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The Determinants of Credit Risk in Public and Private Sector banks of India

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Abstract: Credit risk is one of the risks that begin just with the lending of money by the bank to the borrower, and the banks have very less control over this risk. This study is done on the five private and five public sector banks. The period of the study is 2017-18 to 2021-22. The results offer insights into the financial situation of the banking system in India. The determinants on the basis of the previous studies showed that the public sector banks are wounded, and they need serious attention to recover from this situation. The private sector banks are performing better compared to public sector banks, but they also need to work on their functioning.

Keywords: Credit Risk, Banking system, Private Banks, Public Banks.

1. Introduction:

Regulatory authorities focus on different banks' risks; the most challenging is managing the credit risk (Leo et al., 2019). The taxonomy of the risks faced by the banks can be segregated into financial and non-financial risks. The main financial risks of the banks are credit risk, market risk, principal risk, and liquidity risk. The credit risk or the default risk is faced by the lender, i.e., the banks, if the counterparty fails to pay the obligatory amount (Chance & Brooks,2017; Pathak, 2020). As the banks lend money to the borrower, credit risk comes into play. Credit risk can further be segregated into consumer credit, corporate credit, credit card risk, counterparty risk, concentration risk, and collateral risk (Leo et al., 2019). After the global financial crisis in 2007-08, the regulatory authorities moved their focus on mitigating the credit risk faced by the banks. Many techniques are present for assessing and managing credit risk. Yet, the default in the payment to banks has shown a considerable amount in its brackets, especially in India, even after the Insolvency and bankruptcy code of 2016. According to the rbi publications, on 31st March 2021, the public sector banks had a net non-performing asset (N.P.A.) of Rs. 196450.81 crores, while the private sector banks' net N.P.A. was Rs.55808.98 crores. However, the public sector banks' gross N.P.A. ratio has fallen from 14.8% in March 2018 to 7.4% in March 2022 due to the writing-off of the loans of wilful defaulters from the financial year (F.Y.)2015 and a recovery of Rs. 6.42

lakh crore N.P.A. The N.P.A. has declined in India, but a considerable amount remains as default in payment. There is growth in credits by the banks which builds the importance of credit risk management. The table1 shows the increase in the loans by commercial banks. The loans to the service sector have increased at a significant rate from the second quarter of 2021-22. Only the 1st quarter of 2021-22 showed a substantial decline in the loans in all the sectors, but in the 2nd quarter, things changed as the service sector and the personal loans showed a remarkable rise. In organisation wise loans, the household sectors loans have increased, in which the loans to individuals have shown the highest increase. The share of new loans in the total loans has grown from the 2nd quarter of 2021-22.

Table 1. Increase in New Loans by S.C.B.s: Economic Sectors and Organisations

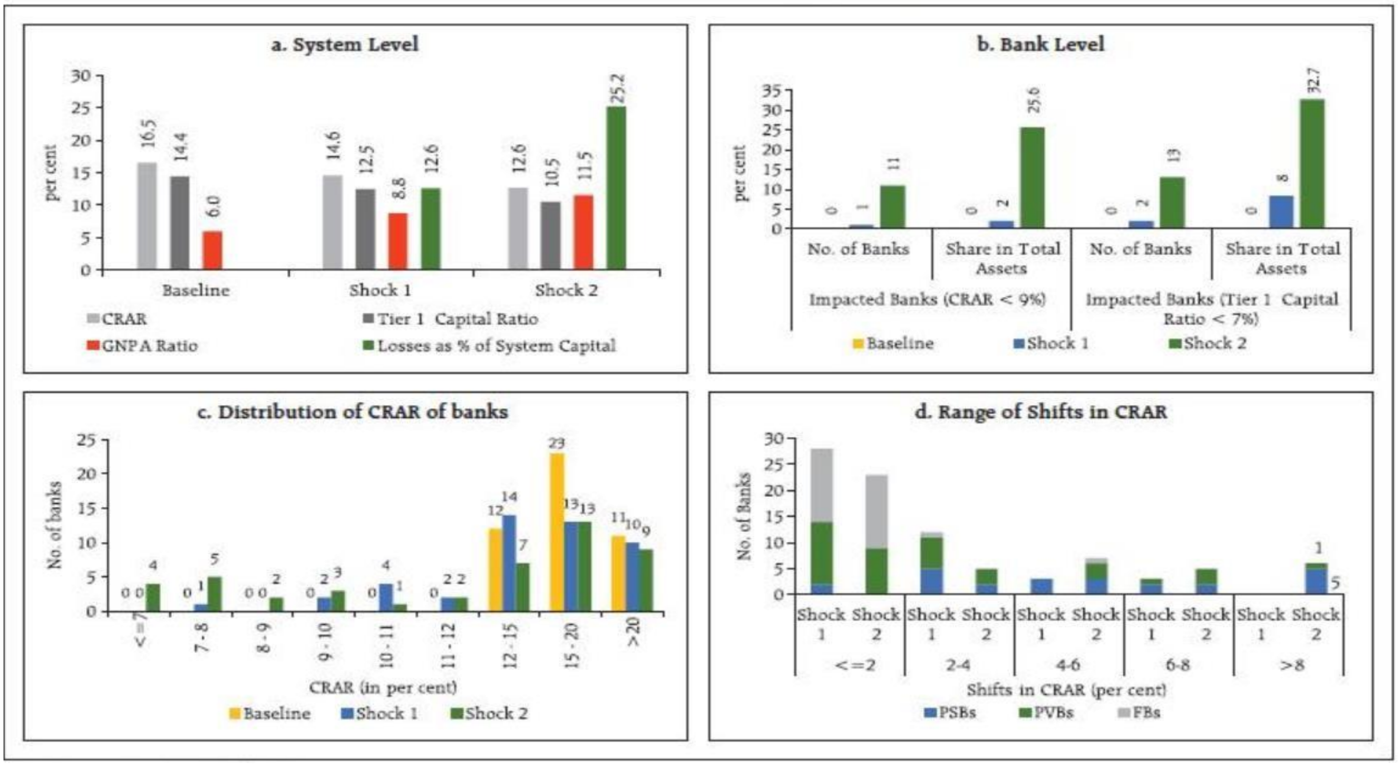
SECTOR	Q4:2020-21	Q1:2021-22	Q2:2021-22	Q3:2021-22	Q4:2021-22
	Increase during the quarter (₹ '000 crore)				
ECONOMIC SECTOR WISE					
AGRICULTURE	13	-50	72	3	24
INDUSTRY	57	-134	63	110	36
SERVICES	121	-226	116	100	116
PERSONAL LOANS	31	-135	114	41	55
ORGANISATION WISE					
PUBLIC SECTOR	64	-133	49	101	57
PRIVATE CORPORATE SECTOR	99	-146	73	74	97
HOUSEHOLD SECTOR	64	-285	268	76	85
OF WHICH: INDIVIDUALS	47	-235	227	58	66
OTHERS	-3	2	3	10	1
TOTAL	223	-562	393	261	239

SHARE OF NEW LOANS IN TOTAL LOANS (PER CENT)	16.7	11.6	15.1	16.8	17.9
Note: *excluding regional rural banks (RRBS).					

(Source: R.B.I.)

As the table1 shows, only the 1st quarter has a fall in the rate of increase in the new loan, where approximately everything was negative. The apex bank of India reported that the rise in the credit growth rate was 16.2% on 9th September 2022, whereas a year ago, it was 6.7%. This resulted from the corporate sector's increased demand and the growth of retail and micro, small, and medium enterprises. The credit risk needs to be managed to avoid any adverse impact on the banks' finance. The management of the threat of default in the payment has evolved with time, from manual calculations to using artificial intelligence, which includes artificial neural networking, support vector machines etc. The factors considered while calculating the credit risk are the chances/ probability of default, loss to be suffered if the default happens, and exposure to default. For managing credit risk, many methods are present in front of the banks, like credit scoring, pricing the risk with the help of scientific measures, quantifying the expected risk, and loan review mechanism techniques (R.B.I., 2022). Yet, the credit risk bothers the banks as the difficulties are there in the process of the assessment of the credit risk. Emerging economies like India are facing the heat of the credit risk in their banking system with recent scams of ABG shipyard scam, DHFL scam and many more. The Basel committee also issues advisories for managing credit risk from time to time. The corona pandemic has also increased the credit risk problem in banks worldwide, and the Bank for International Settlements (BIS), in its publication in March 2022, gave observations on the governance and the practices of the credit risk. The committee also recommended working on the modelling policies of the default risk (B.I.S., 2022). According to the guidelines of the R.B.I., banks are required to bring the system-level capital to the risk-weighted assets ratio to a minimum of 9% if it goes high. The R.B.I. also conducts sensitivity tests to check the possible effects of the shocks on the bank's capital to the risk-weighted assets ratio. Shocks are the rise in the gross N.P.A. ratio, and they are divided into two types: (i) rise by 1 S.D. and (ii) rise by 2 S.D. Figure 1 shows the shock tests conducted by the apex bank.

Figure 1. Credit Risk- Shocks and Outcomes



(Source: R.B.I.)

The shocks are uncertain, and the credit risk keeps changing with negative surprises. Figure 2a shows that under the serve shock, the gross N.P.A. ratio will increase from 6% to 11.5%, and capital impairment would be 25.2%. Figure 2b depicts that, under the shock of level two, 11 banks that will have 25.6% in the share of the total assets would not be able to meet the prescribed minimum capital to the risk-weighted assets ratio. Figure 2d shows that the public and private sector banks' change in capital to the risk-weighted assets ratio is more significant than the foreign banks in case of serve shock. Different techniques and different variables measure credit risk. Machine learning, statistical, and internal rating techniques are famous for measuring banks' credit risk. The following section covers the different studies done on credit risk.

2. Literature Review

2.1 Credit Risk

Credit risk is the chances that the bank's borrower will default in paying the principal, interest, or both (B.I.S., 1999). Many studies have been conducted on credit risk using different proxies. (Leo et al., 2019) (Teng & Lee, 2019) (Srinivasan & Kamlakannan, 2018) (Khemakhem et al., 2018) (Tang et al., 2018) focused on the use of machine learning techniques and mostly used machine learning techniques were support vector machines, artificial neural networks, and decision tree. (Khemakhem et al., 2018) Combined artificial neural networks with the support vector machine were better than the results of these two techniques individually, but (Teng & Lee, 2019) in their study found that the decision tree provides better results than the other techniques present in machine learning.

(Wahab, 2018) (Ozili, 2019) took non-performing loans as the proxy of the credit risk. It was found that loan growth has a negative impact on credit risk, and risky weighted assets have a positive effect on credit risk. Studies stated a very high credit risk in commercial banks across different nations. As we move toward Islamic banking, (Akram & Rahman, 2018) (Chamberlain et al., 2020) (Wahab, 2018) did their studies on Islamic banks and found that the credit risk is less in Islamic banks than in commercial banks. The reasons for this difference were the different principles of commercial and Islamic banks.

(Jabbouri & Naili, 2019) the study took the middle east and north African regions, and the non-performing loans measured the credit risk. Results of their study revealed that bank size, capital adequacy ratio, bank operating efficiency, profitability, G.D.P. growth, unemployment, inflation, and public debt are the main determinants of the non-performing loans in that region. There is a significant negative effect of the capital adequacy ratio on non-performing loans. (Elbadry, 2018) (Chamberlain et al., 2020), in their studies, found that the capital adequacy ratio is one of the vital determinants of credit risk. (Dang, 2019) in his paper checked the impact of loan loss provisions to customer loans, the loan growth rate, the bank's debt quality, and the bank's capital adequacy ratio on credit risk.

(Moudud-ul-huq et al., 2020) (Lambert et al., 2019) (Elbadry, 2018) studied twelve Saudi banks with the dependent variable as credit risk measured by total debts to total assets and the independent variable being the capital adequacy ratio, non-performing loans, leverage ratio, reserve requirements, loan to deposits ratio, liquidity ratio, asset utilisation ratio. It was found that there is a significant adverse effect on the capital adequacy ratio and an effective positive leverage ratio on credit risk. (Akram & Rahman, 2018) (Ozili, 2020) emphasised the 'loss loan provision' and loan quality for the credit risk measurement as they found in their studies that there is a negative and insignificant impact of the capital adequacy ratio on the credit risk.

2.2 Credit Risk and Indian Banking System

(Rizvi et al., 2018) and (Poghosyan and Cihak, 2011), in their studies, advocated for the use of gross non-performing assets as the proxy for credit risk. (Sharifi et al., 2018) studied the impact of the credit risk components on credit risk management and the growth of N.P.A.s of commercial banks in India. Components of the credit risk variable were credit risk perception, credit risk identification, credit risk assessment, credit risk control and credit risk capital requirements. Identification of credit risk significantly affects credit risk performance. Private banks were better than public banks. (Moudud-ul-huq, Akter, & Biswas, 2020) discovered that there is a positive link between the financial and pre-financial crises with the credit risk but a negative one with the post-financial crises. Credit risk impacts the G.D.P., inflation rate, and interest rate. Most of the studies in regard to the Indian banking system state that there should be the implementation of the BASEL norms-III in the banking system.

Based on the review of the literature, we come to the following hypothesis:

H1a: The public sector banks' Capital risk-weighted assets ratio, Credit-to-deposit, Return on Assets, Net interest margin, Management efficiency, Bank's operating efficiency, and Size of the banks do not have a significant impact on credit risk.

H1b: The private sector banks' Capital risk-weighted assets ratio, Credit-to-deposit, Return on Assets, Net interest margin, Management efficiency, Bank's operating efficiency, and Size of the banks do not have a significant impact on credit risk.

3. Methodology

3.1 Sampling and Data set

The sample banks selected are working in the private and public sectors of the Indian banking system. Five public and five private sector banks were selected based on market capitalisation. The dataset consists of records of the previous five years' data, i.e., 2017-18 to 2021-22. Data is collected from R.B.I., banks' annual reports, and the prowess database.

Table 3. List of Banks

Public Sector Banks	Private Sector Banks
1. State Bank of India	1. HDFC Bank
2. Punjab National Bank	2. Axis Bank
3. Canara Bank	3. ICICI Bank
4. Indian Overseas Bank	4. Indusind Bank
5. Bank of Baroda	5. Kotak bank

3.2 Research Model and Variables

This paper has employed Pooled OLS on select private and public sector banks with the help of Eviews software. The determinants of credit risk are selected based on the literature review. The econometric model for the study is:

$$Y_{it} = \beta_0 + \beta_1 CRAR_{it} + \beta_2 CDR_{it} + \beta_3 ROA_{it} + \beta_4 NIM_{it} + \beta_5 ME_{it} + \beta_6 BOE_{it} + \beta_7 SIZE_{it} + e_{it}$$

Where Y_{it} measures the credit risk, the coefficients β_0 represent the constant coefficient of variation, and the coefficients β_1 to β_7 show the slope coefficients for the independent variables, 'i' represents the banks, and 't' represents the time period. The independent variables in the study are Capital to risk-weighted assets ratio (CRAR), Credit to deposit ratio (C.D.R.), Return on Assets (ROA), Net interest margin (NIM), Management efficiency (M.E.), Bank's operating efficiency (B.O.E.), Size of the banks (SIZE). The proxies to measure these variables are based on the literature review. The capital to risk-weighted assets ratio is measured with the help of the capital adequacy ratio; management's efficiency's proxy is net profit divided by total funds; banks' operating efficiency is measured with the use of the operating profit ratio; the size of banks is calculated by taking the natural logarithm of the total assets. The credit risk is measured with the help of the gross non-performing assets ratio. Table 3 shows the list of variables and their proxies and measures.

Table 3. Summary of the variables

Variable	Proxy	Formula
Dependent Variable		
Credit Risk	Gross Non-Performing Assets Ratio	(Gross N.P.A. / Gross Advances) * 100
Independent Variable		
Capital To Risk-Weighted Assets Ratio	Capital Adequacy Ratio	(Tier I Capital + Tier II Capital) / Risk-Weighted Assets
Credit-To-Deposit Ratio	Credit-To-Deposit Ratio	Total Advances/ Total Deposits
Return On Assets	Return On Assets	Net Income/ Average Total Assets
Net Interest Margin	Net Interest Margin	Net Interest Income / Average Interest Earning Assets
Management Efficiency	Net Profit To Total Funds	Net Profit /Total Funds
Bank's Operating Efficiency	Operating Profit Margin	(Operating Profit / Total Revenue) × 100
Size Of The Banks	Total Assets	Natural Logarithm Of The Total Assets

(Source: Author's compilation)

4. Results and Discussion

4.1 Public Sector Banks

It is evident that a higher capital adequacy ratio helps the banks from saving themselves from possible shocks. In the five years, the public sector banks showed an average capital adequacy ratio of 12.922%. The capital adequacy of these banks has increased in 2020-21 and 2021-22.

Before this, the capital adequacy ratio was not that strong to prevent these banks from the shocks of level two. The average return on assets has been negative, which is a negative signal for the financial health of the banks. Management efficiency and banks' operating efficiency in negative figures also show that the public sector banks lack efficiency. Table 4. shows the descriptive statistics of the public sector banks where the wounded condition of the public sector banks is evident.

Table 4. Summary Statistics of the Public Sector Banks

Variables → / *Statistical indicators* ↓	*CRAR*	*CDR*	*ROA*	*NIM*	*ME*	*BOE*	*SIZE*
Mean	12.922	67.6108	-0.2976	2.2132	-2.1736	-22.3964	5.986913
Standard Error	0.370981581	1.322407265	0.199440283	0.038629522	0.467577402	3.172022167	0.078918
Median	13.22	67.95	0.04	2.16	-1.58	-16.61	5.916931
Standard Deviation	1.854907904	6.612036323	0.997201417	0.193147612	2.337887009	15.86011083	0.394592
Sample Variance	3.440683333	43.71902433	0.994410667	0.037306	5.465715667	251.5431157	0.155703
Kurtosis	-0.207039777	-0.011279446	2.663247422	-0.727323265	1.075086967	2.113953616	-0.54492
Skewness	-0.711198197	-0.548524307	-1.75220721	0.022048418	-1.44334147	-1.556737304	0.239409
Range	6.64	26.62	3.9	0.74	8.37	65.07	1.301455
Minimum	9.2	53.76	-3.27	1.81	-7.99	-68.29	5.394396
Maximum	15.84	80.38	0.63	2.55	0.38	-3.22	6.695851
Sum	323.05	1690.27	-7.44	55.33	-54.34	-559.91	149.6728
Observations	25	25	25	25	25	25	25

(Notes: CRAR is capital adequacy ratio, C.D.R. is the credit-to-deposit ratio, ROA is the return on assets, NIM is net interest margin%, M.E. is management Efficiency, B.O.E. is banks' operating efficiency, and SIZE is the natural logarithm of the total assets of the banks.)

After the summary statistics, the Breusch-Pagan test was conducted to check if Pooled OLS regression is fit or fixed regression model is to be used. The null hypothesis was that there is no statistical difference between the Pooled OLS method and the fixed regression model. The results stated that there is no statistically significant difference between the two. Table 5. shows the result of the Breusch-Pagan test.

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Table 5. Breusch-Pagan test on Public Sector Banks

	Test Hypothesis		
	Cross-section	Time	Both
Breusch-Pagan	0.032380 (0.8572)	0.217874 (0.6407)	0.250254 (0.6169)
Honda	0.179943 (0.4286)	-0.466770 (0.6797)	-0.202817 (0.5804)
King-Wu	0.179943 (0.4286)	-0.466770 (0.6797)	-0.202817 (0.5804)
Standardized Honda	2.073649 (0.0191)	-0.057296 (0.5228)	-2.365501 (0.9910)
Standardized King-Wu	2.073649 (0.0191)	-0.057296 (0.5228)	-2.365501 (0.9910)
Gourieroux, et al.	--	--	0.032380 (0.6746)

The Breusch-Pagan test clearly shows, with other tests, that there is no statistical difference between the Pooled OLS and the fixed effect regression. No test says that there is any statistical difference between the two techniques. Hence the study uses the Pooled OLS method for conducting the research. The results of the Pooled OLS show that the model is statistically significant as the p-value of the f-statistics is 0.000757, which is less than 0.05. The R^2 value is 0.729281, which indicates that the model describes approximately 73% of the change in the dependent variable. The value of adjusted R^2 is also suggesting the same. Table 6. shows the estimates of the Pooled OLS method.

Table 6. Estimated results of Pooled OLS

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	42.07793	28.46983	1.477983	0.1577
CRAR	-1.085522	0.782339	-1.387533	0.1832
CDR	-0.020625	0.182490	-0.113022	0.9113
ROA	2.003422	3.900882	0.513582	0.6142
NIM	-0.642520	4.980436	-0.129009	0.8989
ME	-0.807117	1.215999	-0.663748	0.5158
BOE	-0.131291	0.214090	-0.613250	0.5478
SIZE	-3.051467	3.588630	-0.850315	0.4070
R-squared	0.729281	Mean dependent var		11.06400
Adjusted R-squared	0.617809	S.D. dependent var		5.464480
S.E. of regression	3.378229	Akaike info criterion		5.526918
Sum squared resid	194.0113	Schwarz criterion		5.916958
Log likelihood	-61.08647	Hannan-Quinn criter.		5.635098
F-statistic	6.542262	Durbin-Watson stat		1.369564
Prob(F-statistic)	0.000757			

The capital adequacy ratio has a negative relationship with credit risk, which is in line with the literature review. The most surprising element of the study is the *positive relationship* between the return on assets with credit risk. This clearly shows that a negative asset return has a positive relationship with credit risk. The literature review indicates that asset return has an inverse relationship with credit risk. The rest of the model's elements also state negative relation with credit risk, which is in line with the literature review. The overall equation based on the coefficient estimate by Pooled OLS comes to be:

$$Y_{it} = 42.078 + (-1.086)CRAR_{it} + (-0.021)CDR_{it} + (2.003)ROA_{it} + (-0.643)NIM_{it} + (-0.807)ME_{it} + (-0.131)BOE_{it} + (-3.052)SIZE_{it} + e_{it}$$

The table shows that all the determinants have an impact on credit risk, but it is not statistically significant as all the p-values are more than 0.05. Hence the bull hypothesis is accepted, and it can be concluded that the public sector banks' Capital risk-weighted assets ratio, Credit-to-deposit, Return on Assets, Net interest margin, Management efficiency, Bank's operating efficiency, and Size of banks do not have a significant impact on credit risk.

4.2 Private Sector Banks

The private sector banks have an average capital adequacy ratio of 17.76%, which is relatively better than the public sector banks. The management efficiency and return of assets are also indicating a better financial position of the private sector banks. The adverse banks' operating efficiency is a matter of concern for the private sector banks. Although it is better compared to the public sector banks still, the banks' operating efficiency is negative, which shows work needs to be done in this area. Table 7. shows the summary statistics of the private sector banks for the past five years.

Table 7. Summary Statistics of the Private Sector Banks

Variables → / *Statistical indicators* ↓	*CRAR*	*CDR*	*ROA*	*NIM*	*ME*	*BOE*	*SIZE*
Mean	17.7592	88.1684	1.2248	3.364	0.3472	-5.3752	5.838784
Standard Error	0.409497627	0.955989	0.113159	0.091243	0.236701	1.938483	0.058815
Median	17.89	87.35	1.43	3.48	0.68	-3.5	5.942596
Standard Deviation	2.047488136	4.779946	0.565797	0.456216	1.183503	9.692416	0.294077
Sample Variance	4.192207667	22.84788	0.320126	0.208133	1.400679	93.94293	0.086481
Kurtosis	0.825824712	-0.20467	-0.6964	-1.40898	-0.71437	-1.14675	-1.39744
Skewness	0.508134583	0.259252	-0.69159	-0.33648	-0.61633	-0.35608	-0.18864
Range	8.53	19.31	1.96	1.39	3.91	31.55	0.970752
Minimum	14.16	79.75	0.03	2.61	-1.97	-23.35	5.344911
Maximum	22.69	99.06	1.99	4	1.94	8.2	6.315663
Sum	443.98	2204.21	30.62	84.1	8.68	-134.38	145.9696
Observations	25	25	25	25	25	25	25

(Notes: CRAR is capital adequacy ratio, C.D.R. is the credit-to-deposit ratio, ROA is the return on assets, NIM is net interest margin%, M.E. is management Efficiency, B.O.E. is banks' operating efficiency, and SIZE is the natural logarithm of the total assets of the banks.)

Table 7. shows that the public sector banks are way behind the private sector banks. The private sector banks are well prepared for the shocks and can handle them well. After the summary statistics, the Breusch-Pagan test was applied to check if Pooled OLS regression is fit or fixed regression model is to be used. The null hypothesis was that there is no statistical difference between the Pooled OLS method and the fixed regression model. The results stated that there is no statistically significant difference between the two. The Breusch-Pagan test clearly shows, with other tests, that there is no statistical difference between the Pooled OLS and the fixed effect regression. No test says that there is any statistical difference between the two techniques. Hence the study uses the Pooled OLS method for conducting the research. Table 8. shows the result of

the Breusch-Pagan test.

Table 8. Breusch-Pagan test on Private Sector Banks

	Test Hypothesis		
	Cross-section	Time	Both
Breusch-Pagan	0.825258 (0.3636)	0.729400 (0.3931)	1.554658 (0.2124)
Honda	0.908437 (0.1818)	0.854049 (0.1965)	1.246266 (0.1063)
King-Wu	0.908437 (0.1818)	0.854049 (0.1965)	1.214522 (0.1123)
Standardized Honda	2.352480 (0.0093)	1.616204 (0.0530)	-0.872299 (0.8085)
Standardized King-Wu	2.352480 (0.0093)	1.616204 (0.0530)	-0.790612 (0.7854)
Gourieroux, et al.	--	--	1.554658 (0.2211)

Based on the outcomes of this test, the Pooled OLS regression was conducted, as all tests suggested using it. The results of the Pooled OLS regression were a bit different from the public sector banks. The results of the Pooled OLS show that the model is statistically significant as the p-value of the f-statistics is 0.000250, which is less than 0.05. The R^2 value is 0.765281, which indicates that the model describes approximately 76.5% of the change in the dependent variable. The value of adjusted R^2 is also suggesting the same. The results showed an inverse relationship between the return on assets and credit risk. The capital adequacy ratio is *positively correlated* with credit risk. The positive correlation between the two is not in line with the literature. The possible reasons for this could be the simultaneous increase in capital adequacy and the gross non-performing assets. The rest of the variables are in line with the literature review. Table 9. shows the estimates of the Pooled OLS test.

Table 9. Estimated results of Pooled OLS

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.364402	14.18472	0.096188	0.9245
CRAR	0.329174	0.159427	2.064728	0.0545
CDR	-0.058392	0.088590	-0.659124	0.5186
ROA	-0.222365	1.978357	-0.112399	0.9118
NIM	-1.167213	1.173404	-0.994724	0.3338
ME	0.527338	0.416548	1.265972	0.2226
BOE	-0.200740	0.115232	-1.742057	0.0996
SIZE	0.713703	1.157624	0.616524	0.5457

R-squared	0.765281	Mean dependent var	3.292400
Adjusted R-squared	0.668632	S.D. dependent var	2.060071
S.E. of regression	1.185870	Akaike info criterion	3.433169
Sum squared resid	23.90691	Schwarz criterion	3.823209
Log likelihood	-34.91461	Hannan-Quinn criter.	3.541349
F-statistic	7.918162	Durbin-Watson stat	0.741961
Prob(F-statistic)	0.000250		

The test shows the value of the coefficients, and based on them, the following equation is derived:

$$Y_{it} = 1.364 + (0.329)CRAR_{it} + (-0.058)CDR_{it} + (-0.222)ROA_{it} + (-1.167)NIM_{it} + (0.527)ME_{it} + (-0.201)BOE_{it} + (0.714)SIZE_{it} + e_{it}$$

The results of the two banking sectors indicate that the private banking sector performs better than the public sector banks. Most of the results of the private sector banks are in line with the previous studies.

The table shows that all the determinants have an impact on credit risk, but it is not statistically significant as all the p-values are more than 0.05. Hence the bull hypothesis is accepted, and it can be concluded that the private sector banks' Capital risk-weighted assets ratio, Credit-to-deposit, Return on Assets, Net interest margin, Management efficiency, Bank's operating efficiency, and Size of banks do not have a significant impact on credit risk.

Future Research and Limitations

The banking companies' corporate governance index can help get a better view of the determinant of credit risk. In the research, all the determinants had an impact on credit risk, but they were not statistically significant. Future research in this area could be done by building a corporate governance index and examining its impact on credit risk. Another area of research could be exploring the non-banking finance companies with the banking companies. This comparison with the corporate governance index included in the study can tell better about the management style and its impact on credit risk. In the corona period, the capital adequacy of the private and public sector banks increased. A comparison of the credit risk before and during the pandemic period can also be seen.

The study's limitations are that the study's time horizon is just five years. This time period can be increased. Also, the model could have included some more variables. These variables could have produced a more depth understanding of credit risk's determinants.

Conclusion

Credit risk is a kind of risk that banks in their everyday life face. This study was done to see the impact of the different determinants of credit risk based on previous studies. In this study, the main findings were that banks' return on assets in the public sector has a negative relationship with credit risk. This is due to the negative return on assets of those banks. Those banks' size had a negative effect on credit risk. This can be explained by the bleeding results of the banks' efficiency. In contrast, the private sector banks had better results than public sector banks in these areas. Although the private sector banks also have a matter of concern as their capital adequacy ratio has a positive but not statistically significant relationship with the credit risk. The corporate governance index can also be included as a determinant for future work and considering NBFCs. We can conclude that the Indian banking system needs to work more on the policies and functioning to be ready for any kind of shock.

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