -1.2540689 0.75756156

afstgnpa
        Point Forecast       Lo 80     Hi 80      Lo 95    Hi 95
2019 Q1      0.5922099 -0.1918914 1.3763112 -0.6069696 1.791389
2019 Q2      0.1888674 -0.8793890 1.2571238 -1.4448898 1.822625
2019 Q3      0.5269385 -0.7408173 1.7946943 -1.4119267 2.465804
2019 Q4     -0.7246970 -2.1403455 0.6909516 -2.8897446 1.440351
2020 Q1      0.5799846 -0.9908594 2.1508286 -1.8224139 2.982383
2020 Q2     -0.4006651 -2.0669068 1.2655766 -2.9489619 2.147632

afstrepo
        Point Forecast       Lo 80     Hi 80      Lo 95     Hi 95
2019 Q1    -0.11822769 -0.3825889 0.1461335 -0.5225333 0.2860779
2019 Q2    -0.03139071 -0.3654065 0.3026250 -0.5422237 0.4794423
2019 Q3     0.02106316 -0.3426009 0.3847272 -0.5351130 0.5772393
2019 Q4    -0.04290700 -0.4340330 0.3482190 -0.6410826 0.5552686
2020 Q1     0.08577554 -0.3112864 0.4828375 -0.5214783 0.6930294
2020 Q2    -0.01434633 -0.4152849 0.3865922 -0.6275289 0.5988363

afstgdp
        Point Forecast      Lo 80      Hi 80     Lo 95     Hi 95
2019 Q1     -1.8626636 -3.473367 -0.2519607 -4.326021 0.6006939
2019 Q2      1.6973843 -1.143182  4.5379502 -2.646886 6.0416549
2019 Q3      0.8886139 -2.169050  3.9462778 -3.787679 5.5649072
2019 Q4     -0.4444590 -3.687657  2.7987392 -5.404503 4.5155847
2020 Q1     -1.4095399 -4.743326  1.9242460 -6.508125 3.6890457
2020 Q2      1.5300603 -1.977489  5.0376101 -3.834274 6.8943948

afstdep
        Point Forecast      Lo 80    Hi 80     Lo 95    Hi 95
2019 Q1      -2.505517 -6.050058 1.039025 -7.926425 2.915392
2019 Q2       1.811092 -2.090071 5.712254 -4.155221 7.777405
2019 Q3      -2.045350 -6.031001 1.940302 -8.140877 4.050178
2019 Q4       2.145018 -1.997506 6.287541 -4.190425 8.480460
2020 Q1      -1.067478 -5.356368 3.221412 -7.626769 5.491813
2020 Q2       1.406669 -3.027681 5.841020 -5.375085 8.188423
```

A.3.1 VAR(1) results for all other variables in Alternative Model

```
Estimation results for equation crgstcrar:
==========================================
crgstcrar = crgstcredit.l1 + crgstcrar.l1 + crgstrepo.l1 + crgstgdp.l1 + const

               Estimate Std. Error t value Pr(>|t|)
crgstcredit.l1 -0.02334    0.04453  -0.524   0.6043
crgstcrar.l1   -0.11053    0.16141  -0.685   0.4989
crgstrepo.l1    1.70306    0.89063   1.912   0.0658 .
crgstgdp.l1    -0.08244    0.09727  -0.848   0.4037
const           0.13207    0.22672   0.583   0.5647
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


Residual standard error: 1.318 on 29 degrees of freedom
Multiple R-Squared: 0.1995,     Adjusted R-squared: 0.08905
F-statistic: 1.807 on 4 and 29 DF,  p-value: 0.1546


Estimation results for equation crgstrepo:
```

```
==========================================
crgstrepo = crgstcredit.l1 + crgstcrar.l1 + crgstrepo.l1 + crgstgdp.l1 + const

                Estimate Std. Error t value Pr(>|t|)
crgstcredit.l1  0.005214   0.007987   0.653  0.51901
crgstcrar.l1   -0.018642   0.028950  -0.644  0.52467
crgstrepo.l1   -0.526854   0.159738  -3.298  0.00258 **
crgstgdp.l1    -0.007957   0.017446  -0.456  0.65171
const          -0.007963   0.040663  -0.196  0.84610
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Residual standard error: 0.2363 on 29 degrees of freedom
Multiple R-Squared: 0.2989,     Adjusted R-squared: 0.2023
F-statistic: 3.092 on 4 and 29 DF,  p-value: 0.03094


Estimation results for equation crgstgdp:
=========================================
crgstgdp = crgstcredit.l1 + crgstcrar.l1 + crgstrepo.l1 + crgstgdp.l1 + const

                 Estimate Std. Error t value Pr(>|t|)
crgstcredit.l1 -0.0009288  0.0701165  -0.013   0.9895
crgstcrar.l1    0.2162551  0.2541279   0.851   0.4018
crgstrepo.l1    0.7108130  1.4022317   0.507   0.6160
crgstgdp.l1    -0.3783112  0.1531427  -2.470   0.0196 *
const           0.0030680  0.3569487   0.009   0.9932
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Residual standard error: 2.075 on 29 degrees of freedom
Multiple R-Squared: 0.1818,     Adjusted R-squared: 0.06897
F-statistic: 1.611 on 4 and 29 DF,  p-value: 0.1981
```

A.3.2 Forecasting results on Alternative Model

crgstcredit

```
        Point Forecast     Lo 80    Hi 80      Lo 95     Hi 95
2019 Q1     -1.2561892 -6.087099 3.574720  -8.644427  6.132049
2019 Q2      0.8648710 -5.113234 6.842976  -8.277851 10.007593
2019 Q3     -0.7626016 -7.320796 5.795592 -10.792494  9.267291
2019 Q4      0.4821043 -6.397913 7.362121 -10.039974 11.004182
2020 Q1     -0.4777992 -7.541880 6.586282 -11.281378 10.325780
2020 Q2      0.2653086 -6.905469 7.436086 -10.701450 11.232067

crgstcrar
        Point Forecast     Lo 80    Hi 80     Lo 95    Hi 95
2019 Q1    -0.41331858 -2.102079 1.275442 -2.996055 2.169418
2019 Q2     0.41887572 -1.382500 2.220251 -2.336091 3.173842
2019 Q3    -0.05340032 -1.898256 1.791455 -2.874863 2.768063
2019 Q4     0.19409633 -1.664532 2.052725 -2.648430 3.036623
2020 Q1     0.05918462 -1.804599 1.922969 -2.791227 2.909596
2020 Q2     0.14011400 -1.726198 2.006426 -2.714165 2.994393

crgstrepo
        Point Forecast      Lo 80     Hi 80      Lo 95     Hi 95
2019 Q1    0.116827480 -0.1860594 0.4197143 -0.3463980 0.5800529
2019 Q2   -0.067119966 -0.4116667 0.2774267 -0.5940587 0.4598188
2019 Q3    0.023648047 -0.3308002 0.3780963 -0.5184338 0.5657299
2019 Q4   -0.023591455 -0.3809502 0.3337673 -0.5701244 0.5229415
2020 Q1    0.003360751 -0.3551704 0.3618919 -0.5449653 0.5516868
2020 Q2   -0.013549772 -0.3726733 0.3455738 -0.5627818 0.5356823

crgstgdp
        Point Forecast     Lo 80    Hi 80     Lo 95    Hi 95
2019 Q1  -1.557627e-01 -2.814596 2.503070 -4.222097 3.910571
```

```
2019 Q2   5.682176e-02 -2.814051 2.927695 -4.333799 4.447443
2019 Q3   2.364265e-02 -2.872156 2.919441 -4.405099 4.452385
2019 Q4   9.324837e-05 -2.897880 2.898067 -4.431975 4.432161
2020 Q1   2.779014e-02 -2.870371 2.925952 -4.404565 4.460146
2020 Q2   8.186277e-03 -2.890021 2.906393 -4.424239 4.440612
```

A.4. Forecasts using ARIMA model

```
Point Forecast     Lo 80    Hi 80      Lo 95     Hi 95
2019 Q1      -1.2349155 -4.371997 1.902166  -6.032668  3.562837
2019 Q2       0.7247735 -4.238791 5.688338  -6.866343  8.315890
2019 Q3      -2.1107616 -7.640435 3.418912 -10.567667  6.346144
2019 Q4       1.4572946 -4.283528 7.198117  -7.322536 10.237125
2020 Q1      -0.3469996 -6.277562 5.583563  -9.417012  8.723013
2020 Q2       0.2200223 -6.181642 6.621686  -9.570478 10.010523
2020 Q3     -0.13950974 -6.721081 6.442061 -10.205154  9.926135
2020 Q4      0.08845905 -6.564072 6.740990 -10.085709 10.262627
2021 Q1     -0.05608930 -6.736937 6.624758 -10.273564 10.161385
2021 Q2      0.03556459 -6.656634 6.727763 -10.199270 10.270399
```