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MODELLING & FORECASTING THE STABILITY OF INDIAN OVERSEAS BANK USING ARIMA, VAR & REGRESSION: A COMPARATIVE ARIMA STUDY WITH SELECTED INDIAN BANKS

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ABSTRACT - This study explores the financial stability of Indian Overseas Bank (IOB) by employing advanced econometric techniques like ARIMA, VAR & regression, to model & forecast GrossNPA. This Research investigate the dynamic relationships between NPAs and key macroeconomic variables. The ARIMA model forecast a stable trend in IOB's NPAs through 2030, while the VAR highlights a two-way link between GDP and NPAs. Through Regression we identified exchange rate is the most significant predictor of asset quality. A comparative ARIMA analysis with other major Indian banks further supports findings. The study emphasizes the value of predictive models for effective risk management and policy formulation in banking sector.

Keywords:

1. Indian Overseas Bank **2.** Punjab National Bank **3.** Bank of India **4.** Bank of Baroda **5.** State Bank of India **6.**GDP **7.** Exchange rate **8.** Interest rate **9.** Inflation rate **10.** GrossNPA **11.** ARIMA **12.** VAR **13.** Regression.

1.INTRODUCTION

The banking sector plays a fundamental role in maintaining economic stability and promoting growth, especially in developing economies like India. As financial intermediaries, banks support capital formation, channel savings into productive investments, and facilitate smooth monetary transactions. Ensuring the stability of this sector is critical not only for institutional performance but also for macroeconomic resilience. In recent years, the Indian banking system has undergone significant changes-ranging from regulatory reforms and digital transformation to consolidation efforts and the resolution of bad debts. However, persistent issues such as non-performing assets (NPAs), currency fluctuations, inflationary pressures, and interest rate volatility continue to challenge the financial health of banks, particularly those in the public sector.

Indian Overseas Bank (IOB), a well-known public sector bank, is the subject of this study, which applies a strong analytical framework to investigate and predict financial stability. IOB has seen fluctuating asset quality throughout the years, despite its wide-ranging local and global influence. It is used as a case study to assess the general risks and recovery patterns in public banking institutions in India. To predict future non-performing assets (NPAs) and evaluate the relationship between macroeconomic factors and banking performance, the study uses three important econometric models: regression analysis, VAR (Vector Auto Regression), and ARIMA (Auto-Regressive Integrated Moving Average). These models provide information on asset quality and financial fragility over the short and long terms.

This study offers a thorough grasp of the economic factors influencing banking outcomes by combining macroeconomic statistics like GDP, inflation, interest rates, and currency rates. Supporting proactive decision-making among banks executives, legislators, and financial regulators is the aim. The study emphasises the significance of forward-looking tactics to improve financial risk management and guarantee ongoing banking sector stability in the face of changing economic problems using predictive modelling and comparative analysis.

2.1 REVIEW OF LITERATURE

Borio, Drehmann, and Tsatsaronis (2012) contributed significantly to the understanding of financial system vulnerabilities by developing models that measure macroeconomic stress. Their work utilized Vector AutoRegression (VAR) techniques to explore how macroeconomic indicators interact with banking sector performance during periods of economic tension. This approach allowed for the identification of potential pressure points in financial systems, highlighting how macro-level shocks can undermine stability.

Demirgüç-Kunt and Detragiache (1998) examined the root causes of banking crises by applying logistic regression models to a wide range of international data. Their analysis focused on identifying key macroeconomic and institutional variables—such as weak regulatory frameworks, low GDP growth, and inflation—that increase the likelihood of systemic banking failures. Their study is often cited as a foundational work in early-warning systems for financial instability.

In another methodological advancement, Pesaran and Shin (1998) introduced the concept of generalized impulse response functions (GIRFs) within linear multivariate models. Their work has become a cornerstone for analyzing the transmission of economic shocks across financial systems. By removing the limitations of traditional impulse response techniques, their approach enabled a more nuanced understanding of how different variables respond to unexpected changes over time.

Laeven and Valencia (2013) expanded the empirical foundation for financial crisis research through the creation of a comprehensive international database on systemic banking crises. Using this dataset, they applied regression techniques to identify recurring patterns and contributing factors behind major financial breakdowns. Their findings underscored the importance of policy responses, capital adequacy, and macroeconomic stability in preventing banking crises.

Schularick and Taylor (2012) examined long-term credit cycles using VAR methodologies, shedding light on the role of credit booms in triggering financial collapses. Their study emphasized that excessive credit growth often precedes banking crises, and that early detection of credit market trends is vital for maintaining financial stability. This research has been influential in formulating macroprudential policies aimed at curbing unsustainable lending practices.

2.2 OBJECTIVES OF THE STUDY

- sector risk, particularly Gross Non-Performing Assets (NPAs), using the ARIMA (Autoregressive Integrated Moving Average) model, in order to support better financial planning and risk assessment.
- To carry out a comparative ARIMA-based forecast involving Indian Overseas Bank and other major public sector banks in India, aiming to understand post-crisis recovery patterns and risk behaviour, particularly in the context of recent global financial disturbances such as the COVID-19 pandemic and prior economic slowdowns.
- To examine how macroeconomic indicators such as GDP, inflation, interest rates, and exchange rates interact with banking sector performance through the use of the Vector Auto Regression (VAR) model, capturing the dynamic interrelationships among these variable.
- To determine which macroeconomic factors most significantly influence asset quality, especially in terms of NPAs, by using regression analysis to assess the relative impact and statistical relevance of each economic variable.
- To provide data-driven insights and tools that policymakers, regulators, and banking institutions can use for proactive risk management, policy design, and long-term financial stability planning.

3. RESEARCH METHODOLOGY

Here, this study has been conducted on Indian Overseas Bank over a period of 2015 to 2030 for forecasting and to understand the interdependency, this study considered the time period of 2015 to 2025. This data has been collected from the source of IOB's annual reports, IMF and World bank data. The main objective of this study is to find the stability and upcoming risk of the IOB, understanding the economic interactions to enhance the Bank stability and to overcome the risk

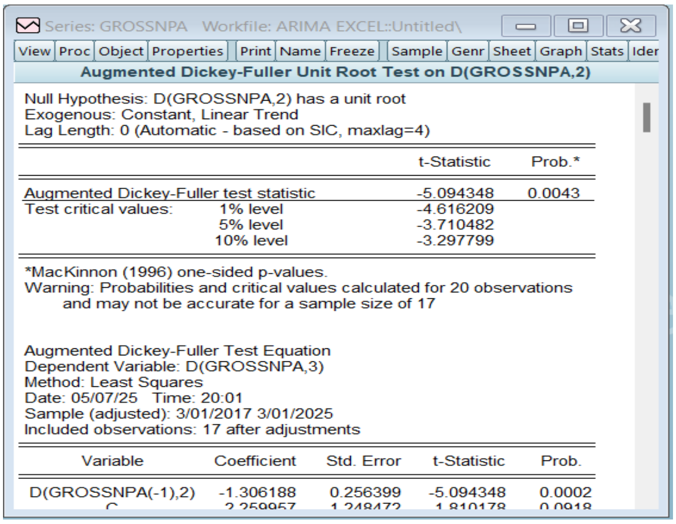
4.DATA ANALYSIS & INTERPRETATION

Box-Jenkins method: Identification

Stationarity check: Which comes before ARIMA modelling, verifies that time series statistics like variance and mean do not alter over time. Differentiating the data makes it stationary if it is not already stationary. Visual assessment and statistical tests, such as Augmented Dickey-Fuller test can be used to determine stationarity.

Null hypothesis (H0): The series Gross NPA has a unit root.

Alternative hypothesis (H1): The series Gross NPA doesn't has a unit root.


Series: GROSSNPA Workfile: ARIMA EXCEL::Untitled\

View Proc Object Properties Print Name Freeze Sample Genr Sheet Graph Stats Ider

Augmented Dickey-Fuller Unit Root Test on D(GROSSNPA,2)

Null Hypothesis: D(GROSSNPA,2) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.094348	0.0043
Test critical values:	1% level	-4.616209	
	5% level	-3.710482	
	10% level	-3.297799	

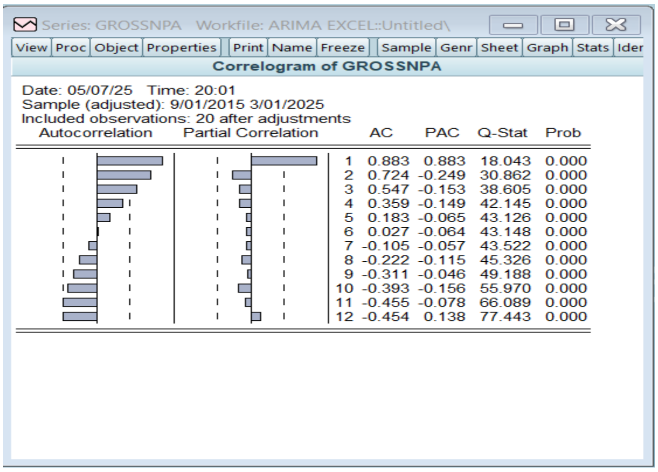
*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations and may not be accurate for a sample size of 17

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GROSSNPA,3)
Method: Least Squares
Date: 05/07/25 Time: 20:01
Sample (adjusted): 3/01/2017 3/01/2025
Included observations: 17 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(GROSSNPA(-1),2)	-1.306188	0.256399	-5.094348	0.0002
C	2.259957	1.248472	1.810178	0.0918

Fig 4.1: Unit Root Test (GrossNPA)

Interpretation: As the p-value of gross NPA becomes less than 0.05 at 2nd difference after conducting “Augmented Dickey-Fuller” test. So, we fall to reject the null hypothesis means the grossnpa variable doesn’t has unit root. Thus, the data has converted into stationary.


Series: GROSSNPA Workfile: ARIMA EXCEL::Untitled\

View Proc Object Properties Print Name Freeze Sample Genr Sheet Graph Stats Ider

Correlogram of GROSSNPA

Date: 05/07/25 Time: 20:01
Sample (adjusted): 9/01/2015 3/01/2025
Included observations: 20 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.883	0.883	18.043	0.000
		2	0.724	-0.249	30.862	0.000
		3	0.547	-0.153	38.605	0.000
		4	0.359	-0.149	42.145	0.000
		5	0.183	-0.065	43.126	0.000
		6	0.027	-0.064	43.148	0.000
		7	-0.105	-0.057	43.522	0.000
		8	-0.222	-0.115	45.326	0.000
		9	-0.311	-0.046	49.188	0.000
		10	-0.393	-0.156	55.970	0.000
		11	-0.455	-0.078	66.089	0.000
		12	-0.454	0.138	77.443	0.000

Fig 4.2: ACF and PACF plots for Grossnpa

Interpretation: The correlogram reveals that a strong autocorrelation exists in the GROSSNPA series. This means where the past values of GROSSNPA have huge influence on future values of this series. Statistical significance of autocorrelation up to 12 lags. The correlogram of GROSSNPA shows high autocorrelation at lag1(0.883) and gradually declining values, indicating strong persistence in the series. The partial autocorrelation is also significant at lag1, suggesting an AR (1) structure.

Model selection: The precise model must be chosen based on the ordering of (p, d and q) in the ARIMA model identification process. In this step, the patterns found in the partial autocorrelation function (PACF) and autocorrelation function (ACF) during the identification phase are used to determine the autoregressive (AR) and moving average (MA) lags. We can compare many candidate models using metrics like the Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC), even though the ordering may not be the best ones. We can select the one with the lowest AIC or BIC. Here, we got 3equations:

contents	**(1,1,1)**	**(2,1,1)**	**(3,1,1)**
AR value	0.784551	0.579163	0.190772
MA value	-0.003652	0.938164	0.653611
R-squared value	0.466808	0.504871	0.394376
Akaike(A.I.C) value	4.538878	4.492411	4.656894
Schwarz(S.C) value	4.737708	4.691240	4.855723
Hanna(H.Q.C) value	4.572528	4.526061	4.690544

Table 4.3: ARIMA Model Selection Table (Comparison of (1,1,1), (2,1,1), (3,1,1) Models).

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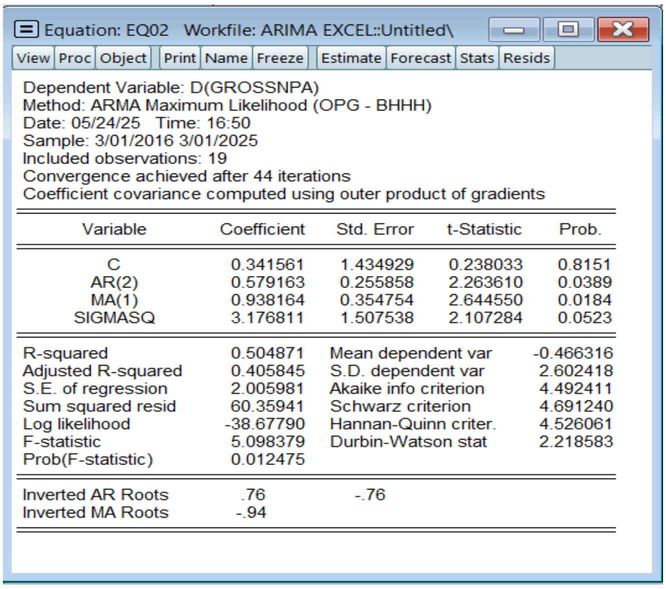
Interpretation: The R-squared value reflects how well the independent variable explain the variability of the dependent variable, with higher values indicating a better fit. Metrics such as AR, MA, AIC, SC, and HQC assess model adequacy by indicating the amount of information lost; lower values are preferred. In this study, the (2,1,1) model is selected as it satisfies above conditions, demonstrating optimal forecasting performance.


Equation: EQ02 Workfile: ARIMA EXCEL::Untitled\

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: D(GROSSNPA)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 05/24/25 Time: 16:50
Sample: 3/01/2016 3/01/2025
Included observations: 19
Convergence achieved after 44 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.341561	1.434929	0.238033	0.8151
AR(2)	0.579163	0.255858	2.263610	0.0389
MA(1)	0.938164	0.354754	2.644550	0.0184
SIGMASQ	3.176811	1.507538	2.107284	0.0523

R-squared	0.504871	Mean dependent var	-0.466316
Adjusted R-squared	0.405845	S.D. dependent var	2.602418
S.E. of regression	2.005981	Akaike info criterion	4.492411
Sum squared resid	60.35941	Schwarz criterion	4.691240
Log likelihood	-38.67790	Hannan-Quinn criter.	4.526061
F-statistic	5.098379	Durbin-Watson stat	2.218583
Prob(F-statistic)	0.012475		

Inverted AR Roots	.76	-.76
Inverted MA Roots	-.94	

Fig 4.4: Equation (2,1,1)

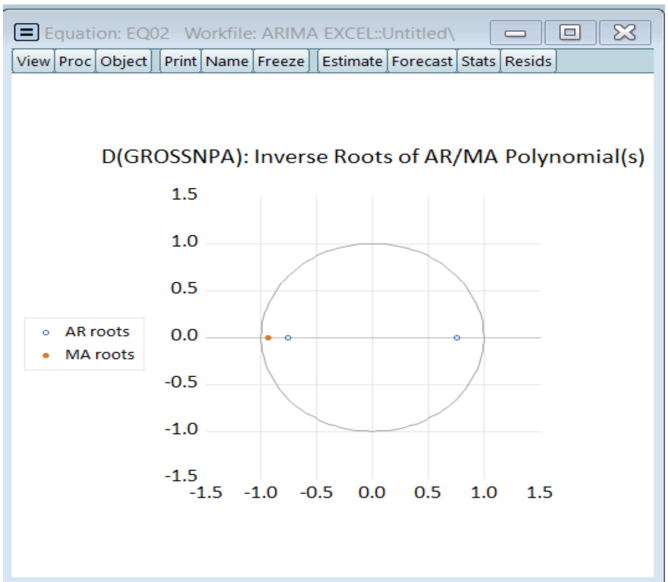


Fig 4.5: Inverse root graph of Gross NPA

Interpretation: In the ARMA structure, all roots of the ARIMA model lying within the unit circle indicate stability and suggest that the model is well-suited for forecasting.

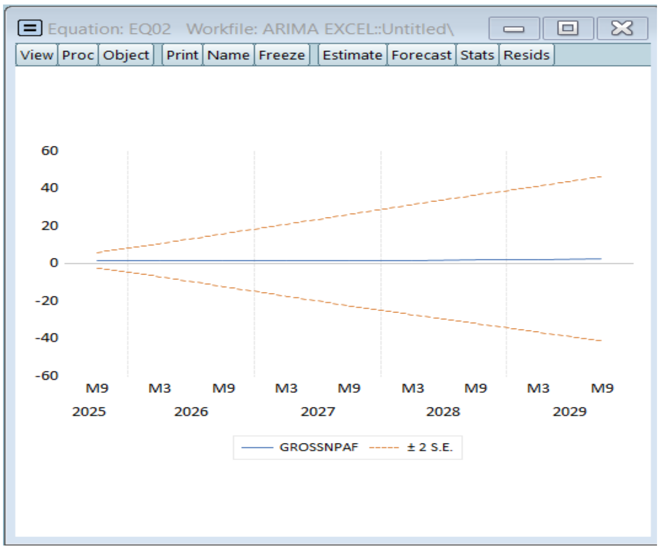


Fig 4.6:Standard error graph

Interpretation: The ARIMA model forecast that the value of GROSSNPAF will remain relatively stable over the years 2025-2030, suggest a stable trend with no expected significant changes, although uncertainity increases as we move further into the future. This model may be useful for short-term planning.

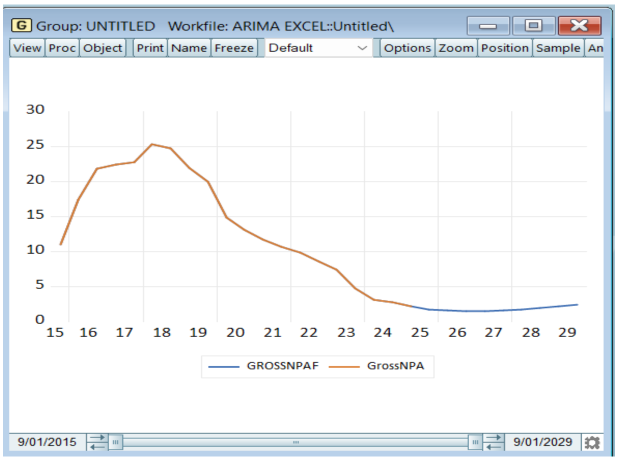


Fig 4.7: ARIMA Forecast Graph for Gross NPA

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Interpretation: This graph illustrates that GROSSNPA rose sharply between year 15 and 18, peaked, and then declined steadily. The ARIMA model forecasts that this trend will flatten out from 25 onwards, suggesting a period of stability in non-performing assets in the future. This indicates a potentially positive outlook for financial health if current trends continue.

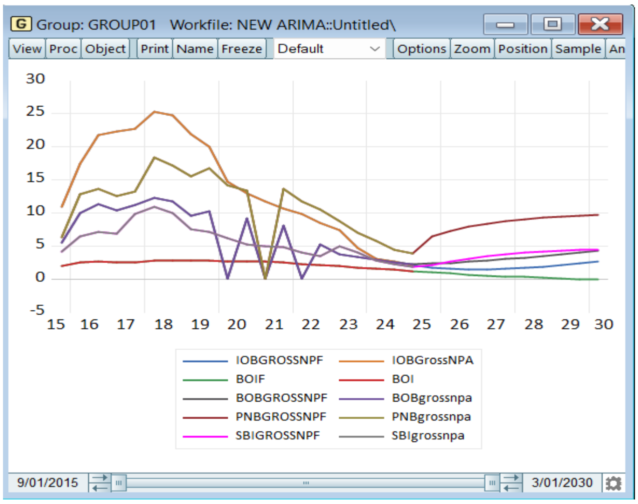

Fig 4.8: Comparative ARIMA Forecast of Gross NPA across Indian Banks (IOB, SBI, PNB, BOB, BOI)

Interpretation: The graph shows how the bad loans (Gross NPAs) of major Indian public sector banks have changed from 2015 and how they are expected to behave until 2030. From 2015 to around 2019, banks like Bank of Baroda (BOB) and Punjab National Bank (PNB) had very high levels of bad loans, even crossing 25%, which means a large portion of their loans were not being repaid. However, after 2019, most banks started to improve, and their bad loan levels began to fall. This improvement was likely due to better loan recovery methods, government support, and selling of bad loans to recovery agencies. Around 2020 to 2023, there were some ups and downs, likely because of the impact of COVID-19. Looking at the forecast from 2025 to 2030, the graph shows that bad loans are expected to remain mostly stable for banks like Indian Overseas Bank (IOB) and State Bank of India (SBI), while banks like PNB and BOB might see a slight increase again. Overall, the graph suggests that although the situation has improved since the peak of the crisis, banks still need to manage their loans carefully to avoid a rise in bad loans again.

VAR analysis:

On the other hand, the VAR approach is employed when we wish to simultaneously examine the relationship between several time series. For instance, the VAR model shows us how factors like GDP, inflation, and exchange rate and interest rates affect one another over time. if that is of interest to us. The VAR model examines multiple time series simultaneously, in contrast to the Box-Jenkins technique, which only examines one. This feature of the VAR model helps to explain complicated systems with numerous interrelated components.

Stationary Check: Which comes before VAR analysis, verifies that time series statistics like variance and mean do not alter over time. Differentiating the data makes it stationary if it is not already stationary. Visual assessment and statistical tests, such as Augmented Dickey-Fuller test can be used to determine stationarity.

Null hypothesis (H0): The series Exchange rate has a unit root.

Alternative hypothesis (H1): The series Exchange rate doesn't has a unit root.

Series: EXCHANGE_RATE Workfile: VAR::Var\

Augmented Dickey-Fuller Unit Root Test on D(EXCHANGE_RATE)

Null Hypothesis: D(EXCHANGE_RATE) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.674264	0.0083
Test critical values:	1% level	-4.571559	
	5% level	-3.690814	
	10% level	-3.286909	

*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations and may not be accurate for a sample size of 18

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(EXCHANGE_RATE,2)
Method: Least Squares
Date: 05/17/25 Time: 10:25
Sample (adjusted): 9/01/2016 3/01/2025
Included observations: 18 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(EXCHANGE_RATE(-1))	-1.181087	0.252679	-4.674264	0.0003
C	1.244919	1.479179	0.841629	0.4132
@TREND("9/01/2015")	-0.004107	0.123418	-0.033278	0.9739

R-squared	0.592980	Mean dependent var	-0.143333
Adjusted R-squared	0.538711	S.D. dependent var	3.998894
S.E. of regression	2.715980	Akaike info criterion	4.987194
Sum squared resid	110.6482	Schwarz criterion	5.135589
Log likelihood	-41.88475	Hannan-Quinn criter.	5.007656
F-statistic	10.92662	Durbin-Watson stat	2.013793
Prob(F-statistic)	0.001181		

Fig 4.9: Stationarity Check for Exchange Rate.

Interpretation: As the p-value of Exchange rate becomes less than 0.05 at 1st difference after conducting "Augmented Dickey-Fuller" test. So, we fall to reject the null hypothesis means the

Exchange rate variable doesn't has unit root. Thus, the data has converted into stationary.

Null hypothesis (H0): The series GDP has a unit root.

Alternative hypothesis (H1): The series GDP doesn't has a unit root.

Series: GDP Workfile: VAR::Var\

Augmented Dickey-Fuller Unit Root Test on D(GDP)

Null Hypothesis: D(GDP) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.918982	0.0058
Test critical values:	1% level	-4.616209	
	5% level	-3.710482	
	10% level	-3.297799	

*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations and may not be accurate for a sample size of 17

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GDP,2)
Method: Least Squares
Date: 05/17/25 Time: 10:26
Sample (adjusted): 3/01/2017 3/01/2025
Included observations: 17 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(GDP(-1))	-1.906686	0.387618	-4.918982	0.0003
D(GDP(-1),2)	0.485225	0.242005	2.005017	0.0662
C	-1.932287	4.648978	-0.415637	0.6845
@TREND("9/01/2015")	0.152745	0.386038	0.395674	0.6988

R-squared	0.727194	Mean dependent var	-0.054706
Adjusted R-squared	0.664239	S.D. dependent var	13.42729
S.E. of regression	7.780429	Akaike info criterion	7.143424
Sum squared resid	786.9559	Schwarz criterion	7.339474
Log likelihood	-56.71911	Hannan-Quinn criter.	7.162912
F-statistic	11.55097	Durbin-Watson stat	2.100180
Prob(F-statistic)	0.000572		

Fig 4.10: Stationarity Check for GDP

Interpretation: As the p-value of GDP becomes less than 0.05 at 1st difference after conducting "Augmented Dickey-Fuller" test. So, we fall to reject the null hypothesis means the GDP variable doesn't has unit root. Thus, the data has converted into stationary.

Null hypothesis (H0): The series Gross NPA has a unit root.

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Alternative hypothesis (H1): The series Gross NPA doesn't has a unit root.

Series: GROSS_NPA Workfile: VAR::Var\

View | Proc | Object | Properties | Print | Name | Freeze | Sample | Genr | Sheet | Graph | Stats | Ider

Augmented Dickey-Fuller Unit Root Test on D(GROSS_NPA,2)

Null Hypothesis: D(GROSS_NPA,2) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.094348	0.0043
Test critical values:	1% level	-4.616209	
	5% level	-3.710482	
	10% level	-3.297799	

*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations and may not be accurate for a sample size of 17

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GROSS_NPA,3)
Method: Least Squares
Date: 05/17/25 Time: 10:26
Sample (adjusted): 3/01/2017 3/01/2025
Included observations: 17 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(GROSS_NPA(-1),2)	-1.306188	0.256399	-5.094348	0.0002
C	-2.259957	1.248472	-1.810178	0.0918
@TREND("9/01/2015")	0.167879	0.101604	1.652279	0.1207

R-squared	0.650608	Mean dependent var	0.107647
Adjusted R-squared	0.600695	S.D. dependent var	2.995660
S.E. of regression	1.892976	Akaike info criterion	4.272963
Sum squared resid	50.16703	Schwarz criterion	4.420000
Log likelihood	-33.32018	Hannan-Quinn criter.	4.287579
F-statistic	13.03479	Durbin-Watson stat	2.090995
Prob(F-statistic)	0.000636		

Fig 4.11: Stationarity Check for Gross NPA

Interpretation: As the p-value of gross NPA becomes less than 0.05 at 2nd difference after conducting "Augmented Dickey-Fuller" test. So, we fall to reject the null hypothesis means the grossnpa variable doesn't has unit root. Thus, the data has converted into stationary.

Null hypothesis (H0): The series Inflation rate has a unit root.

Alternative hypothesis (H1): The series Inflation rate doesn't has a unit root.

Series: INFLATION_RATE Workfile: VAR::Var\

View | Proc | Object | Properties | Print | Name | Freeze | Sample | Genr | Sheet | Graph | Stats | Ider

Augmented Dickey-Fuller Unit Root Test on D(INFLATION_RATE)

Null Hypothesis: D(INFLATION_RATE) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.190925	0.0215
Test critical values:	1% level	-4.616209	
	5% level	-3.710482	
	10% level	-3.297799	

*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations and may not be accurate for a sample size of 17

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(INFLATION_RATE,2)
Method: Least Squares
Date: 05/17/25 Time: 10:26
Sample (adjusted): 3/01/2017 3/01/2025
Included observations: 17 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(INFLATION_RATE(-1))	-1.488964	0.355283	-4.190925	0.0011
D(INFLATION_RATE(-1...	0.453874	0.247161	1.836352	0.0893
C	0.049998	0.751283	0.066550	0.9480
@TREND("9/01/2015")	-0.002492	0.062385	-0.039946	0.9687

R-squared	0.611779	Mean dependent var	0.019412
Adjusted R-squared	0.522190	S.D. dependent var	1.822476
S.E. of regression	1.259765	Akaike info criterion	3.502051
Sum squared resid	20.63110	Schwarz criterion	3.698102
Log likelihood	-25.76744	Hannan-Quinn criter.	3.521539
F-statistic	6.828701	Durbin-Watson stat	2.146682
Prob(F-statistic)	0.005278		

Fig4.12: Stationarity Check for Inflation Rate.

Interpretation: As the p-value of Inflation rate becomes less than 0.05 at 1st difference after conducting "Augmented Dickey-Fuller" test. So, we fall to reject the null hypothesis means the inflation rate variable doesn't has unit root. Thus, the data has converted into stationary.

Null hypothesis (H0): The series Interest rate has a unit root.

Alternative hypothesis (H1): The series Interest rate doesn't has a unit root.

Series: INTERESTRATE Workfile: VAR::Var\

View | Proc | Object | Properties | Print | Name | Freeze | Sample | Genr | Sheet | Graph | Stats | Ider

Augmented Dickey-Fuller Unit Root Test on D(INTEREST_RATE,2)

Null Hypothesis: D(INTEREST_RATE,2) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.940349	0.0056
Test critical values:	1% level	-4.616209	
	5% level	-3.710482	
	10% level	-3.297799	

*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations and may not be accurate for a sample size of 17

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(INTEREST_RATE,3)
Method: Least Squares
Date: 05/17/25 Time: 10:27
Sample (adjusted): 3/01/2017 3/01/2025
Included observations: 17 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(INTEREST_RATE(-1)...	-1.252668	0.253559	-4.940349	0.0002
C	0.181508	0.426202	0.425873	0.6767
@TREND("9/01/2015")	-0.015164	0.035394	-0.428427	0.6749

R-squared	0.637396	Mean dependent var	0.014706
Adjusted R-squared	0.585596	S.D. dependent var	1.110569
S.E. of regression	0.714920	Akaike info criterion	2.325494
Sum squared resid	7.155556	Schwarz criterion	2.472532
Log likelihood	-16.76670	Hannan-Quinn criter.	2.340110
F-statistic	12.30483	Durbin-Watson stat	2.096206
Prob(F-statistic)	0.000824		

Fig4.13: Stationarity Check for Interest Rate.

Interpretation: As the p-value of Interest rate becomes less than 0.05 at 2nd difference after conducting "Augmented Dickey-Fuller" test. So, we fall to reject the null hypothesis means the inflation rate variable doesn't has unit root. Thus, the data has converted into stationary

Determine lag length:

Var: UNTITLED Workfile: VAR::Var\

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Impulse | Resids

VAR Lag Order Selection Criteria
Endogenous variables: D(GROSS_NPA) D(GDP) D(EXCHANGE_RATE) D(INFL...
Exogenous variables: C
Date: 05/19/25 Time: 15:24
Sample: 9/01/2015 3/01/2025
Included observations: 17

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-171.4315	NA*	711.9030	20.75665	21.00171*	20.78101
1	-151.0470	26.37996	1434.889	21.29965	22.77002	21.44580
2	-109.0941	29.61383	571.0258*	19.30518*	22.00087	19.57314*

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Fig 4.14: VAR Lag Length Selection Table

Interpretation: The lag 2 has been selected based on it has lower AIC value, lower HQC value, and lower SC value it provides a better model fit while minimizing prediction errors. which indicates that the less information a model losses. And it also accurately captures relationship between the variables.

Var: UNTITLED Workfile: VAR::Var\

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Impulse | Resids

Vector Autoregression Estimates

Vector Autoregression Estimates
Date: 05/19/25 Time: 15:23
Sample (adjusted): 3/01/2017 3/01/2025
Included observations: 17 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	D(GROSS_...	D(GDP)	D(EXCHAN...	D(INFLATI...	D(INTERE...
D(GROSS_NPA(-1))	0.251891	2.748146	0.440446	-0.062557	0.216948
	(0.28329)	(1.04802)	(0.56212)	(0.22633)	(0.10455)
	[0.88916]	[2.62224]	[0.78354]	[-0.27640]	[2.07507]
D(GROSS_NPA(-2))	-0.040067	-2.160790	-0.610573	-0.070011	-0.140916
	(0.21759)	(0.80495)	(0.43175)	(0.17384)	(0.08030)
	[-0.18414]	[-2.68436]	[-1.41418]	[-0.40275]	[-1.75482]
D(GDP(-1))	0.112631	-0.462643	0.152195	-0.106781	-0.010032
	(0.06795)	(0.25139)	(0.13484)	(0.05429)	(0.02508)
	[1.65748]	[-1.84035]	[1.12874]	[-1.96690]	[-0.40004]
D(GDP(-2))	0.128323	-0.856984	-0.166850	-0.058994	0.012816
	(0.07788)	(0.28810)	(0.15453)	(0.06222)	(0.02874)
	[1.64776]	[-2.97459]	[-1.07974]	[-0.94819]	[0.44593]
D(EXCHANGE_RATE(...	-0.601994	0.701323	-0.216231	0.204843	-0.021502
	(0.22310)	(0.82532)	(0.44268)	(0.17823)	(0.08233)
	[-2.69837]	[0.84975]	[-0.48846]	[1.14929]	[-0.26115]
D(EXCHANGE_RATE(...	-0.233188	0.863101	0.333407	0.068165	0.122136
	(0.20752)	(0.76772)	(0.41178)	(0.16579)	(0.07659)
	[-1.12367]	[1.12424]	[0.80967]	[0.41114]	[1.59473]
D(INFLATION_RATE(-1))	-0.223595	-3.955573	-0.408838	-0.158251	-0.002627
	(0.35626)	(1.31796)	(0.70691)	(0.28462)	(0.13148)
	[-0.62762]	[-3.00129]	[-0.57834]	[-0.55601]	[-0.01998]
D(INFLATION_RATE(-2))	0.018926	1.009744	0.116537	-0.661704	-0.094141
	(0.32595)	(1.20581)	(0.64676)	(0.26040)	(0.12029)
	[0.05807]	[0.83740]	[0.18019]	[-2.54108]	[-0.78261]
D(INTEREST_RATE(-1))	0.349674	1.305728	-0.599678	-0.462042	0.545989
	(0.71634)	(2.65005)	(1.42140)	(0.57230)	(0.26437)
	[0.48814]	[0.49272]	[-0.42189]	[-0.80735]	[2.06526]
D(INTEREST_RATE(-2))	-1.027278	-0.671287	0.439618	0.084555	-0.134503
	(0.76028)	(2.81258)	(1.50858)	(0.60740)	(0.28058)
	[-1.35119]	[-0.23867]	[0.29141]	[0.13921]	[-0.47937]
C	-0.018134	-0.988540	0.884916	-0.375816	-2.83E-05
	(0.54479)	(2.01540)	(1.08099)	(0.43524)	(0.20106)
	[-0.03329]	[-0.49049]	[0.81861]	[-0.86347]	[-0.00014]
R-squared	0.691951	0.837623	0.540662	0.672468	0.699121
Adj. R-squared	0.178536	0.566996	-0.224901	0.126580	0.197655
Sum sq. resids	13.34291	182.6076	52.53449	8.516297	1.817311
S.E. equation	1.491247	5.516757	2.959012	1.191379	0.550350
F-statistic	1.347741	3.095115	0.706229	1.231880	1.394155
Log likelihood	-22.06302	-44.30203	-33.71214	-18.24649	-5.117186
Akaike AIC	3.889767	6.506121	5.260251	3.440763	1.896140
Schwarz SC	4.428905	7.045259	5.799389	3.979901	2.435278
Mean dependent	-1.154706	-0.175294	1.010588	-0.016471	0.000000
S.D. dependent	1.645339	8.383741	2.673599	1.274789	0.614410

Determinant resid covariance (dof adj.)	47.10968
Determinant resid covariance	0.258001
Log likelihood	-109.0941
Akaike information criterion	19.30518
Schwarz criterion	22.00087
Number of coefficients	55

Fig 4.15: VAR estimation table

Interpretation: The values falling between -1.96 and +1.96 indicate the following influences:

The VAR model reveals that rising Gross NPA's significantly reduce GDP, while GDP increases tend to mildly raise NPA's, indicating a two-way relationship between banking stress and economic activity and economic activity. Aditionally, inflation is effectively controlled by interest changes and exchange rate movements are weakly linked to macroeconomic variables.

Ganger-causality test:

H0: Variable X does not Ganger-cause variable Y

H1: Variable X Ganger-cause variable Y

Var: UNTITLED Workfile: VAR::Var\

VAR Granger Causality/Block Exogeneity Wald Tests
Date: 05/19/25 Time: 15:25
Sample: 9/01/2015 3/01/2025
Included observations: 17

Dependent variable: D(GROSS_NPA)

Excluded	Chi-sq	df	Prob.
D(GDP)	3.510661	2	0.1729
D(EXCHANGE_RATE)	7.281766	2	0.0262
D(INFLATION_RATE)	0.398024	2	0.8195
D(INTEREST_RATE)	1.850121	2	0.3965
All	8.751314	8	0.3637

Dependent variable: D(GDP)

Excluded	Chi-sq	df	Prob.
D(GROSS_NPA)	8.186695	2	0.0167
D(EXCHANGE_RATE)	1.433226	2	0.4884
D(INFLATION_RATE)	9.758951	2	0.0076
D(INTEREST_RATE)	0.242903	2	0.8856
All	20.16867	8	0.0097

Dependent variable: D(EXCHANGE_RATE)

Excluded	Chi-sq	df	Prob.
D(GROSS_NPA)	2.116524	2	0.3471
D(GDP)	5.492918	2	0.0642
D(INFLATION_RATE)	0.369018	2	0.8315
D(INTEREST_RATE)	0.189680	2	0.9095
All	6.520073	8	0.5892

Dependent variable: D(INFLATION_RATE)

Excluded	Chi-sq	df	Prob.
D(GROSS_NPA)	0.832180	2	0.6596
D(GDP)	3.899281	2	0.1423
D(EXCHANGE_RATE)	1.328044	2	0.5148
D(INTEREST_RATE)	0.722259	2	0.6969
All	8.537042	8	0.3828

Dependent variable: D(INTEREST_RATE)

Excluded	Chi-sq	df	Prob.
D(GROSS_NPA)	4.444733	2	0.1084
D(GDP)	0.806549	2	0.6681
D(EXCHANGE_RATE)	3.616426	2	0.1639
D(INFLATION_RATE)	0.612629	2	0.7362
All	11.08259	8	0.1971

Fig 4.16: Ganger-causality table

Interpretation: Ganger-causality test is useful to know whether past values of an independent variable will be able to forecast the future values of a dependent variable or not. Here, The p-value of Exchange rate is 0.0262 which is <0.05. which is proving that the Exchange rate is the key macroeconomic variable in forecasting the future values of a IOB's NPA.

Diagnostic check:

Analyze the residuals by looking for signs of normality, heteroscedasticity, and autocorrelation.

AR root table: The AR root table in VAR is used to access the stability of the model. Stability plays a crucial role in producing reliable and accurate forecasting.

AR root table, the modules should be less than 1, having all unit circle implies that the system is stable over time.

Var: UNTITLED Workfile: VAR::Var\

VAR Stability Condition Check

Roots of Characteristic Polynomial
Endogenous variables: D(GROSS_NPA) D(GDP) D(EXCHANGE_RATE) D(INFLATION_RATE) D(INTEREST_RATE)
Exogenous variables: C
Lag specification: 1 2
Date: 05/19/25 Time: 15:26

Root	Modulus
0.075845 - 0.865350i	0.868668
0.075845 + 0.865350i	0.868668
-0.398994 - 0.690531i	0.797514
-0.398994 + 0.690531i	0.797514
-0.765275	0.765275
0.753124	0.753124
0.560597 - 0.472412i	0.733104
0.560597 + 0.472412i	0.733104
-0.250995 - 0.354044i	0.433988
-0.250995 + 0.354044i	0.433988

No root lies outside the unit circle.
VAR satisfies the stability condition.

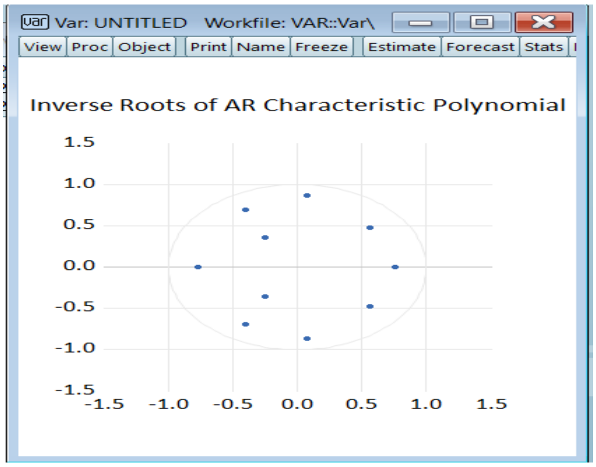


Fig 4.17: Inverse Roots of AR Characteristic Polynomial

Interpretation: All the modulus values listed are less than 1 (e.g., 0.868668, 0.797514, 0.765275, etc.), and the output clearly states:

"No root lies outside the unit circle. VAR satisfies the stability condition."

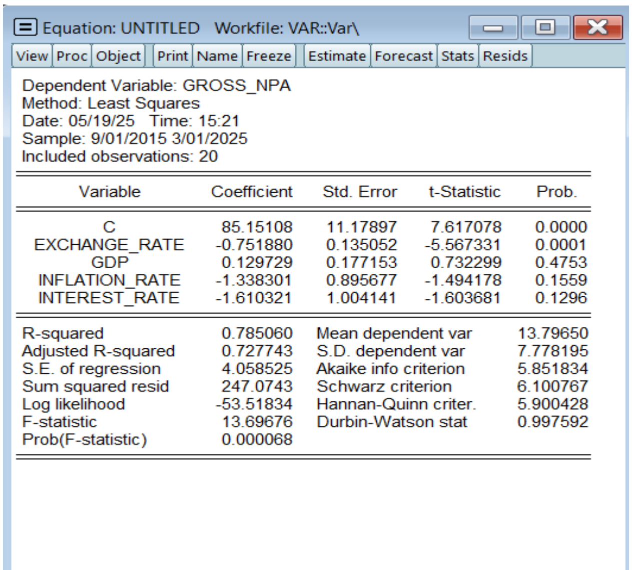
This means your VAR(2) model is stable and dynamically well-behaved, making it valid for forecasting.

Fig 4.18: Impulse Response Function

Interpretation: The analysis of impulse responses indicates that Gross NPA tends to stabilize over time following its own disturbances, showing a short-lived rise due to GDP but a mild decline when affected by exchange rate movements. Inflation and interest rate changes appear to have little direct influence on NPAs. GDP is negatively impacted by NPA shocks, suggesting that rising bad loans can hinder economic performance, while GDP itself remains resilient and continues to grow after its own shocks, with limited response to changes in exchange rate or interest rates. The exchange rate is mainly driven by its own fluctuations, showing little sensitivity to other macroeconomic variables. Inflation follows a temporary upward trend after a shock but returns to its average over time, and it slightly increases with exchange rate depreciation, though this effect is weak; higher interest rates tend to bring inflation down. Interest rates respond modestly to changes in GDP and inflation, suggesting a policy response to overheating or price pressures, and tend to remain steady over time, indicating a gradual approach to policy adjustments.

Regression Analysis:

Regression analysis is a statistical method used to model and analyze the relationship between a dependent variable and independent variable. The main goal is to know how the changes independent variable brings changes in dependent variable.



Equation: UNTITLED Workfile: VAR::Var\

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: GROSS_NPA
Method: Least Squares
Date: 05/19/25 Time: 15:21
Sample: 9/01/2015 3/01/2025
Included observations: 20

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	85.15108	11.17897	7.617078	0.0000
EXCHANGE_RATE	-0.751880	0.135052	-5.567331	0.0001
GDP	0.129729	0.177153	0.732299	0.4753
INFLATION_RATE	-1.338301	0.895677	-1.494178	0.1559
INTEREST_RATE	-1.610321	1.004141	-1.603681	0.1296

R-squared	0.785060	Mean dependent var	13.79650
Adjusted R-squared	0.727743	S.D. dependent var	7.778195
S.E. of regression	4.058525	Akaike info criterion	5.851834
Sum squared resid	247.0743	Schwarz criterion	6.100767
Log likelihood	-53.51834	Hannan-Quinn criter.	5.900428
F-statistic	13.69676	Durbin-Watson stat	0.997592
Prob(F-statistic)	0.000068		

Fig 4.19: Regression table

Interpretation: The Exchange rate is statistically significant predictor of the Exchange rate($p<0.05$), Where all the four macroeconomic variables will explain 78.5 variance in Gross NPA. other factors, which are not included in this model play a role in explaining and helps to forecast the GrossNPA.

5.1 FINDINGS

- The ARIMA model predicts that Indian Overseas Bank's (IOB) non-performing assets (NPAs) will remain stable between 2025 and 2030 One major contributing strategy behind this stability is the use of **factoring-like mechanisms**, specifically the sale of NPAs to Asset Reconstruction Companies (ARCs).
- The Vector Auto Regression (VAR) analysis shows that GDP and Gross NPAs affect each other. When the economy grows (GDP increases), the level of bad loans (NPAs) usually goes down.
- Granger Causality Test Highlights Exchange Rate's Predictive Role in NPAs. It indicates that exchange rate movements play a meaningful role in forecasting changes in Gross NPAs, with statistical significance ($p = 0.0262$).
- The regression analysis shows that out of all the macroeconomic factors considered-GDP, inflation, interest rates, and exchange rate-only the exchange rate has a significant effect on Gross NPAs.
- Since 2019, NPA levels in public sector banks like IOB, SBI, PNB, BOI, and BOB have declined mainly due to strong recovery efforts, sale of bad loans to ARCs, stricter lending checks, and better risk management. RBI's tighter loan monitoring rules and bank mergers also played a key role in improving asset quality and overall financial stability.

5.2 LIMITATIONS OF THE STUDY

The research uses just 10 years of data. A larger dataset might have given more reliable and broader results.

Important things like changes in government policy, leadership decisions, or new technologies were not included in the analysis, even though they can greatly impact how stable a bank is.

The models used (ARIMA, VAR, and regression) assume the relationship between variables is straightforward and stable over time. In reality, economic conditions can change suddenly, and these models may not always capture such changes.

5.3 SUGGESTIONS

As the ARIMA model predicts stable NPAs for Indian Overseas Bank, the bank should continue implementing strict credit appraisal and recovery mechanisms to sustain asset quality.

Add additional macroeconomic variables like fiscal deficit and unemployment rate to capture the dynamic relationships.

Since GDP and NPAs influence each other, government and financial institutions should promote growth-oriented policies, as a healthy economy directly lowers the risk of loan defaults.

Given that exchange rate changes significantly impact NPAs, banks should integrate currency risk assessments into their credit risk frameworks, especially for borrowers with foreign exposure.

The weak short-term impact of most macro variables on NPAs suggests that banks should also consider micro-level data (e.g., borrower profiles, sectoral exposures) in their risk forecasting models.

5.4 CONCLUSIONS

This study found that Indian public sector banks, especially IOB and SBI, are likely to maintain stable or slightly improved NPA levels from 2025 to 2030. BOB and PNB may see a minor increase in NPAs, but no major risks are expected. NPAs peaked between 2016 and 2019 but declined due to better recovery strategies. The exchange rate has a strong impact on asset quality, while inflation and interest rates show minimal influence. Continued economic growth and active risk management are key to maintaining banking sector stability.

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