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Editorial Board

EDITORIAL

This fifteenth volume of Business *Spectrum* brings together five carefully researched articles that collectively reflect the interdisciplinary nature of contemporary economic and business issues. They address informal credit, corporate sustainability reporting, banking sector consolidation, financial distress prediction, and the evolving relationship between credit and output in Indian states.

The first article, by Sengupta and Mondal, titled “Heterogeneous Effects of Socio-economic Factors on Informal Credit in India: Empirical Insights from NSSO Data,” explores how different socio-economic factors shape the use of informal credit across the country. The authors show that although institutional credit has expanded, especially in urban areas, nearly one-third of rural borrowing still relies on non-institutional sources because they offer speed, flexibility, and trust-based relationships.

The second article by Patra, Das, Mazumdar, and Rajak shifts focus to "Sustainability Reporting and Firm Performance: Evidence from Selected Indian Companies." Using panel regression analysis on 252 observations from Nifty 50 companies (2018-2023), the authors navigate the complex relationship between ESG disclosures and financial outcomes.

Mahato and Kumari's article on "Post-Merger Performance Assessment of Bank of Baroda: A Balanced Scorecard Analysis" arrives as the Indian banking sector continues its structural evolution. Using the BSF across four dimensions—financial, customer satisfaction, internal processes, and learning-growth—the authors document BoB's robust post-merger integration following the absorption of Dena Bank in December 2020.

Sarkar, Bhabak, and Maji contribute "Financial Distress Prediction using Natural Language Processing: An Empirical Study with Special Reference to the Indian Manufacturing Sector." This article bridges emerging computational technologies with classical financial risk assessment. By applying NLP to manufacturing firms' disclosures, the authors pioneer a frontier where machine learning becomes a practical tool for stakeholders and regulators to identify distress signals earlier than traditional financial analysis permits.

Finally, Ghosh and Panja's panel analysis on "Interplays between Credit and Output: New Empirical Evidence from the Panel of Indian States" maps the financial-real sector nexus across India's diverse regional economies. Their examination of credit's causal relationship with output reveals important state-level variations, suggesting that monetary transmission mechanisms operate differently across India's vast economic landscape.

I extend my sincere thanks to our peer reviewers, whose careful evaluation has been crucial in maintaining the quality of this issue, and to all contributing authors for their intellectual effort and commitment. I also acknowledge with gratitude the continued support of the IAA South Bengal Branch, which enables *Business Spectrum* to remain a platform for rigorous and relevant scholarship. The editorial team warmly invites submissions for upcoming issues from scholars and practitioners engaged in these and related domains.

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Heterogeneous Effects of Socio-economic Factors on Informal Credit in India: Empirical Insights from NSSO Data

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Abstract

This paper examines the dynamics of the non-institutional credit market in India, with particular attention to role of various socio-economic factors in shaping non-institutional borrowing behaviour. Using unit-level data from the All India Debt and Investment Survey (AIDIS), National Sample Survey Organization (NSSO) for the NSS 70th Round, 2012-13 and NSS 77thRound, 2018-19, the study reveals a dual structure of the informal credit system. On the one hand, small loansoften continue to serve poor and asset-deficient households, meeting essential needs such as health care, education, and other social obligations. On the other hand, large loansare increasingly accessed by relatively affluent households for various commercial purposes. Further, we make an empirical attempt to analyse rural-urban variations in the disbursement of loans from the non-institutional credit market.

Key Words: Household Credit, Non-institutional Credit, Informal Credit, All India Debt and Investment Survey, National Sample Survey Organization

1. Introduction

In developing economies, access to credit plays a pivotal role in shaping household welfare, consumption smoothing, and small-scale investment (Basu, 1997, Banerjee et. al., 2013). While the expansion of formal banking has been a key policy goal since independence in India, various Reserve Bank of India (RBI) and National Sample Survey Organization (NSSO) reports reveals large segments of the population particularly rural and urban low-income households continue to rely heavily on non-institutional sources of finance (Sengupta and De, 2018). According to the NSSO classifications, non-institutional credit market broadly includes moneylenders, market traders, commission agents, friends and relatives, and other informal lenders who operate outside the regulatory purview of the central monetary authority.

The resilience of this market lies in its flexibility and accessibility. Unlike formal institutions, informal lenders often extend credit without stringent documentation, collateral requirements, or bureaucratic delays. Borrowing arrangements are typically personalized, relying on social ties, trust, or local reputation (Aleem, 1990; Kurup, 1976; Ray, 1998). Loan sizes may range from very small amounts, used for daily consumption, education, or health expenses, to large sums tied to agricultural or business activities. In many cases, the terms of borrowing are interlinked with other economic transactions, such as crop sales or input supply, making these credit relations deeply embedded within local economic structures (Sarap, 1987; Bell et. al., 1997).

Despite these advantages, the non-institutional credit sector is often criticized for its exploitative practices. Trust, local information, interlinked contracts, exotic forms of collateral and often zero rate of interest make this market operationally easy accessible one than formal sector (Stiglitz and Hoff, 1990; Braverman and Guasch, 1986). Moreover, the persistence of this sector highlights the limited reach of formal finance, particularly in rural areas, even after decades of financial sector reforms and policies aimed at financial inclusion.

1.1 Theoretical Framework

Let us assume a situation where a borrower with ‘C’ (C>0) amount of collateral requires ‘L’ amount of loan and he finds both formal loaning agency i.e. Commercial Bank (say, B) and Informal lender i.e. Local Moneylender (say, M) in his locality.

Assumptions:

(i) Bank offers L amount of loan at the rate of interest r_B whereas, moneylender offer at rate of interest r_M where, $r_M > r_B$

(ii) Each credit source requires some transaction cost which is T_B for bank and T_M for moneylender where, $T_M < T_B$

(iii) Bank is more centrally regulated, structured and collateral based. Bank offers L amount loan if borrower meet collateral requirement $C \geq C_{min}$ and strong collateral-based bank loan function is defined as,

$\phi_B (C) = \alpha. C$ ……….(1) ;where, $\alpha \epsilon (0,1)$ and $\phi_B^{/}(C)>0$

(iv) Local moneylender's economic activity is more flexible where no official collateral is required but loan disbursement more depends on trust and personalized relation. Thus, borrowers' loan availability depends on Trust (t), Borrowers' history of past transaction and reputation in the locality (R), and small informal and exotic collateral (C_I). Trust and relationship based informal loan function is defined as,

$\phi_M(t, R, C_I) = \alpha_1.t + \alpha_2.R + \alpha_3.C_I$ ……….(2) ;where, α is weights attached to the factors associated with informal loan; $\alpha_1,\alpha_2,\alpha_3 >0$; $t \epsilon (0,1)$; $R \epsilon (0,1)$; $C_I \epsilon (0,1)$ and $\phi_M^{/} (t,R,C_I)>0$

(v) Both formal and informal loaning involves some disbursement delay which is δ_B for bank and δ_M for moneylender and $\delta_M<\delta_B$, δ is measured in time unit.

(vi) Borrower obtains utility U(L) from loan amount L which diminishes with rate of interest and transaction cost i.e. $U^{/}_r<0$ and $U^{/}_T<0$

If the borrower obtains loan from Bank, then borrowers' utility function is defined as,

$U_B = \{U(L) - r_B.L - T_B – \theta_B.\delta_B\}$ ……….(3); where, θ_B is utility cost per unit of time delay from Bank

If the borrower obtains loan from Local Moneylender, then borrowers' utility function is defined as,

$U_M = \{U(L) – r_M.L – T_M – \theta_M.\delta_M + \phi_M(t, R, C_I)\}$ ……….(4); where, θ_M is utility cost per unit of time delay from Moneylender

Borrower chooses moneylenders' loan over bank loan if $U_B< U_M$ ……….(5)

By substituting equations (3) and (4) we get,

$=\{U(L) – r_M.L – T_M – \theta_M.\delta_M + \phi_M(t, R, C_I)\} > \{U(L) - r_B.L - T_B – \theta_B.\delta_B\}$ ……….(6)

$=(r_M - r_B).L + (T_M - T_B) + (\theta_M.\delta_M - \theta_B.\delta_B) <\phi_M(t, R, C_I)$ ……….(7)

In the event, borrower has sufficient collateral i.e. $C \geq C_{min}$, borrower will choose moneylender iff-

Proposition 1: if T_B (transaction cost of bank) is high and δ_B (disbursement delay of Bank) is long

Proposition 2: if t (trust) is high i.e. t $\rightarrow 1$, and R (credit history and reputation in locality) is high

Then, trust and personalised relation premium (ϕ_M) is greater than accumulated cost advantage of bank (i.e. summation of interest cost differential i.e.(r_M - r_B), transaction cost differential i.e.(T_M - T_B), and disbursement delay cost differential i.e.($\theta_M.\delta_M$ - $\theta_B.\delta_B$)) and non-pecuniary benefits of trust out weight the higher interest cost (i.e. $r_M > r_B$).

1.2 Non-Institutional Credit in India

Table 1: Region and Agency-wise Break-up of Household Credit (%) in India Since 1992

Sources of Credit	NSS 48th Round, 1992		NSS 59th Round, 2002		NSS 70th Round, 2013		NSS 77th Round, 2019	
Region	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban
Institutional	64	70	57.1	75.1	56	84.5	66.1	87.1
Non-institutional	36	30	42.9	24.9	44	15.5	33.9	12.9

Source: Various Reports of AIDIS, NSSO

The data reveal a clear contrast between rural and urban areas (see Table 1), as well as a gradual transformation in the overall composition of credit sources. In rural India, the share of institutional credit declined from 64% in 1992 (NSS 48th Round) to 56% in 2013 (NSS 70thRound), indicating a growing reliance on non-institutional lenders. This trend reversed by 2019 (NSS 77thRound), with institutional credit improving to 66.1%, though non-institutional borrowing still accounted for over one-third of total rural credit.

In contrast, urban areas demonstrate a more consistent and steadier shift toward formal financial channels. Institutional credit in urban regions rose from 70% in 1992 to 87.1% in 2019, while dependence on non-institutional sources sharply fell from 30% to just 12.9% over the same period. This divergence underscores the limited penetration of formal finance in rural areas relative to urban regions, despite three decades of financial liberalization and targeted inclusion policies.

Table 2: Share (%) of Various Size of Non-institutional Loan Borrowed Originally (in Rs.) to Total Non-institutional loan Borrowed Originally (in Rs.)

Size of Non-institutional Loan Borrowed Originally (in Rs.)	NSS 70th Round, 2013			NSS 77th Round, 2019		
Region	Rural	Urban	All India	Rural	Urban	All India
<4,000	11.75	9.25	10.77	4.88	3.95	4.58
4,000-7,000	14.32	11.54	13.23	8.20	6.40	7.63
7,000-10,000	15.91	13.34	14.90	11.61	9.22	10.85
10,000-20,000	18.97	17.05	18.22	17.02	13.64	15.94
20,000-35,000	11.64	11.10	11.43	13.03	12.80	12.96
35,000-60,000	14.21	16.12	14.96	19.37	18.07	18.95
60,000-1,00,000	7.25	9.90	8.29	11.50	13.31	12.08

1,00,000-2,00,000	3.99	6.65	5.03	8.32	10.89	9.14
2,00,000-4,00,000	1.42	3.29	2.15	4.01	6.76	4.89
>4,00,000	0.54	1.75	1.02	2.05	4.95	2.98
Total	100	100	100	100	100	100

Source: Author’s calculation using Unit Level AIDIS, NSSO Data

At the lower end of the loan spectrum, small borrowings (<Rs.20,000) accounted for a dominant share of non-institutional loans in 2013, nearly 61% in rural areas and 51% in urban areas (see Table 2). By 2019, however, this share had dropped significantly, to about 42% in rural and 34% in urban India. Conversely, the share of medium and large loans (Rs. 35,000 and above) increased substantially between 2013 and 2019. For instance, loans in the Rs.35,000-60,000 range rose from 14.2% to 19.4% at the all-India level, while those above Rs.1,00,000 more than doubled from about 8.2% in 2013 to 19% in 2019. This upward shift was especially pronounced in urban areas, where large loans above Rs.4,00,000 grew from just 1.8% in 2013 to nearly 5% in 2019.

These figures highlight two important dynamics. First, the non-institutional credit market is no longer confined to small, short-term borrowings; it is increasingly catering to higher-value credit demand, particularly for commercial or investment-related purposes. Second, the rural-urban gap in loan size distribution is narrowing, with both regions witnessing a rise in large-value loans, although the trend is more prominent in urban India.

In this paper, we make an empirical attempt to analyse rural-urban variations in the disbursement of loans from the non-institutional credit market, and examine how different socio-economic factors influence such borrowings.

Our paper is organized into six sections. Section 1 introduces the study, theoretical structure and provides a brief overview of non-institutional credit in India. Section 2 outlines the methodology, while Section 3 describes the data and the variables used in the analysis. Section 4 presents the empirical results, and Section 5 concludes the study.

2. Methodology

In this study, we examine and compare the socio-economic and demographic characteristics of households using data from the NSS 70th Round (2012-13) and the NSS 77th Round (2018-19), across different quantiles of non-institutional credit. Further, we investigate whether these determinants vary with the size of the loan. The Ordinary Least Squares (OLS) method, which estimates only the conditional mean effect of explanatory variables on the dependent variable, often fails to account for the heterogeneous nature of data. To overcome this limitation, we employ the Simultaneous Quantile Regression (SQR) technique. Unlike OLS, SQR estimates conditional quantile functions, enabling us to capture the distributional impact of explanatory variables on the dependent variable across different strata. The Quantile Regression (QR) framework was originally introduced by Roger Koenker and Gilbert Bassett (1978).

The q-th conditional quantile of Y_i given X_i is defined as:

$Q_q(Y_i|X_i) = X_i.ß_q$ ………(1)

;where 0<q<1 represents the different quantiles (e.g. q= 0.10, 0.25, 0.50, 0.75, 0.90) and $ß_q$ is vector of quantile-specific unknown parameters associated with qth quantile

The linear quantile regression is described by the following equation:

$Y_i = X_i.ß_q + \varepsilon_i$ ………(2)

OLS minimizes $\Sigma_i\, \varepsilon_i^2$ (i.e. error sum of squares), instead QR minimizes $\Sigma_i\, |\varepsilon_i|$ (i.e. absolute deviation of residuals).

Quantile regression estimator $ß_q$ is obtained by solving the following minimization problem:

$\min \sum_{i=1}^{n}(Yi - Xi.ßq) = \Sigma_i q|\varepsilon_i| + \Sigma_i (1-q)|\varepsilon_i|$ ……….(3)

i.e. a sum that gives the asymmetric penalties $q|\varepsilon_i|$and $(1-q)|\varepsilon_i|$ for overprediction.

qth quantile regression estimator $ß_q^{/}$ minimizes over $ß_q$ the objective function-

$Q(ß_q) = \sum_{i:Yi \geq Xi.ß}^{N} q.|Y_i - X_i.\,ß_q| + \sum_{i:Yi<Xi.ß}^{N} (1-q).|Y_i - X_i.\,ß_q|$ ………(4)

We use $ß_q$ instead of ßto make clear that different choices of q estimate different values of ß.

For jth regressor, marginal effect is the coefficient for the qth quantile, $\frac{dQq(Yi|Xi)}{dXj} = ß_{qj}$

A quantile regression parameter $ß_{qj}$ estimates the change in specified quantile q of the dependent variable Y_i produced by a one unit change in the independent variable X_j. The marginal effects are for infinitesimal changes in the regressor, assuming that the dependent variable remains in the same quantile.

3. Data and Variables

3.1 Data:

For the present analysis, we draw upon data from two rounds of the All India Debt and Investment Survey (AIDIS), undertaken by the National Sample Survey Office (NSSO) under the Ministry of Statistics and Programme Implementation (MOSPI), Government of India. Specifically, the study utilizes the 70^{th}Round (2012-13) and the 77^{th}Round (2018-19). AIDIS furnishes detailed information at both the household and individual levels. At the household level, the survey records information on the stock of assets and liabilities, incidence of indebtedness, capital formation, religion, caste, principal occupation, and other socio-economic characteristics of rural and urban households. At the individual level, data include demographic and educational variables such as age, gender, and educational attainment.

AIDIS classifies household credit into two broad categories: institutional sources and non-institutional sources. Institutional sources comprise Scheduled Commercial Banks, Co-operative Banks, Non-Banking Financial Companies (NBFCs), Insurance Companies, Provident Funds, Microfinance Institutions (MFIs), and others. Non-institutional sources include landlords, agricultural and professional moneylenders, market traders, input suppliers, friends and relatives, and other miscellaneous non-institutional credit agencies. Furthermore, AIDIS collects loan-specific details such as loan type, purpose of borrowing, interest rate, and source of credit.

3.2 Description of Variables:

Amount Borrowed originally from Non-Institutional Credit Sources: In our present study, amount borrowed originally from various non-institutional credit source has been taken as dependent variable.

Gender of Household Head: The gender of the household head is included as an explanatory variable to capture the influence of gender dynamics on household borrowing behaviour. In the analysis, male-headed households serve as the reference category.

Age of Household Head: The age of the household head is incorporated as an explanatory variable to examine the effect of ageing on informal borrowing behaviour. Since financial needs and creditworthiness are likely to vary across life stages, age is categorized into three groups: 0-30 years, working age (31-59 years), and elderly (>59 years). In this study, the 0-30 years category serves as the base group.

Education of Household Head: Highly educated individuals are expected to rely less on non-institutional credit compared to the less educated. For analytical purposes, education is classified into two categories: illiterate and literate, with illiterate household heads serving as the reference group.

Household Size: Household size is incorporated as an explanatory variable to capture the influence of family structure on credit demand. Larger households are expected to have greater consumption needs and, consequently, a higher dependence on credit markets.

Household Type: Household type, defined by the primary source of livelihood, is a key determinant of income, creditworthiness, and access to credit. For this study, both rural and urban households are classified into four categories: self-employed, regular wage/salary earners, casual labourers, and others. The “others” category-which includes pensioners, remittance-dependent households, the unemployed, and similar groups-serves as the reference category. Since households with stable and higher income sources are expected to rely less on non-institutional credit, this classification helps to capture occupational differences in borrowing patterns.

Religion-Caste Category: Religious and caste affiliations are critical socio-cultural identifiers in the Indian context, often shaping households' access to credit. In our analysis, households are classified into major religion-caste groups: Christianity, Hindu Upper Caste, Islam Unreserved, and Jainism. Households belonging to other religious communities (such as Sikhism, Buddhism, Zoroastrianism, and others) are treated as the reference category. This categorization allows us to examine how religious–caste identity influences reliance on non-institutional credit.

Social Group: To capture these dynamics, we classify households into four categories: Scheduled Tribes (ST), Scheduled Castes (SC), Other Backward Classes (OBC), and Others. The Others category, which largely represents unreserved or general caste households, is used as the reference group. This classification enables us to evaluate how households from historically disadvantaged groups compare with relatively affluent groups in their reliance on non-institutional credit.

Region: Various NSSO suggests that regional variations play a crucial role in shaping heterogeneity in access to non-institutional credit. To account for these differences, households in our study are classified into six regional groups: Northern, Western, Southern, Eastern, EAG (Empowered Action Group) States, and North-east. We designate the North-east region as the reference category, primarily due to its relatively small population share.

Type of Loan: The tenure of loans constitutes an important dimension in the analysis of the non-institutional credit market. Informal credit requirements are often sudden and unproductive in nature, typically arising from consumption needs or family emergencies. In such cases, households tend to rely on short-term borrowing. By contrast, long-term loans are generally associated with relatively affluent households, often undertaken for investment or business purposes. For the purpose of this study, loans are classified into three categories: short-term, medium-term, and long-term, with long-term loans serving as the reference category.

Rate of Interest: Incorporating the rate of interest as a continuous variable in our model enables us to examine how borrowing costs shape household decisions regarding reliance on non-institutional credit.

Purpose of Loan: Recent AIDIS data (NSS 77th Round, 2019) indicate that a substantial share of household demand for non-institutional credit arises from business activities, medical needs, housing, and other household expenditures. To capture these dynamics, we classify loan purposes into nine categories: business expenditure, litigation, debt repayment, financial investment, education, medical treatment, housing, other household expenditure, and miscellaneous purposes. In our analysis, other expenditure serves as the reference category. This classification enables us to assess the extent to which non-institutional loans are utilized across different purposes.

Household Member having Bank Account: It is commonly expected that a household member having bank account is likely to obtain bank loans and less likely to take a non-institutional loan.

4. Empirical Analysis

Table 3: Simultaneous Quantile Regression of selected quantiles for Rural and Urban areas for NSS 70th Round, 2012-13

Area	**Rural Area** Number of Observations =8,765 0.10 Pseudo R^2 =0.1127 0.25 Pseudo R^2 =0.1088 0.50 Pseudo R^2 =0.0960 0.75 Pseudo R^2 =0.1041 0.90 Pseudo R^2 =0.1205					**Urban Area** Number of Observations =7,490 0.10 Pseudo R^2 =0.1349 0.25 Pseudo R^2 =0.1253 0.50 Pseudo R^2 =0.1370 0.75 Pseudo R^2 =0.1512 0.90 Pseudo R^2 =0.1509				
Explanatory Variables	**10th Quantile**	**25th Quantile**	**50th Quantile**	**75th Quantile**	**90th Quantile**	**10th Quantile**	**25th Quantile**	**50th Quantile**	**75th Quantile**	**90th Quantile**
1.Gender of Household Head *Male (Ref. Category)*										
(a)Female	-.1818664*** (0.0764422)	-0.1513208*** (0.0614755)	-0.121535*** (.0518946)	-0.1407304*** (.0473533)	-0.0653024 (.0749391)	0.0162652 (.087334)	-0.1352524** (0.0672443)	-0.1889734*** (.0528707)	-0.0979854 (.0776753)	0.0239192 (.1232317)
2. Age of Household Head *(0-30 years) (Ref. Category)*										
(a)Working Age (31-59)	-0.0020704 (0.0607796)	-0.069594 (.0573758)	-0.0381353 (0.0835131)	0.0930469 (0.0647727)	0.1001391 (0.0748364)	0.2633063*** (0.0709076)	0.3132405*** (0.0528754)	0.272565*** (0.0697678)	0.352325*** (0.0733102)	0.3982065*** (0.0997628)
(b)Elderly (>59)	-0.0353086 (0.0983829)	-0.0500842 (.0621787)	0.0030294 (0.0921997)	0.1158263 (0.0750324)	0.1660158* (0.1019735)	0.3167652*** (0.0989216)	0.2900685*** (0.0786883)	0.256561*** (0.0803102)	0.4525551*** (0.1018013)	0.3979041*** (0.1170979)
3.Literate Household Head *Not literate (Ref. Category)*	0.1327338** (0.0615141)	0.0676278 (0.0500398)	0.0547656 (0.0474866)	0.0559316 (0.0355429)	0.01924 (0.0522005)	0.2633063*** (0.0697253)	0.2520141*** (0.0776613)	0.3660599*** (0.0384123)	0.4440293*** (0.0587373)	0.3910523*** (0.0755351)
4.Household Size	.0674985*** (0.0121031)	0.069594*** (0.0075545)	0.0735919*** (0.011018)	0.0672806*** (0.0087125)	0.0520694*** (0.0082934)	0.0429779*** (0.0107756)	0.0496661*** (0.0114393)	0.0546301*** (0.0099206)	0.0455219*** (0.0090451)	0.0341764** (0.0152546)
5.Household Type *Other (Ref. Category)*										

(a)Self-employed	0.1495625 (0.1699756)	0.0174747 (0.1011106)	-0.0542117 (0.0629187)	0.0898763 (0.093084)	0.0200935 (0.1428585)	0.0888651 (0.128842)	0.041223 (0.101992)	0.0313375 (0.109675)	0.0770259 (0.0842176)	0.1217764 (0.1612461)
(b)Regular Wage/Salary Earning	0.0405798 (0.181174)	-0.0657127 (0.0968842)	-0.0098041 (0.1073384)	0.1442797 (0.1291429)	0.0922594 (0.1504899)	0.0911942 (0.1057231)	-0.0181945 (0.1027253)	-0.0131724 (0.1218081)	-0.045636 (0.1026368)	-0.0738267 (0.1707889)
(c)Casual Labour	-0.1975177 (0.1677331)	-0.2787187*** (0.0869236)	-0.3496252*** (0.0753103)	-0.2010364** (0.0884165)	-0.2960273** (0.1510207)	-0.1585562 (0.1059923)	-0.3394412*** (0.0957808)	-0.3237722*** (0.1322391)	-0.3743805*** (0.1014157)	-0.3519955** (0.1796569)
6.Religion-Caste Category *Other (Ref. Category)*										
(a)Christianity	-0.1050642 (0.1485952)	-0.0225957 (.0960116)	-0.0984021 (0.1113816)	-0.1631873 (0.1090344)	-0.1702435 (0.154197)	-0.0578591 (0.1797851)	-0.0510863 (0.1022115)	-0.0679316 (0.1360811)	-0.0238904 (0.1522261)	0.1353751 (0.1240536)
(b)Hindu Upper Caste	-0.1415654 (0.1599122)	-0.3104968*** (.1057492)	-0.3620914*** (0.1114678)	-0.5085015*** (0.0899748)	-0.4734934*** (0.1203153)	-0.1031662 (0.1826207)	-0.0938675 (0.0905179)	-0.1024901 (0.1142846)	-0.1911691 (0.1282658)	-0.3422635*** (0.1178288)
(c)Islam Unreserved	-0.3132817** (0.1627305)	-0.4996856*** (.1033159)	-0.6693783*** (0.1105008)	-0.9495572*** (0.0845731)	-0.889526*** (0.0935145)	-0.2805373 (0.1838553)	-0.1667057* (0.0978461)	-0.1566893 (0.1132189)	-0.3489048*** (0.1226822)	-0.5482959*** (0.1396727)
(d)Jainism	0.3691857** (0.163824)	0.3759838*** (0.139029)	0.231874 (0.1508133)	0.2340656 (0.1511199)	0.3199667 (0.2571196)	0.6734307*** (0.2664907)	0.6260056*** (0.1965831)	0.3938436** (0.1877775)	0.2425496* (0.1476763)	0.4804528* (0.2838157)
7.Social Group *Other (Ref. Category)*										
(a)ST	-0.5292196*** (0.1462277)	-0.8327313*** (0.075743)	-0.8359642*** (0.1031312)	-0.9372806*** (0.1105782)	-1.051332*** (0.1053168)	-0.5696725*** (0.1429371)	-0.6229343*** (0.1124383)	-0.4370356*** (0.1194603)	-0.5080526*** (0.1442107)	-0.947737*** (0.1340876)
(b)SC	-0.5289822*** (0.1345225)	-0.7323384*** (0.1035465)	-0.7059836*** (0.0949794)	-0.9048194*** (0.1189889)	-0.9520801*** (0.1276621)	-0.3692327* (0.2070521)	-0.4062431*** (0.1146225)	-0.3531651*** (0.128045)	-0.3692499** (0.1682588)	-0.6141553*** (0.1245314)
(c)OBC	-0.524786*** (0.20979)	-0.3549725** (0.152273)	-0.2927301*** (0.1132903)	-0.3881301*** (0.1184427)	-0.1672491 (0.13636)	-0.2286646 (0.1715922)	-0.145898 (0.1209422)	-0.0629581 (0.1180977)	-0.2861529* (0.1642208)	-0.4458342*** (0.1501238)
8.Region *North-East (Ref. Category)*										
(a)Northern	0.2211194*** (0.0705706)	0.2659288*** (0.060702)	0.3085017*** (0.0516145)	0.2889754*** (0.0591422)	0.4542824*** (0.0607249)	0.2904674*** (0.0884158)	0.3660914*** (0.0975486)	0.3543759*** (0.0601421)	0.4734546*** (0.0463038)	0.3497595*** (0.0850296)
(b)Western	0.490036*** (0.0760254)	0.5035208*** (0.0670349)	0.3990349*** (0.0966238)	0.3908572*** (0.0836951)	0.4289504*** (0.0896734)	0.3422645*** (0.1088131)	0.4446213*** (0.0713555)	0.3417313*** (0.0754)	0.4809734*** (0.0846786)	0.4557178*** (0.0772754)
(c)Southern	0.707941*** (0.0972091)	0.6730684*** (0.0621925)	0.5879707*** (0.0525623)	0.5737103*** (0.0577674)	0.5420065*** (0.0903547)	0.7710131*** (0.0716795)	0.7488387*** (0.0581547)	0.5748485*** (0.0719053)	0.5428766*** (0.0687996)	0.3447469*** (0.0750332)
(d)Eastern	0.6132471*** (0.1205314)	0.643636*** (0.1055938)	0.539275*** (0.1197128)	0.4703771*** (0.0965885)	0.4961941*** (0.1466448)	0.6211476*** (0.0923086)	0.4422515*** (0.0703212)	0.3435303*** (0.0706848)	0.3129483*** (0.0941619)	0.3696114*** (0.1060336)
(e)EAG	0.1732491*** (0.0678696)	0.2425723*** (0.0608863)	0.2408529*** (0.0453381)	0.2345212*** (0.0457639)	0.2226776*** (0.0469024)	0.3388017*** (0.0582695)	0.3736711*** (0.0590291)	0.2243108*** (0.0512551)	0.3029224*** (0.054126)	0.2890264*** (0.0431614)
9.Type of Loan *Long-term (Ref. Category)*										

(a)Short-term pledged	-0.5612788*** (0.0733915)	-0.5353271*** (0.0709844)	-0.6370111*** (0.0841795)	-0.6055765*** (0.0734895)	-0.5841816*** (0.0860568)	-0.7892427*** (0.1031643)	-0.8777961*** (0.0625062)	-0.9685467*** (0.0772956)	-0.5080526*** (0.1442107)	-0.9930614*** (0.0675421)
(b)Short-term non-pledged	-0.5937149*** (0.0576955)	-0.5448474*** (0.046571)	-0.6489173*** (0.0653303)	-0.5548544*** (0.0521376)	-0.5560321*** (0.0734575)	-0.8728286 (0.0760042)	-1.022406*** (0.0608744)	-0.9629243*** (0.0468004)	-0.3692499*** (0.1682588)	-0.9770085*** (0.0720744)
(c)Medium-term	-0.1421415*** (0.0602729)	-0.1300757** (0.0620555)	-0.2223194*** (0.0639109)	-0.2545291*** (0.0397257)	-0.3379559*** (0.0654861)	-0.1529357*** (0.0606105)	-0.3048269*** (0.0581808)	-0.3415788*** (0.0433446)	-0.4400535*** (0.0338491)	-0.5108103*** (0.0494989)
10. Rate of Interest	0.0017333** (0.0008437)	0.0009752* (0.0005282)	0.0000741 (0.000911)	-2.09e-17 (0.0007805)	-0.000897 (0.0011084)	0.001639 (0.0012444)	0.0000878 (0.0008764)	-0.0013662** (0.0006655)	-0.0023795*** (0.0006779)	-0.0041698*** (0.0011988)
11.Purpose of Loan *Other (Ref. Category)*										
(a)Expenditure in Business	0.0411675 (0.0776727)	0.1074863* (0.0574588)	0.1899673*** (0.0763611)	0.1645384* (0.1019531)	0.2296555** (0.0985488)	0.1320658 (0.1337099)	0.0377985 (0.09984)	0.1530674** (0.0747327)	0.1256988 (0.1024429)	0.2193288* (0.1243719)
(b)Litigation	0.3262011 (0.555406)	0.9564286* (0.5086085)	0.4460207 (0.4396892)	0.2684425 (0.5642581)	0.14999 (0.3844542)	-0.8139718 (1.666729)	1.95738 (1.631612)	1.249175 (0.8816677)	1.117988*** (0.3280941)	1.00174**(0.4762804)
(c)Repayment of Debt	0.2613505 (0.2017667)	0.238783*(0.1407466)	0.1433282 (0.1381159)	0.112112 (0.1967483)	-0.0545166 (0.1500465)	-0.2684172 (0.192976)	-0.1882962 (0.236857)	-0.1474967 (0.1959652)	-0.1088882 (0.1212283)	-0.2470571 (0.2573686)
(d)Financial Investment	-0.2883254 (0.6036603)	0.7762333 (0.7445538)	0.3052382 (0.3550527)	0.0275235 (0.1830078)	-0.6728117 (0.4897996)	-0.0944489 (0.8042429)	0.5799398*** (0.2095502)	0.0544069 (0.27134)	-0.2233638 (0.4260514)	0.3218728 (0.5736989)
(e)Education	-0.1481935 (0.172583)	-0.149872 (0.1176749)	-0.00418 (0.132667)	0.0440976 (0.1271299)	-0.0866028 (0.1237456)	-0.4895458*** (0.1442914)	-0.4804004*** (0.0872823)	-0.2707336** (0.125678)	-0.2688857* (0.1434274)	-0.2940764** (0.1360167)
(f)Medical Treatment	-0.1718807 (0.1110887)	-0.148056*** (0.0517497)	-0.1406173** (0.0722346)	-0.1694267* (0.0911424)	-0.2474428** (0.1191032)	-0.4166158*** (0.0876566)	-0.4717675*** (0.0930289)	-0.4371959*** (0.1045749)	-0.5486349*** (0.0764538)	-0.4867758*** (0.0949956)
(g)Housing	0.2801672*** (.098575)	0.2436915*** (0.0519314)	0.3229112*** (0.0734299)	0.3241466*** (0.1041261)	0.2536998*** (0.0848615)	0.3117468*** (0.1031455)	0.3448271*** (0.0737094)	0.4255241*** (0.0842336)	0.3670347*** (0.0773605)	0.283123*** (0.0893373)
(h)Other Household Expenditure	-0.2862106*** (0.0756033)	-0.3079834*** (0.0581852)	-0.2395309*** (0.0693376)	-0.2055046*** (0.09473)	-0.264839*** (0.0958931)	-0.5316817*** (0.0909615)	-0.4939958*** (0.0665981)	-0.4641613*** (0.0730258)	-0.4619428*** (0.078065)	-0.3816099*** (0.087308)
12. Household Member Having Bank Account	-0.2491784*** (0.0533565)	-0.3448592*** (0.0363983)	-0.3675113*** (0.0440404)	-0.3230881*** (0.0430087)	-0.3830293*** (0.0636937)	-0.4465679*** (0.0621556)	-0.4492048*** (0.0532541)	-0.4747549*** (0.0477176)	-0.5460763*** (0.0489545)	-0.5305242*** (0.0642746)
Constant	8.627917*** (0.2312714)	9.731495*** (0.1497801)	10.67172*** (0.1770397)	11.3489***(0.1091481)	12.32728*** (0.2143411)	8.83829***(0.3101082)	9.747094*** (0.2248212)	10.61076*** (0.2112034)	11.55463*** (0.2418048)	12.50494*** (0.2598556)

Note: Standard errors in parentheses, *p<0.10, **p<0.05, ***p<0.01

Source: Authors' calculation from unit level data of NSS 70th Round, AIDIS (2012-13)

Table 4: Model Specification Test for Rural Area for NSS 70th Round, 2012-13[1]

Amount Borrowed Originally from Non-Institutional Credit Sources	Coefficient	t	p-value
$\hat{Y}$	0.7054232 (1.349693)	0.52	0.601

[1] *Insignificance of $\hat{Y}^2$ (p-value = 0.870) indicates no functional misspecification of the model and the application of Simultaneous Quantile Regression estimation is statistically justified.*

$\hat{Y}^2$	-0.0130835 (0.0799747)	-0.16	**0.870**
Constant	-1.048279 (5.681293)	-0.18	0.854

Note: Standard errors in parentheses, *p<0.10, **p<0.05, ***p<0.01

Source: *Authors' calculation from unit level data of NSS 70th Round, AIDIS (2012-13)*

Table 5: Model Specification Test for Urban Area for NSS 70th Round, 2012-13[2]

Amount Borrowed Originally from Non-Institutional Credit Sources	Coefficient	t	p-value
$\hat{Y}$	1.310837 (0.4846432)	2.70	0.007
$\hat{Y}^2$	-0.0096836 (0.0283989)	-0.34	**0.733**
Constant	-0.2990147 (2.061486)	-0.15	0.885

*Note: Standard errors in parentheses, *p<0.10, **p<0.05, ***p<0.01*

Source: *Authors' calculation from unit level data of NSS 70th Round, AIDIS (2012-13)*

To understand how socio-economic variables influence non-institutional credit across various sectors of the economy, it is essential to capture rural-urban differences, as these reflect the underlying structure of the informal financial landscape. Using AIDIS NSS 70th Round, 2012-13 data, several distinct patterns emerge (see Table 3).

Female-headed households are significantly negative with non-institutional credit across almost all credit sizes in rural areas, while in urban areas this negative effect is significant only for small and medium credit. This may be attributed to lack of asset ownership and bargaining power of women in rural credit markets, which restrict their ability to negotiate with informal lenders. In urban areas, women's greater labour market participation partly reduces this disadvantage, although male-headed households still dominate overall access to non-institutional credit.

In rural areas, age has no significant effect on informal borrowing. Informal lenders in villages rely more on community reputation and collateral than age of the borrower. In urban areas, however, age becomes significantly positive with high non-institutional credit size. Working and elderly persons with strong asset base making them more attractive to informal lenders.

In rural areas, literacy matters only for small credit, suggesting that informal lenders prioritize trust and local knowledge over formal education while extending credit. In contrast, in urban areas, education is positively significant across loan sizes. This reflects that educated borrowers may have better repayment capacity associated with stable income.

[2]*Insignificance of $\hat{Y}^2$ (p-value = 0.733) indicates no functional misspecification of the model and the application of Simultaneous Quantile Regression estimation is statistically justified.*

Both rural and urban areas show a positive relationship between household size and non-institutional borrowing at small and medium loans, but the effect diminishes for larger loans.

Casual labour households are consistently less likely to borrow informally in both rural and urban areas, with the negative effect stronger at larger loans. Our finding also suggests that rural casual labour households borrow more than their urban counterparts, since village level informal credit networks are often the only available option.

However, we observe a dissimilar pattern when analysing the effect of religion-caste affiliation on non-institutional credit. Among Hindu upper-caste and Muslim unreserved households, the association with informal borrowing is significantly negative across all loan sizes in rural areas, but this effect is confined only to the upper quantiles in urban areas. For Jain households, the relationship is significantly positive at lower quantiles in rural areas, while in urban areas it is positive and significant across all quantiles. This reflects the strong business orientation of Jain communities, where informal credit often plays a crucial role in financing trade and entrepreneurial activity. Overall, the evidence indicates that Hindu upper-caste, Muslim unreserved, and Jain households in urban areas are more indebted to informal credit than their rural counterparts.

While formal sector loan is based on strong collateral requirement, social status and caste remains crucial in obtaining informal credit (Khanna and Majumdar, 2020; Karthick and Madheswaran, 2018). In the case of social groups, compared to general households, our empirical analysisfinds a similar negative relationship with backward household and distribution of non-institutional credit in rural and urban areas. Overall, backward households in urban areas are in a relatively more privileged position than their rural counterparts in assessing informal credit. It is noteworthy that both in rural and urban India, households across all regions of the country exhibit a positive reliance on non-institutional credit.

Type of loan shows a negative association with non-institutional credit in both areas, stronger in urban markets. This indicates that compared to urban households, rural households are depending on short- and medium-term informal loans due to inaccessibility of formal credit, whereas urban households partly substitute towards formal institutions.

Interest rates also reveal distinct dynamics. Several studies (Mishra and Bharadwaj, 2022; Bottomley, 1975) found a positive relation between rate of interest charged by informal lenders and informal credit. Although informal credit becomes exploitative one, they prefer their neighbourhood informal lender. In rural areas, demand for small loans remains positive despite high interest rates, reflecting inelastic demand due to urgent needs such as consumption smoothing and medical expenses. In urban areas, however, medium and large loans are negatively associated with high interest rates, as borrowers switch to formal credit options.

Rural households positively rely on non-institutional credit for business activities across all quantiles, suggesting that small-scale enterprises and agriculture still depend heavily on local moneylenders and traders for working capital. In urban areas, such relation appears only at medium and large loans, suggesting that formal lenders often hesitate to fund high capital requirements in urban business highlighting interlinkage characteristics of informal credit market (Bardhan and Rudra, 1978; Besley, 1994). Credit taken for litigation shows a significantly positive relationship with non-institutional credit at lower quantiles in rural areas, but the effect shifts to higher quantiles in urban areas. This suggests that in villages, small legal disputes are often financed through informal sources due to absence of institutional credit, whereas in urban areas, larger and costly legal cases push households towards high value informal loans. Repayment of old debt through non-institutional credit is positive significant only at the lower quantiles in rural areas, indicating that rural households often repay old loans with small informal borrowing to manage liquidity pressures. In contrast, in urban areas, non-institutional borrowing at lower quantiles is positively associated with financial investment, reflecting that small informal loans often serve as pretty trade or business ventures in cities. For education, negative significance in urban areas suggests greater reliance on formal credit schemes, whereas informal loans are less preferred. Borrowing for medical treatment shows a negative relationship at all quantiles in both sectors, but the effect is less pronounced in rural areas. This indicates that rural households still turn to informal lenders in times of health shocks, while urban households may seek institutional loan or insurance. For housing related borrowing, the relationship is significantly positive across all quantiles in both rural and urban areas. However, for other household expenditures, the relationship is significantly negative across all quantiles in both the areas. The stronger negativity in urban areas implies that rural households remain more dependent on informal sources for day-to-day consumption smoothing.

Finally, in the both the sectors, households with a bank account are significantly negatively related with non-institutional credit. This demonstrates that formal channels substitute informal borrowing when formal channels are accessible and efficient.

Table 6: Simultaneous Quantile Regression of selected quantiles for Rural and Urban areas for NSS 77th Round, 2018-19

Area	**Rural Area** Number of Observations =7,576 0.10 Pseudo R^2 =0.1583 0.25 Pseudo R^2 =0.1611	**Urban Area** Number of Observations = 3,921 0.10 Pseudo R^2 =0.1747 0.25 Pseudo R^2 =0.1608

	0.50 Pseudo R^2 =0.1657 0.75 Pseudo R^2 =0.1753 0.90 Pseudo R^2 =0.1590					0.50 Pseudo R^2 =0.1605 0.75 Pseudo R^2 =0.1678 0.90 Pseudo R^2 =0.1663				
Explanatory Variables	**10^{th} Quantile**	**25^{th} Quantile**	**50^{th} Quantile**	**75^{th} Quantile**	**90^{th} Quantile**	**10^{th} Quantile**	**25^{th} Quantile**	**50^{th} Quantile**	**75^{th} Quantile**	**90^{th} Quantile**
1.Gender of Household Head *Male (Ref. Category)*										
(a)Female	-0.1211739**(0.0640241)	-0.1835164***(0.0506277)	-0.0662415 (0.0521931)	-0.1374578***(0.0586042)	-0.0063781 (0.0679231)	0.1572895** (0.0818441)	0.1211086 (0.0864496)	0.0396871 (0.0607384)	-0.0296073 (0.066233)	-0.0956758 (0.1170359)
2. Age of Household Head *(0-30 years) (Ref. Category)*										
(a)Working Age (31-59)	0.110935**(0.0675025)	0.1451765***(0.0462764)	0.162929**(0.0698369)	0.2000929***(0.0708273)	0.2329787***(0.0859443)	0.3017277***(0.1207789)	0.3253111***(0.1068644)	0.3138323***(0.1220748)	0.3918423***(0.0952483)	0.4357682***(0.1581476)
(b)Elderly (>59)	0.0895639 (0.090057)	0.280478***(0.0454974)	0.2981418***(0.0766867)	0.2690594***(0.0740152)	0.3481279***(0.0875408)	0.3796819***(0.1006177)	0.3687919***(0.0848196)	0.325922***(0.1035589)	0.4417609***(0.0927478)	0.513775***(0.2046715)
3.Literate Household Head *Not literate (Ref. Category)*	0.101595**(0.0436378)	0.088858* (0.0494174)	0.0863189***(0.0318294)	0.0779056 (0.0501333)	0.1206424*(0.0695278)	0.4169992***(0.1139132)	0.3593776***(0.0994323)	0.2227155***(0.0761349)	0.2375873***(0.0815538)	-0.0956758**(0.1170359)
4.Household Size	0.0619334***(0.01268)	0.0675087***(0.010867)	0.0662415***(0.011201)	0.0587271***(0.0078243)	0.0538541***(0.0098236)	0.0813057***(0.0245103)	0.0681808***(0.0165643)	0.0718973***(0.0168929)	0.0469388***(0.0116257)	0.066898***(0.0173681)
5.Household Type *Other (Ref. Category)*										
(a)Self-employed	0.1554994 (0.1221047)	0.1286189 (0.1098498)	0.0569359 (0.0809222)	0.005953 (0.0791303)	0.0376957 (0.1442642)	0.1793334 (0.166782)	0.2219146*(0.1351925)	0.122942 (0.1273408)	0.0935533 (0.157512)	0.1067491 (0.1598507)
(b)Regular Wage/Salary Earning	0.0366437 (0.1312731)	-0.0012097 (0.14287)	-0.0150117 (0.1290583)	-0.0437318 (0.1293908)	0.0699418 (0.1830151)	0.0787331 (0.1605048)	0.1125884 (0.1426555)	0.0254447 (0.1416742)	-0.0329114 (0.1495341)	-0.0256533 (0.1445448)
(c)Casual Labour	-0.0613899 (0.1398134)	-0.055746 (0.1171482)	-0.1005066 (0.0820499)	-0.222172***(0.0707869)	-0.2681908 (0.175702)	-0.2370433 (0.1543809)	-0.1687707 (0.1413366)	-0.2632008**(0.1170781)	-0.1934323 (0.1551319)	-0.3733526**(0.1799587)
6.Religion-Caste Category *Other (Ref. Category)*										
(a)Christianity	-0.1288662 (0.1149415)	-0.0766642 (0.085271)	-0.3622599***(0.0665981)	-0.410526***(0.0817762)	-0.4052872***(0.1168473)	-0.0688801 (0.1937541)	-0.0363866 (0.1230558)	-0.1345231 (0.1217846)	-0.1538737 (0.1289603)	0.0056571 (0.1662778)

(b)Hindu Upper Caste	-0.2401909**(0.1187597)	-0.2433231***(0.0922515)	-0.46536***(0.0910768)	-0.4879638***(0.112558)	-0.4997576***(0.138861)	-0.1054911(0.1648687)	-0.3512087***(0.1428356)	-0.3708998***(0.143339)	-0.3087035**(0.1430635)	-0.3593633**(0.1647251)
(c)Islam Unreserved	-0.4180901***(0.1212625)	-0.5174033***(0.1056741)	-0.7025538***(0.1166787)	-0.7780703***(0.1053823)	-0.8064203***(0.1625774)	-0.029169(0.1702041)	-0.3434995**(0.1633097)	-0.4300818***(0.1543971)	-0.4549382***(0.1451041)	-0.4840354***(0.1474841)
(d)Jainism	0.3626077(0.4377757)	0.2570829(0.2909823)	-0.3385545(0.4134444)	-0.4714056(0.5860186)	-0.6959966(0.8734211)	0.488846*(0.28696)	-0.2818065(0.3461127)	-0.0719973(0.3004249)	-0.1821541(0.2846738)	-0.1292937(0.3487787)
7.Social Group *Other (Ref. Category)*										
(a)ST	-0.4662452***(0.0801296)	-0.6192396***(0.0740423)	-0.8102565***(0.0821697)	-0.9160097***(0.1095798)	-1.080068***(0.1259614)	-0.2549589(0.2169424)	-0.3807121**(0.179027)	-0.3437092**(0.1537949)	-0.2625565**(0.1299807)	-0.6480104***(0.1634475)
(b)SC	-0.2755213***(0.1083188)	-0.2986653***(0.1123069)	-0.5644563***(0.0636495)	-0.4800666***(0.0908623)	-0.3853856***(0.1418157)	-0.7336987***(0.2156127)	-0.7337355***(0.1643816)	-0.6202388***(0.1358103)	-0.5983411***(0.1786778)	-0.682528**(0.2953404)
(c)OBC	-0.1735357*(0.0959804)	-0.3021548***(0.0903285)	-0.2726699***(0.1080633)	-0.3453241***(0.10331)	-0.3437696***(0.1194506)	-0.2076054(0.2121795)	-0.3066561**(0.1502033)	-0.28414**(0.124031)	-0.3923331***(0.1624495)	-0.5340002***(0.1258168)
8.Region *North-East (Ref. Category)*										
(a)Northern	0.4883763***(0.0594942)	0.4730588***(0.0500704)	0.4916924***(0.0477507)	0.4709443***(0.0539786)	0.584779***(0.0773378)	0.4483574***(0.0884634)	0.4758615***(0.0885272)	0.4056822***(0.0714221)	0.468024***(0.0892732)	0.3583429***(0.1019125)
(b)Western	0.8072682***(0.0877937)	0.8030629***(0.0629603)	0.7079483***(0.0501965)	0.5594559***(0.0560922)	0.5218037***(0.0931387)	0.718018***(0.1221117)	0.6296221***(0.0919063)	0.4449859***(0.1050257)	0.48307***(0.1460842)	0.3014775***(0.1164276)
(c)Southern	0.4973322***(0.0667583)	0.3864576***(0.047888)	0.3784505***(0.0524417)	0.2511146***(0.0598309)	0.2004568***(0.0772492)	0.8946424***(0.1596769)	0.7871425***(0.1160532)	0.5038351***(0.0974209)	0.5024117***(0.10473)	0.3548818***(0.1128794)
(d)Eastern	0.7534941***(0.1130636)	0.7791492***(0.1049284)	0.7321369***(0.0839379)	0.6296403***(0.1178773)	0.6323435***(0.1202341)	0.9403331***(0.1407696)	0.8291373***(0.1095678)	0.7298536***(0.104228)	0.6258966***(0.1132578)	0.5462299***(0.1751475)
(e)EAG	0.4478283***(0.0638656)	0.4187418***(0.038106)	0.441782***(0.0471082)	0.4356334***(0.0465959)	0.5359975***(0.06612)	0.6762601***(0.0601296)	0.6646709***(0.0866774)	0.6100568***(0.0661082)	0.5407631***(0.0729599)	0.5248207***(0.1077665)
9.Type of Loan *Long-term (Ref. Category)*										
(a)Short-term	0.71379***(0.0555024)	0.6886688***(0.0330788)	0.6068278***(0.0453328)	0.5581555***(0.0533867)	0.4599184***(0.0722028)	0.9444293***(0.0940656)	0.9338073***(0.082304)	0.7380663***(0.0670754)	0.6980722***(0.0791242)	0.6920362***(0.1067106)
(b)Medium-term	1.011296***(0.0594169)	1.024764***(0.0456081)	1.019528***(0.0482336)	1.088186***(0.0481777)	0.9583181***(0.0635629)	1.276806***(0.0897982)	1.428289***(0.0950949)	1.361808***(0.0933085)	1.470908***(0.0799656)	1.390177***(0.1192737)
10. Rate of Interest	0.0041412***(0.0007543)	0.0038348***(0.0010731)	0.003412***(0.0009314)	0.0031841***(0.0007026)	0.0031339***(0.0011982)	0.0036626***(0.0012458)	0.0046235***(0.0014092)	0.0022433(0.0018602)	-0.0000357(0.001479)	-0.0015972(0.0022888)
11.Purpose of Loan										

Other (Ref. Category)										
(a)Expenditure in Business	0.192481***(0.0753074)	0.2202189***(0.0466062)	0.2381375***(0.0505785)	0.3343632***(0.0799588)	0.4234036***(0.0923551)	0.1711964 (0.1510129)	0.1959776***(0.0735744)	0.4478882***(0.1080264)	0.5093719***(0.1460229)	0.5686864***(0.1736859)
(b)Litigation& Financial Investment	0.1325844 (0.6319536)	0.2919554 (0.4011766)	0.0726515 (0.3808656)	0.5015032 (0.4232492)	0.3985184 (0.8080998)	0.1158562 (0.3007483)	-0.1850994 (0.366406)	-0.1072674 (0.3856899)	0.4525254 (0.6371536)	0.1852395 (0.5017632)
(c)Repayment of Debt	0.2425827*(0.1310983)	-0.0285371 (0.1260589)	0.1245955 (0.1648816)	0.1849863 (0.188194)	0.213577 (0.1715101)	0.1918794 (0.3078424)	0.154036 (0.2603866)	0.1882041 (0.1692029)	0.2747688 (0.2176358)	0.2982564**(0.1560861)
(d)Education	-0.2115091**(0.1092526)	-0.1288056 (0.1219317)	0.0726515 (0.0847226)	0.0184348 (0.1041763)	0.0383105 (0.1547891)	-0.0721203 (0.2223709)	-0.0834338 (0.1692277)	-0.021855 (0.1024905)	0.0029797 (0.1719661)	0.2524118 (0.1808919)
(e)Medical Treatment	-0.0177431 (0.0927367)	-0.1381328***(0.0501388)	-0.1915175***(0.0575705)	-0.2236375***(0.0801026)	-0.1155145 (0.0926395)	-0.2721836*(0.1696956)	-0.197054*(0.1058833)	-0.1303931 (0.0949813)	-0.0838747 (0.0796088)	-0.0510055 (0.1038555)
(f)Housing	0.2596185***(0.0940064)	0.2830498***(0.0737342)	0.219498**(0.0998994)	0.3651203***(0.0978528)	0.3631803***(0.0874394)	0.3739755*(0.2296805)	0.318664***(0.1268398)	0.4989874***(0.0904761)	0.395183***(0.0862218)	0.4110472***(0.0800517)
(g)Other Household Expenditure	-0.3556039***(0.0639881)	-0.3190689***(0.0516216)	-0.2921158***(0.0488128)	-0.2413293***(0.0752946)	-0.1299229 (0.0850238)	-0.326223*(0.198494)	-0.2910489***(0.1224454)	-0.2838924***(0.0792362)	-0.1988031***(0.0818566)	-0.1723486*(0.104903)
12. Household Member Having Bank Account	-0.0964144***(0.0265083)	-0.114564***(0.0211542)	-0.0849544***(0.0228854)	-0.0793432***(0.0216726)	-0.0957894***(0.0310938)	-0.0404076 (0.0472362)	-0.128449***(0.0309919)	-0.0947685***(0.0288775)	-0.107292***(0.0402446)	-0.0381959 (0.0467155)
Constant	7.85214***(0.1514631)	8.565939***(0.1766717)	9.634181***(0.1908867)	10.53241***(0.1958896)	11.15733***(0.2369872)	6.872259***(0.2696397)	7.972583***(0.2292656)	9.087742***(0.2735457)	9.921785***(0.2111631)	10.57763***(0.3192328)

*Note: Standard errors in parentheses, *p<0.10, **p<0.05, ***p<0.01*

Source: Authors' calculation from unit level data of NSS 77th Round, AIDIS (2018-19)

Table 7: Model Specification Test for Rural Area for NSS 77th Round, 2018-19[3]

Amount Borrowed Originally from Non-Institutional Credit Sources	Coefficient	t	p-value
Ŷ	1.058779 (0.0181911)	58.20	0.000
Ŷ²	-0.0153024 (0.0169479)	-0.90	**0.367**
Constant	10.77112 (0.0130413)	825.92	0.000

Note: Standard errors in parentheses, *p<0.10, **p<0.05, ***p<0.01

Source: *Authors' calculation from unit level data of NSS 77th Round, AIDIS (2018-19)*

Table 8: Model Specification Test for Urban Area for NSS 77th Round, 2018-19[4]

[3]*Insignificance of Ŷ² (p-value = 0.367) indicates no functional misspecification of the model and the application of Simultaneous Quantile Regression estimation is statistically justified.*

Amount Borrowed Originally from Non-Institutional Credit Sources	Coefficient	t	p-value
$\hat{Y}$	0.9008001 (1.986192)	0.45	0.650
$\hat{Y}^2$	-0.0207888 (0.1102962)	-0.19	**0.851**
Constant	-2.399613 (8.911502)	-0.27	0.788

*Note: Standard errors in parentheses, *p<0.10, **p<0.05, ***p<0.01*

Source: *Authors' calculation from unit level data of NSS 77th Round, AIDIS (2018-19)*

To capture rural-urban differences in 2018-19, we use the AIDIS NSS 77th Round data, which reflect several distinct patterns (see Table 6). Female-headed households show a significantly negative association with non-institutional credit across almost all credit sizes in rural areas, while in urban areas this relationship is positive only for small credit sizes which may reflect easier access of neighbourhood and community-based small informal loans for various activities. This pattern is slightly different from what we observed in the 2012-13 results, suggesting a shift in both credit demand and lender behaviour overtime.

In rural areas, although age had no significant role in determining access to informal credit in the 2012-13 data, the 2018-19 results show a positive and significant association between age and borrowing from informal lenders. Urban areas also reflect the same trend. This suggests that working and elderly household heads are increasingly perceived as more creditworthy, possibly because they possess greater social capital, stronger reputation within the community, and accumulated assets that can serve as implicit collateral.

In rural areas, while literacy mattered only for small-sized loans in the 2012-13 data, the 2018-19 results suggest that informal lenders increasingly prioritize education when extending credit. Households with a literate head show a significantly positive association with non-institutional credit across almost all loan sizes, possibly because education enhances financial awareness, record-keeping ability, and repayment credibility in the eyes of informal lenders. In contrast, in urban areas, education remains positively significant across most loan sizes, but the relationship turns negative for very large loans, indicating that better-educated households may rely more on institutional sources for higher credit needs, thereby reducing dependence on informal lenders.

Both rural and urban areas show a positive relationship between household size and non-institutional borrowing. Unlike the 2012-13 data, the 2018-19 results suggest a positive and significant relationship between non-institutional credit and self-employed households, but only for small-sized loans in urban areas. This may reflect the short-term working capital

[4] *Insignificance of $\hat{Y}^2$ (p-value = 0.851) indicates no functional misspecification of the model and the application of Simultaneous Quantile Regression estimation is statistically justified.*

needs of petty traders and service providers, who often rely on neighbourhood moneylenders for quick liquidity. By contrast, casual labour households are consistently less likely to borrow from informal sources in both rural and urban areas, with significance observed only at larger credit sizes. Our results also reaffirm the earlier 2012-13 pattern that rural casual labour households borrow more than their urban counterparts, possibly due to greater income volatility in agriculture-linked employment and the absence of stable formal credit avenues in rural markets.

However, we observe a dissimilar pattern in 2018-19 compared to 2012-13, when analysing the effect of religion-caste affiliation on non-institutional credit. Christian households show a significantly negative association at medium and large loan sizes, but only in rural areas, possibly reflecting both their relatively stronger integration with institutional sources and the presence of church-based community support networks that reduce reliance on informal lenders. Among Hindu upper-caste and Muslim unreserved households, the relationship with informal borrowing is significantly negative across all loan sizes in both rural and urban areas, which may indicate their greater access to formal finance. For Jain households, we find a contrasting result compared to the 2012-13 data, the relationship with non-institutional credit is significantly positive only at the lower quantiles in urban areas, suggesting that while Jains may access informal credit for small working capital needs in business, they rely more heavily on institutional finance for larger loans. Overall, we find evidence broadly consistent with the 2012-13 results that Hindu upper-caste and Muslim unreserved households in urban areas are more indebted to informal credit than their rural counterparts.

In the case of social groups, both rural and urban areas display a similar negative relationship with the distribution of non-institutional credit. However, compared to 2012-13, we observe a contrasting pattern among ST households. In 2018-19, ST households in urban areas appear to be in a relatively more privileged position than their rural counterparts in accessing informal loans, perhaps due to occupational diversification and stronger community-based networks in cities. By contrast, SC and OBC households show the opposite trend, indicating continued barriers to informal credit access in urban settings, possibly linked to social discrimination, and dependence on insecure low-wage employment. It is noteworthy that both in rural and urban India, households across all regions of the country exhibit a positive reliance on non-institutional credit.

Both short-term and medium-term loans show a positive association with non-institutional credit in both rural and urban areas, with the effect being stronger in urban markets. This indicates that, compared to rural households, urban households are more dependent on short-and medium-term informal loans, pattern that contrasts with the 2012-13 data. One possible explanation is the rising cost of living and increasing demand for quick liquidity in urban areas, where households often face frequent cash-flow mismatches and resort to informal lenders for consumption smoothing or small business financing.

Interest rates also reveal distinct dynamics compared to the 2012-13 results. In rural areas, we find a significantly positive relationship between the rate of interest charged by informal lenders and all loan sizes, suggesting that rural borrowers remain highly dependent on informal lending practices across the credit spectrum. In urban areas, however, the relationship is significantly positive only for small loans, indicating that while informal lenders charge higher rates for small credit, may face competition from institutional sources for medium- and large-sized loans.

We find contrasting results regarding the purposes of borrowing in 2018-19 compared to 2012-13. Both rural and urban households show a positive and significant reliance on non-institutional credit for business activities across almost all quantiles, suggesting that small-scale entrepreneurial and livelihood activities continue to depend heavily on informal lenders. Repayment of old debt through informal borrowing is significant only at the lower quantiles in rural areas and at the higher quantiles in urban areas. This indicates that rural households often resort to small informal loans to roll over existing debt and manage short-term liquidity pressures, whereas in urban areas large informal borrowing is frequently used to refinance accumulated debt burdens. For education, we observe a significantly negative relationship in rural areas at the lower quantiles, suggesting that rural households with small education-related loans increasingly rely on formal sources such as government schemes, scholarships, or microfinance initiatives. Borrowing for medical treatment shows a negative association across loan sizes in rural areas, but in urban areas the effect is significantly negative only at the lower quantiles, possibly reflecting the growing availability of health insurance, employer support, and microfinance products for healthcare expenses. Housing-related borrowing, by contrast, is positively significant across all quantiles in both rural and urban areas. Finally, for other household expenditures, the relationship is significantly negative across all quantiles in both areas, suggesting that such short-term consumption needs are increasingly met through formal or semi-formal sources rather than costly informal credit. However, in both the sectors, households with a bank account are significantly negative with non-institutional credit.

5. Conclusion

The analysis of AIDIS data demonstrates that the non-institutional credit market continues to occupy a vital space in India's financial landscape, though its nature has evolved over time. Small loans remain indispensable for vulnerable households,which serves as a survival mechanism in the absence of adequate institutional finance. At the same time, the growing prevalence of large-value informal loans reflects the market's adaptive capacity, meeting the credit needs of asset-rich households engaged in commercial activities.Policymakers must recognize that informal finance simultaneously provides crucial support for the livelihood of poor households and avenues for entrepreneurial activity among the better-off. Strengthening financial inclusion requires not only expanding institutional outreach but also addressing the structural socio-economic constraints that continue to shape household dependence on non-institutional credit in India.

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Sustainability Reporting and Firm Performance: Evidence from Selected Indian Companies

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Abstract

The association between financial performance and sustainability reporting is complex and overlapping. The existing studies show conflicting results on this association and there exists very few studies in the Indian context. The prime objective of the present paper is to investigate the relationship between sustainability reporting and firm performance from selected Indian companies. The impact of sustainability reporting is examined using the Discroll kraay robust measure in fixed effect Model. Yearly panel data between 2018–2023 for 252 observations for 43 companies have been used for the study. Data were collected from the respective companies' annual reports. The ESG scores considered as a proxy for sustainability reporting have been collected from the Bloomberg database. The study reveals that risk and leverage have significant negative relationship with Tobin’s Q but Current Ratio and ESG scores have positive significant relationship with Tobin’s Q. Leverage, size and ESG scores have significant negative relationship with ROA but Current Ratio and Growth have positive significant relationship with ROA. Risk, Current Ratio and Growth have positive significant relationship with ROCE but Size and ESG scores have negative relationship with ROCE.

Key Words: Discroll kraay Robust Measure, ESG, Firm performance, Panel regression, Sustainability reporting.

1. Introduction

After the financial meltdowns and the stock market crisis, it was felt that traditional reporting could not support the information needs of multiple stakeholders, primarily capital lenders. The Sustainability Report linked this information gap by providing an extensive interdisciplinary account of economic, environmental and social elements into one report [Ackers 2009 & KPMG 2008]. So, nowadays the most critical issue confronting an organization is sustainability. Environmental, social, and governance (ESG) issues are covered by sustainable reporting, which stakeholders want from organizations to manage opportunities and risks. There is a propensity to establish a new worldwide system for sustainable reporting in order to ensure accountability and transparency. Sustainability reporting is also known as CSR reporting, triple-bottom-line reporting, non-financial reporting and so on [Buallay, *et al.* 2020].

Sustainability reporting can be defined as the practice of measuring, disclosing and being accountable to internal and external stakeholders for organizational performance towards the goal of sustainable development [Girón, *et al.* 2021]. Previously, profit maximization was considered the most important goal of the firm, but now a days, financial analysts, investors and other stakeholders are increasingly demanding information on a company's non-financial performance *i.e.,* Environmental, Social and Governance (ESG) performance, in addition to financial information, in order to make more rational and informed investment decisions. [Aggarwal, 2013]. KPMG (2011) observed in its International Survey on Corporate Responsibility Reporting that 95% of the world's 250 largest companies report on corporate responsibility. In Asia Pacific, approximately half of the companies report on corporate responsibility. According to Hubbard G. (2008), the number of investors seeking to invest in Socially Responsible Investments (SRI) is rapidly increasing, prompting the development of various sustainability indices such as the Dow Jones Sustainability Index. Companies attempt to make money from sustainable reporting and publish their reports in light of these benefits. Nonetheless, research in the area also indicates a negligible or negative correlation between Sustainability reporting and financial execution. According to certain research, financial performance has improved. [Buallay A. 2022, Emeka-Nwokw & Osisioma, 2019] and other researchers show mixed and no relationship between sustainability reporting and financial performance. [Buallay & Al Marri 2022, Goel P. 2020]. It confirmed that the social, political and economic aspects of developing nations influence how these nations' businesses approach social responsibility [Haider, Shannon & Moschis 2022]

Sustainability reporting is widely believed to lay the groundwork for maintaining and increasing a company's value through a variety of strategic benefits, including enhanced stakeholder engagement or relationships, better customer access, customer loyalty, new products, new markets, good brand image, improved employee morale, retention and loyalty, risk avoidance, easier access to capital, strengthened license to operate, cost savings, productivity etc. [Warren & Thomsen, 2012]. Over the past ten years, numerous studies have examined the relationship between financial performance and sustainability reporting. But the results are inconsistent, conflicting, and frequently mixed. Sustainable reporting and related initiatives can help businesses strengthen their brand reputation and cultivate trust-based connections with customers in order to boost financial performance. Companies who are actively pursuing sustainable reporting are fully aware of how this strategy supports their attempts to enhance and safeguard their company's reputation, to appease its stakeholders through sustainable reporting and to achieve a variety of financial performance goals. Thus, the purpose of this research is to clarify how sustainability reporting and performance of companies are related in Indian companies. This research takes into account the accounting and market indicators that demonstrate the effects of sustainability reporting on firm’s performance in Indian context.

2. Review of Literature

Numerous studies have been undertaken concerning sustainability reporting and its impact on financial performance. The previous studies did not show a clear and precise link between sustainability reporting and financial performance. The findings are conflicting and ambiguous, so we divided the literature review into four categories: positive relationships, negative relationships, mixed relationships and no relationships in order to provide a clearer understanding of the nature of the relationship between sustainability reporting and corporate financial performance.

Positive Relationship

Most of the research studies demonstrate that sustainability disclosures are positively and significantly correlated with financial performance due to several advantages, such as an improvement in shareholder value and market performance, etc. (M. Lawrence 2022; Thomas C.J *et al* 2021; Jadhav A. *et al* 2020; Wardhani P.P.C. *et al* 2019; etc.). Most of the authors in this study have used financial performance indicator variables such as return on assets, return on equity, Tobin's Q, Net Profit Margin, Return on Capital Employed, EPS and DPS for equity valuation, etc. as well as sustainability reporting indicator variables such as environmental, social, governance, economic, community, employee, health and safety scores. To determine the relationship between sustainability reporting and corporate financial performance they used least square panel techniques and panel regression techniques. (Buallay A. 2022; Al Hawaj A.Y *et al.* 2022, M Lawrence 2022; D Dissanayake *et al* 2021; SS Motwani *et al* 2016 and others). The majority of the studies were conducted in developed countries namely the United Kingdom, United States, New Zealand, Switzerland etc.

Negative Relationship

According to Oprean-StanC. *et al* 2020; MJ Islam 2020; N Emeka- Nwokeji *et al* 2019; Cormier and Magnan 2007, full disclosure of information about new product and process development, risk management techniques, eco-efficiency, training and development etc. may incur expenses and pose risks. The initial cost increases associated with sustainability programs are significant and have a short-term negative impact on financial performance. They used parameters for sustainability reporting such as ESG scores as well as indicators for financial performance, including return on assets, return on equity, Tobin's Q and applied panel regression methods to determine the relationship between a company's financial performance and sustainability reporting. Most research studies were executed in developed countries like Spain, Germany, Switzerland etc.

Mixed Relationship

It is challenging to determine any clear or substantial correlation between sustainability reporting and financial performance because sustainability disclosures include a variety of components that may have diverse impacts that balance against one another (Buallay A. 2022; Buallay A and A Marri M. 2022; Nugrahani T.S and Artanto D.A.2022; Goel P. 2019 etc). Consequently, it is preferable to analyze each aspect of sustainability's effect on financial performance separately in order to reach conclusions that are more precise and specific. They used financial performance indicator variables, such as return on assets, return on equity, return on capital employed and earnings per share and Tobin's Q as well as measurements for sustainability reporting such as environmental, social and governance scores (ESG scores) and the regression analysis has been utilized to figure out the relationship between the financial performance of companies and sustainability reporting (Alhawaj A *et al* 2022; Buallay A and Al Marri M. 2022 Buallay A. *et al*

2021; Buallay A.M. 2020). Except few studies from developing countries such as Indonesia, Malaysia and India, most of the research studies have taken place in developed countries such as Saudi Arabia, the United Kingdom and Switzerland.

No Relationship

According to some researchers, companies' financial performance is not significantly impacted by sustainability disclosures (Buallay A. 2022; Goel P. and Misra R. 2020; Ching H.Y. *et al* 2017; P Aggarwal 2013 etc.*)*. Most of the authors in this study have used key performance indicators for financial performance, including return on assets, return on equity, return on sales, Tobin's Q, earning per share, share price volatility etc. and indicators for sustainability reporting, including environmental, social, and governance scores (ESG scores) (Buallay A. 2022; Abughniem M.S *et al* 2019; Oluseyi S.O., Owolabi A.A. and Iyoha F.O. 2019; Said R.M., *et al*., 2015 etc). The majority of the studies were conducted in developing nations, like Malaysia, Brazil, India, Jordan and others.

3. Research Gap

After reviewing all existing literature related to this topic, we found that there has not been any recent work on sustainability reporting and firm performance in India. It motivates us to carry out a study in the Indian context.

4. Objective of the study

The prime objective of the study is to investigate the relationship between sustainability reporting and firm performance in selected Indian companies.

5. Research hypotheses

To attain the objectives of the present study the following research hypotheses are proposed

H1: Sustainability reporting has positive impact on market performance.

H2: Sustainability reporting has positive impact on accounting performance.

H3: Sustainability reporting has positive impact on profitability and efficiency performance.

6. Database and Methodology

Study Period, Source of Data and Sample

This study employs a panel dataset comprising 252 firm year observation (The total potential observation were 258 which is 43 companies × 6 years, however 6 observations were excluded due to missing ESG score and financial dataset) from 43 listed Indian companies out of top fifty stocks listed in Nifty 50 index over the period 2018-2023. This period has been chosen for the study as ESG scores are started to integrate into typical investment strategies which are also backed by regulatory attention, growing public awareness, and increased pressure from institutional investors. Besides, the revision of global sustainability agendas and the Global Reporting Initiative (GRI) standards influenced corporations to disclose ESG information during this period.

The independent variables such as leverage, risk, size, growth and current ratio have been collected from the respective annual reports of the companies and the ESG scores considered as a proxy for sustainability reporting have been collected from the Bloomberg database. The dependent variables are Tobin's Q, ROCE and ROA. In Model 1, Tobin's Q is a market-oriented measure for long-term financial performance, whereas ROA is an accounting-oriented measure that discloses the company's short-term financial performance in Model 2 and ROCE measures the profitability and efficiency of a company's capital investments in Model 3. These are variables used in similar studies in the literature to measure different aspects of performance. In this study, the fixed effect panel regression model has been applied. To normalize skewed distributions and meet the statistical assumptions, the variables namely risk, size, and growth were transformed using natural logarithms. The Jarque-Bera test also confirmed the improved normality after transformation.

To estimate the relationship between sustainable reporting and financial performance Model 1, Model 2 and Model 3 have been applied. As the results of the relationships between variables are mixed in the literature on accounting measures (ROA model), profitability and efficiency measures (ROCE model) and market measures (Tobin's Q model), therefore, the study aims to investigate the relationship between sustainable reporting and firm performance from selected Indian companies using three equations based on accounting, profitability and efficiency and market dimensions of performance. The different variables used in the present study are as follows:

Table1: Variables used in the study

Variable	Definition
Tobin's Q*	Total market value of the stock/Total asset value of firm
ROA	Return on Asset—net income/Total asset
ROCE	Operating Profit or EBIT / Capital Employed
Leverage	Total liabilities/Total assets
Risk	Natural logarithm of (Total debt/Total asset)
Size	Natural logarithm of total assets

Growth	Natural logarithm of yearly sales growth
Current Ratio	Current asset/Current liabilities
ESG	Environmental, Social and Governance score provided by Bloomberg database.

The following panel regression models have been considered for the present study is examining the relationship between the firm performance and sustainability reporting.

Model 1: Tobin's $Q_{it} = \beta_0 + \beta_1 \text{ Risk}_{i,t} + \beta_2 \text{ Leverage}_{i,t} + \beta_3 \text{ Size}_{i,t} + \beta_4 \text{ Current Ratio}_{i,t} + \beta_5 \text{ Growth}_{i,t} + \beta_6 \text{ ESG}_{i,t} + \varepsilon_{i,t}$;

Model 2: $ROA_{it} = \beta_0 + \beta_1 \text{ Risk}_{i,t} + \beta_2 \text{ Leverage}_{i,t} + \beta_3 \text{ Size}_{i,t} + \beta_4 \text{ Current Ratio}_{i,t} + \beta_5 \text{ Growth}_{i,t} + \beta_6 \text{ ESG}_{i,t} + \varepsilon_{i,t.}$

Model 3: $ROCE_{it} = \beta_0 + \beta_1 \text{ Risk}_{i,t} + \beta_2 \text{ Leverage}_{i,t} + \beta_3 \text{ Size}_{i,t} + \beta_4 \text{ Current Ratio}_{i,t} + \beta_5 \text{ Growth}_{i,t} + \beta_6 \text{ ESG}_{i,t} + \varepsilon_{i,t.}$

The study employed Driscoll-Kraay robust measure to control the panel data set's heteroscedasticity and auto-correlation. Various specification tests are employed in order to identify the best panel regression model for every dependent variable. These include the Wald Chi² test for model fit under random effects, the F-test for fixed effects, the Hausman test to determine between fixed and random effects models, and the Breusch-Pagan Lagrange Multiplier (BPLM) test to compare random effects with pooled OLS.

7. Analysis and Interpretation

The steps stated in the methodology section were followed to determine the model *i.e.*, pooled OLS, fixed effect and random effect models for panel regression. In this case, all three models are accepted as fixed effect model because here null hypotheses are significant by the fixed effect model as well as the BPLM test and the null hypotheses of the Hausman test is also significant that's why the fixed effect model was chosen. The test results are shown in Table 2.

Table 2 Selection of Appropriate Model for Panel Regression Result

Dependent variables	Random Effect Wald Chi2 Value	BPLM Test Chibar2 Value	Fixed Effect F Value	Hausman Test Chi2 Value	Appropriate Model Applied
Tobin's Q	201.55***	71.41***	21.15***	10.97*	Fixed Effect

ROA	43.56***	283.48***	4.89***	39.92***	Fixed Effect
ROCE	34.05***	217.05***	5.16***	28.89***	Fixed Effect

Source: Author's Own Tabulation

The result of the study shows that ESG score has a negative and significant relationship with financial performance in Model 2 (ROA) and Model 3 (ROCE) again it has a significantly positive relationship with market performance in Model 1 (Tobin's Q). The fixed-effect models have an R-squared value of 0.3847, 0.1264 and 0.1322 in Model1 Model2 and Model3 respectively. It implies that independent variables explain 38.47%, 12.64% and 13.22% of the variation in the dependent variables. The F-statistics of the model are 275.29 for Model 1, 33.39 for Model 2 and 29.43 for Model 3 which are statistically significant at the 1% level.

The study shows that there is a significantly negative relationship between risk and market performance (Tobin's Q). On the other side, there is a positive and significant relationship between risk and financial performance (ROCE), the result is not similar to studies of M. Lawrence (2022); Thomas C.J. Tuyon *et al.*, (2021). Risk is related to the stability of the company. This can lead to a lower market valuation and raise concerns about the companies' ability to maintain profitability and financial stability. Companies with such relationships may need to address risk factors, improve transparency and demonstrate effective risk management to regain market confidence and enhance their financial performance. According to Tobin's Q, the higher risk of a company affects market perception negatively. It signifies efficient use of capital, competitive strength, investor confidence and a strategic focus on maximizing returns. However, it's essential to consider other factors and conduct a comprehensive financial analysis to ensure that this relationship is sustainable and not driven by short-term gains at the expense of long-term success.

Table 3: Results of Panel Regression Model Estimations

Fixed Effects Estimation with Driscoll and Kraay standard errors			
	Tobin's Q (Model-1)	ROA (Model-2)	ROCE (Model-3)
Independent Variables	Co-efficient	Co-efficient	Co-efficient
Risk	-1.681281*** (-4.85)	-0.226334 (-0.31)	4.682746** (3.07)
Leverage	-1.006673** (-2.28)	-1.692777*** (-5.00)	-1.248489 (-1.03)

Size	-1.18991 (-1.19)	-3.862299** (-3.60)	-9.761915*** (-4.22)
Current Ratio	0.3527369*** (8.47)	0.063771*** (3.78)	0.096412*** (5.7)
Growth	0.1424644 (0.97)	0.6876997** (3.42)	1.270933** (3.23)
ESG	0.0248484* (1.85)	-0.009357* (-1.81)	-0.028594* (-1.75)
Constant	53.98752 (4.55)	53.98752*** (4.55)	125.9043*** (4.76)
Observations	252	252	252
F-test	275.29	33.39	29.43
Sig.	0.0000	0.0000	0.0000
R^2	0.3847	0.1264	0.1322

Notes: Authors' own Calculation

*Figures in the parentheses indicate t statistics; *** indicates significant at 1% level, ** indicates significant at 5% level,* indicates significant at 10%, level.*

There is significantly negative relationship between leverage and financial performance for both Tobin's Q and ROA which is similar to the study carried out by Oprean-StanC. *et al.* (2020); MJ Islam (2020). It suggests that the company may be facing financial challenges, reduced profitability and lower market valuation due to its debt burden. Managing leverage prudently and aligning it with the company's financial capacity and risk tolerance are essential to mitigate these adverse effects and maintain financial health.

Size has a negative and significant impact on financial performance according to both ROA and ROCE which is consistent with the studies Oprean-Stan C. *et al.* (2020); MJ Islam (2020). Accordingly, the market also responds negatively to the size as even in the long term; it is very difficult to reach higher profits from investments made by big companies. It is a clear indicator that the companies need to address these issues to enhance their financial health and long-term sustainability. Identifying the specific causes of these negative impacts is crucial for implementing effective strategies to improve financial performance and create value for shareholders and stakeholders.

Current ratio is an important tool for indicating liquidity and the coefficients of current ratio have a positive and significant impact on Tobin's Q, ROA and ROCE, which is similar to the studies carried out by M. Lawrence (2022); Thomas C.J. Tuyon J. *et al.* (2021); I Yilmaz (2021); Jadhav A. *et al.* (2020). It indicates that a company is effectively managing its liquidity, utilizing its assets efficiently and creating value for shareholders.

Growth has a positive and significant impact on ROA and ROCE which is consistent with the studies M. Lawrence (2022); Thomas C.J. Tuyon J. *et al.* (2021); I Yilmaz (2021); Jadhav A. *et al.* (2020). It indicates that the companies are not only expanding but doing so in a way that enhances profitability, efficiency and long-term value.

8. Major Findings and Conclusions

The purpose of this study is to examine the relationship between sustainable reporting and financial performance taking into consideration the market-oriented, accounting-oriented and profitability and efficiency-oriented measures that enable a long-term and short-term perspective in select Indian companies. The ESG shows a significantly negative impact on ROA (short-term oriented measure) and Tobin’s Q (long-term market measure) and a significantly positive impact on ROCE (profitability and efficiency measure). The evidence presented in the study highlights that risk has a considerable impact on market measures, as well as profitability and efficiency measures of the financial performance of a developing nation like India. In addition, because of its high debt load, the company may experience financial difficulties, decreased profitability and a decrease in market value. Leverage has a substantial impact on Tobin's Q and ROA. ROA and ROCE are significantly impacted by size and growth. Additionally, current ratio has a substantial impact on all three models, a positive and significant impact of the current ratio on Tobin's Q, ROA, and ROCE indicates that maintaining a healthy level of liquidity can benefit the companies’ ability to pursue growth opportunities, enhance profitability and generate better returns on its capital, ultimately contributing to its overall financial performance and attractiveness to stakeholders. ESG score has a considerable impact on Tobin's Q, ROA and ROCE suggesting that companies in developing nations like India place more emphasis on sustainability reporting as a means of improving financial performance. According to the findings of the study, it may be conclude that ESG Disclosure has significantly negative effects on firm performance and significantly positive impact on market performance. This suggests that businesses that are open about sustainability may gain the public's trust and investor’s confidents. For policy maker it implies that while encouraging ESG discloser may be costly for firm in the short run but it is beneficial for long run by promoting sustainable business and market efficiency. The study has certain limitations which are as follows: a) the study is restricted to 43 companies from the Nifty 50 index which may not reflect the performance of entire Indian corporate sector. b) The selected time frame is restricted to five years only *i.e.*, 2018-2023.

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Post-Merger Performance Assessment of Bank of Baroda: A Balanced Scorecard Analysis

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Abstract:
This study comprehensively evaluates post-merger performance of Bank of Baroda (BoB) from 2020-21 to 2023-24 using the Balanced Scorecard framework (BSF). Addressing a research gap in holistic assessments that often over-rely on financial metrics, this descriptive study analyzes secondary data from annual reports of BoB and RBI website. The research findings indicate significant improvements across all four BSF perspectives. Financially, the bank shows robust profitability, enhanced stability, and improved asset quality. Internal business processes demonstrate increased operational efficiency and successful digital transformation. Customer engagement remains stable with effective complaint redressal. Furthermore, the bank achieved enhanced human capital efficiency, evidenced by increased business and profit per employee despite a reduced workforce. While acknowledging limitations due to reliance on secondary data and a single-case study, the research concludes that the merger largely achieved its strategic objectives, positioning BoB as a more resilient and competitive entity.

Keywords: Balanced Scorecard, Bank of Baroda, Post-Merger Performance

1. Introduction

The merger of Public Sector Banks (PSBs) in India in the year 2019-20 was a milestone event in the country's banking history, aiming to consolidate and strengthen the financial sector (Iswanto et al., 2022). The PSBs at that time were facing significant challenges, including burgeoning non-performing assets, capital adequacy concerns, and subdued profitability, which necessitated a strategic overhaul to ensure their long-term viability and competitiveness. This consolidation aimed to create larger, more resilient entities capable of achieving economies of scale, improving operational efficiency, and enhancing their capacity for credit disbursement to support economic growth. This strategic move sought to achieve economies of scale and enhance global competitiveness, addressing the evolving landscape of the financial industry (Ghosh & Das, 2022). In this merger process, 13 PSBs were merged to form 5 large PSBs. Among these consolidated entities, Bank of Baroda's (BoB) merger with Dena Bank and Vijaya Bank established it as the third-largest public sector bank in India. Vijaya Bank’s and Dena Bank’s integration into BoB was completed in September 2020 and December 2020, respectively. This transformation necessitates a comprehensive evaluation of its post-merger performance through a robust framework to assess its effectiveness across multiple dimensions.

A focus only on financial metrics would offer an incomplete picture of the merger's true impact, as organisational success hinges on a broader spectrum of factors beyond immediate financial gains (Basha, V, 2016). Therefore, this study employs the Balanced Scorecard framework (BSF), which integrates financial performance with customer satisfaction, internal business processes, and learning and growth perspectives, providing a comprehensive view of the bank's operational and strategic achievements (Kaplan & Norton, 1996). Specifically, this research will explore how the merger has impacted key performance indicators within each of these perspectives, offering insights into operational efficiencies, customer retention, employee satisfaction, and financial outcomes (Nzuve&Nyaega, 2013).

In the coming sections, we will elaborate on the literature review, focusing on the previous research in this field, followed by a detailed methodology outlining the data collection and analytical approach, and ultimately presenting the results and their implications for future strategic direction.

2. Literature Review

This review examines the existing literature on bank mergers, performance assessment frameworks, and the application of the BSF in the banking sector, particularly within the Indian context. The review will synthesise findings regarding the drivers and outcomes of bank consolidations, the efficacy of various performance measurement tools, and the specific challenges and opportunities presented by mergers in emerging economies (Pathak, 2016).

Previous researchers have adopted various approaches to analyse the performance of the banking sector. Approaches like the two-stage approach, which combines both competition and efficiency, have been used to identify actionable strategies that optimise resource allocation and mitigate systemic risks in the banking sector. Other approaches like the CAMELS framework, Data Envelopment Analysis, and Stochastic Frontier Analysis have been widely employed to assess bank performance, focusing on distinct aspects such as asset quality, management efficiency, and technological adoption. However, these traditional methods often lack the holistic perspective offered by the BSF, which integrates financial metrics with non-financial indicators like customer satisfaction, internal process efficiency, and organisational learning and growth, providing a more comprehensive view of performance (Camilleri, 2020). This holistic approach, which encompasses financial, customer, internal process, and learning and growth perspectives, offers a more robust framework for evaluating the multifaceted impacts of mergers, particularly in dynamic markets. The shift towards non-financial indicators is essential because traditional financial ratio analysis, while continuously used by regulators, often provides an incomplete picture of a bank's overall health and strategic progress (Dzeawuni& Tanko, 2008).

(Raut & Sahasrabuddhe, 2021) compared the performance of five PSBs and Private Sector Banks (PvtBs) employing the BSF to provide a comparative analysis of their strategic achievements and operational efficiency.(Annapurna &Manchala, 2017) studied the BSF evaluation of the performance of Indian PSBs. They noted that due to liberalisation, PSBs have undergone transformation in both financial and non-financial perspectives of the BSF. (Murthy &Holeyachi, 2024) conducted a performance assessment of fivePSBs in India, including SBI, BoB, Canara Bank, Union Bank of India, and UCO Bank, using the BSF. Their research underscores BSF's ability to significantly enhance bank performance, especially as banks increasingly compete in global markets.(Panicker & Seshadri, 2013) in a case study, attempted to devise a BSF to determine the performance of Standard Chartered Bank.(Sigiro, 2019)analyzed the BSF as a tool of measurement performance at the Bank of Bengkulu for the period 2013-2015.(Albright & Burgess, 2013)considered the best practices of high-performing banking employees in the context of a BSF.(Csikósová et al., 2016) assessed the efficiency of marketing activities in a selected enterprise from the banking sector using the BSF.

These studies collectively demonstrate the widespread adoption and utility of the BSF in evaluating and improving bank performance across various regions and contexts.

A. The Balanced Scorecard Framework (BSF)

The BSF offers a holistic performance measurement framework, translating strategic vision into action across four key perspectives:

i. **Financial Perspective (FP)**: It focuses on profitability and shareholder value, assessing if strategies lead to bottom-line improvements through metrics like ROI and revenue growth (Pandey, 2005; Romeo et al., 2013).

ii. **CustomerSatisfaction Perspective (CSP)**: It measures customer satisfaction, retention, and acquisition, ensuring the company meets customer expectations regarding quality, service, and cost (Perkins et al., 2014; Romeo et al., 2013).

iii. **Internal Business Process Perspective (IBPP)**: It identifies critical internal operations that drive customer satisfaction and financial goals, focusing on efficiency, innovation, and operational excellence (Pandey, 2005; Romeo et al., 2013).

iv. **Learning and Growth Perspective (LGP)**: It evaluates the organisation's capacity for innovation, improvement, and adaptation. This includes employee capabilities, training, information systems, and organisational culture, vital for sustained long-term success (Abueid et al., 2022; Pandey, 2005).

These interconnected perspectives provide a balanced view of performance beyond just financial metrics (Kaplan & Norton, 1997).

B. Research Gaps

After going through existing studies, it is observed that there isaprevalent reliance on traditional financial metrics, which offer an incomplete picture of bank merger impacts and often fail to capture long-term strategic success. Moreover, a trend analysis on the various perspectives of BSF on the post-merger performance of the BoB has not been done yet.This study addresses the lack of a holistic assessment of post-merger performance in Indian PSBs, which typically overlooks non-financial dimensions like CSP, IBPP efficiency, and LGP.

C. Research Objectives

The objectives of this study are to comprehensively evaluate BoB's post-merger performance using the BSF. Specifically, it aims to analyse the merger's impact on key performance indicators across the FP, CSP, IBPP and LGP.

3. Research Methodology

To assess the performance of BoB post-merger, the principles of the BSFhave been utilised in this study. This approach integrates the four core perspectives of the BSF—FP, CSP, IBPP and LGP—to provide a comprehensive assessment of the merger's impact on BoB's strategic objectives.

A. **Nature of the study**: This study is based on a descriptive method of research.

B. **Nature and sources of data**: The required data to facilitate this comprehensive analysis has been gathered from BoB's annual reports and other regulatory disclosures, complemented by industry-specific data from the Reserve Bank of India to ensure a robust and comparative assessment. These secondary datahave been sourced from respective websites.

C. **Study period:**Since the integration of Dena Bank into BoB was completed in December 2020, the post-merger performance analysis has been done for the period 2020-21 to 2023-24, providing a clear snapshot of the integrated entity's operational and strategic efficacy.

D. **Data analysis:**The collected data and calculated ratios about each of the four BSF perspectives are presented in tabular form and analysed in the subsequent sections. This study employs both quantitative metrics and qualitative insights to delineate the performance trajectory. The findings have been interpreted with the help of trend analysis.

4. Data Analysis and Finding

A. FP

The FP of the BSF focuses on profitability and shareholder value, assessing if strategies lead to bottom-line improvements (Pandey, 2005).

Table 1: Performance of BoB on the FP of BSF

YEAR	2020-21	2021-22	2022-23	2023-24
Return on Equity (ROE) %	1.11	8.93	15.33	16.91
Profit (Loss) during the year (Amount in ₹ Crores)	828.96	7272.28	14109.62	17788.78

Return on Investment (ROI) %	6.37	6.11	6.53	6.79
Capital Adequacy Ratio (CAR) %	14.99	15.68	16.24	16.31
Credit Deposits Ratio (CDR) %	73.04	74.30	78.18	80.32
Net Interest Margin Ratio (NIM) %	2.49	2.68	3.02	2.94
Return on Assets (ROA)%	0.07	0.60	1.03	1.17
Ratio of net NPA to net advances (NNPANA) %	3.09	1.72	0.89	0.68

Source: Annual report of BoB, RBI and the Author's calculation based on data

The measures of FP of BSF have been presented in Table 1, and findings have been summarised as follows:

- **Return on Equity (ROE):** ROE indicates how much profit the bank generates for each unit of shareholder equity. The data shows a substantial and consistent increase in ROE (2020-21: 1.11% to 2023-24: 16.91%). This strong upward trend signifies improved profitability and efficiency in utilising shareholders' funds, indicating that the merger has successfully enhanced the bank's ability to generate returns for its owners.
- **Profit during the year:** The profit figure shows a dramatic and continuous increase(2020-21: ₹828.96 Crores to 2023-24: ₹17788.78 Crores). The significant jump, particularly between 2020-21 and 2021-22, highlights a strong recovery and growth trajectory, suggesting that the integration efforts from the merger have paid off in terms of increased revenue and controlled expenses.
- **Return on Investment (ROI):** ROI is a ratio that evaluates the efficiency of an investment. ROI is relatively stable(2020-21: 6.37% to 2023-24: 6.79%) with slight fluctuations, showing overall consistent returns on the investments made by the bank.
- **Capital Adequacy Ratio (CAR):** The CAR is a measure of a bank's financial strength and stability. The CAR has shown a steady increase(2020-21: 14.99% to 2023-24: 16.31%). This positive trend signifies that the BoB is strengthening its capital base relative to its risk exposure, which is crucial for resilience and aligns with the merger's aim to create more resilient entities.
- **Credit Deposits Ratio (CDR):** This ratio implies how much of a bank's deposits are given out as credit (loans).The CDR has gradually increased(2020-21: 73.04% to 2023-24: 80.32%). This suggests an improved

capacity for credit disbursement, which was the .key purpose of the merger to support economic growth.

- **Net Interest Margin (NIM):** A higher NIM indicates better profitability from core lending and borrowing activities. The NIM saw a significant increase up to 2022-23 before a slight dip in 2023-24(2020-21: 2.49% to 2023-24: 2.94%). The overall positive trend points to improved efficiency in managing interest-bearing assets and liabilities, contributing to core profitability.
- **Return on Assets (ROA):** A higher ROA implies better asset utilisation and operational efficiency. This metric shows a very strong and consistent upward trend(2020-21: 0.07% to 2023-24: 1.17%). This reflects improved operational efficiency post-merger.
- **Ratio of net NPA to net advances (NNPANA):** A lower ratio indicates better asset quality and reduced credit risk. This ratio has shown a significant and continuous decline(2020-21: 3.09% to 2023-24: 0.68%), which is a crucial positive trend.

In summary, the financial data strongly suggests that the BoB has significantly improved its financial performance and stability in the years following the merger, aligning well with the strategic objectives of the consolidation mentioned in your document.

B. **IBPP:**

The IBPP of the BSF focuses on the operational effectiveness and efficiency of the bank's internal functions, ensuring they are aligned to meet customer and financial objectives (Romeo et al., 2013).

Table 2: Performance of BoB on the IBPP of BSF

YEAR	**2020-21**	**2021-22**	**2022-23**	**2023-24**
Business Per Employee Growth %	4.26	12.67	20.91	14.25
Credit Growth %	2.34	10.03	21.08	13.26
Cost to Income Ratio (CIR)%	49.21	49.24	47.72	47.71
WA banking total no of new Registrations (in Lakhs)	6.11	13.78	44.01	36.59
Successful end-to-end WA Banking Transactions (Lakhs)	14.65	59.29	189.68	368.08
ATMs (No.of ATMs)	9988	9845	9764	9426
No. of Active Debit Cards (in lakhs)	654	745	825	954

Source: Annual report of BoB, RBI and the Author's calculation based on data

The measures of IBPP of BSF have been presented in Table2, and findings have been summarised as follows:

- **Business Per Employee Growth:** This metric is a key indicator of employee productivity and the efficiency of the bank's human capital. The consistent growth(2020-21: 4.26% to 2023-24: 14.25%), especially the significant jump in 2022-23, suggests that the bank's employees are becoming more productive over time. This could be due to better training, technology integration, or streamlined processes post-merger, contributing to improved operational efficiency.
- **Credit Growth:** This refers to the percentage increase in the total amount of loans and advances extended by the bank. The robust and sustained credit growth (2020-21: 2.34% to 2023-24: 13.26%)signifies the bank's enhanced capacity for credit disbursement, which was a strategic aim of the merger to support economic development.
- **Cost to Income Ratio (CIR):** This ratio indicates how much it costs the bank to generate its income. The gradual decline in the CIR (2020-21: 49.21% to 2023-24: 47.71%) demonstrates improved cost management and operational efficiency.
- **WA banking total no of new Registrations:** This metric indicates the number of new customers registering for WhatsApp banking services. It reflects the adoption rate of digital channels. The explosive growth in new registrations(2020-21: 6.11 Lakhs to 2023-24: 36.59 Lakhs), especially the peak in 2022-23, highlights the success of the bank's digital transformation initiatives and the increasing customer preference for convenient digital platforms.
- **Successful end-to-end WA Banking Transactions:** This metric measures the actual volume of successful transactions conducted through the WhatsApp banking channel. The continuous and dramatic increase in successful transactions (2020-21: 14.65 Lakhs to 2023-24: 368.08 Lakhs) signifies the effectiveness of the WhatsApp banking platform in facilitating customer interactions and reducing the load on traditional channels.

- **ATMs:** This refers to the total number of Automated Teller Machines operated by the bank. The consistent decrease in the number of ATMs (2020-21: 9988 to 2023-24: 9426)suggests a strategic shift by the bank towards digital channels. As customers increasingly use online and mobile banking, the need for physical ATM infrastructure may decrease, leading to cost efficiencies.
- **No. of Active Debit Cards:** This metric is an indicator of customer engagement and the reach of the bank's payment solutions. The continuous increase in active debit cards (2020-21: 654 Lakhs to 2023-24: 954 Lakhs) indicates successful customer acquisition and retention efforts, as well as a growing customer base that prefers card-based transactions.

Overall, the trends in the IBPP suggest that the BoB has significantly improved its operational efficiency and embraced digital transformation post-merger.

C. CSP:

The CSP evaluates how well the bank is serving its customers, which directly impacts customer loyalty and market share.

Table 3: Performance of BoB on CSP of BSF

YEAR	**2020-21**	**2021-22**	**2022-23**	**2023-24**
Customer Complaints Redressed %	100.49	100.43	97.23	102.81
Growth in Customer Saving Bank Deposits %	14.99	11.35	7.64	6.16
Growth in Term Deposit %	-5.46	5.81	18.99	11.53
Growth in Demand Deposit %	21.82	12.95	17.04	15.78
Ratio of Marketing Expenses to Volume of Business %	0.0052	0.0096	0.0090	0.0075
Ratio of Priority Sector Advances to total Advances %	31.07	29.71	28.03	27.32
Market Share in Deposits (MSD) %	6.21	6.09	6.31	6.11

Source: Annual report of BoB, RBI and the Author's calculation based on data

The measures of CSP of BSF have been presented in Table 3, and findings have been summarised as follows:

- **Customer Complaints Redressed:** This metric indicates the bank's effectiveness in resolving customer grievances.The consistently high percentage (2020-21: 100.49% to 2023-24: 102.81%) signifies a robust and effective complaint redressal system.

- **Growth in Customer Savings Bank Deposits:** This measures the year-on-year percentage increase in the total value of customer savings bank deposits. While remaining positive, the decreasing growth rate (2020-21: 14.99% to 2023-24: 6.16%) could suggest a maturing market for savings deposits or a diversification of customer investments.
- **Growth in Term Deposit:** This tracks the percentage growth in fixed or term deposits, which are typically held for a specified period. After an initial decline, there was a strong recovery and significant growth in term deposits (2020-21: -5.46% to 2023-24: 11.53%), peaking in 2022-23. This indicates successful strategies to attract long-term funds, which can enhance a bank's financial stability.
- **Growth in Demand Deposit:** This refers to the percentage growth in deposits that can be withdrawn on demand, such as current and transactional accounts.The growth in demand deposits, while showing some fluctuation, has remained positive(2020-21: 21.82% to 2023-24: 15.78%), indicating a healthy inflow of operational funds from customers.
- **Ratio of Marketing Expenses to Volume of Business:** This ratio indicates the proportion of marketing expenses relative to the total volume of business (e.g., deposits plus advances). The ratio remains very low (2020-21: 0.0052% to 2023-24: 0.0075%), suggesting either highly efficient marketing strategies or that a significant portion of business growth is driven by factors other than direct marketing spend, such as reputation or brand strength post-merger.
- **Ratio of Priority Sector Advances to total Advances:** In India, priority sector lending is a regulatory mandate aimed at ensuring that crucial sectors of the economy receive adequate financial support from the banking system. This ratio shows a gradual decline (2020-21: 31.07% to 2023-24: 27.32%). This trend warrants attention to ensure continued adherence to the regulatory targets of 40% for priority sector lending.
- **Market Share in Deposits:** This metric represents the bank's proportion of the total deposits within the banking industry, serving as an indicator of its competitive standing. The market share in deposits has remained relatively

stable with minor fluctuations(2020-21: 6.21% to 2023-24: 6.11%). This indicates that the bank is largely maintaining its competitive position in the deposit market.

In summary, the CSP data suggests that Bank of Baroda effectively manages customer complaints and attracts various types of deposits. While the growth rate for savings deposits has seen a slowdown, term deposits have shown a strong recovery. The bank maintains a relatively stable market share in deposits and appears to manage its marketing expenses efficiently. The slight decline in priority sector advances might be an area for further analysis.

D. LGP:

The LGP focuses on the bank's ability to innovate, improve, and learn, ensuring it has the necessary infrastructure and human capital to support long-term strategic objectives (Abueid et al., 2022; Pandey, 2005).

Table 4: Performance of BoB on LGP of BSF

YEAR	**2020-21**	**2021-22**	**2022-23**	**2023-24**
Number of Employees	82695	79375	77167	74886
Business Per Employee (BPE) in ₹ lakh	1957	2205	2666	3046
Profit Per Employee (PPE) in ₹ lakh	1	9	18	24
Percentage of Employees receiving Training during the year	90	99	90	80
Employee Engagement Score % (as per Employee Engagement Survey)	74	74	75	71
Ratio of Wage Bills to Total Income (RWBTI) %	13.72	14.72	13.41	12.44

Source: Annual report of BoB, RBI and the Author's calculation based on data

The measures of LGP of BSF have been presented in Table 4, and findings have been summarised as follows:

- **Number of Employees:** This metric represents the total headcount of the bank. The continuous decline in the number of employees (2020-21: 82695 to 2023-24: 74886) suggests a strategic effort towards optimising human resources, potentially through automation, digital initiatives, or consolidation efficiencies post-merger.
- **Business Per Employee (BPE):** This metric measures the total business (deposits + advances) generated by each employee. The consistent and strong

upward trend in BPE is a very positive sign (2020-21: ₹1957 lakh to 2023-24: ₹3046 lakh). Despite a decreasing number of employees, the business's generated per employee is significantly increasing.

- **Profit Per Employee (PPE):** This metric measures the profit attributable to each employee. This metric shows a remarkable and continuous increase (2020-21: ₹1 lakh to 2023-24: ₹24 lakh). This reinforces the observation from BPE, indicating that employees are not only generating more business but also contributing significantly more to the bank's bottom line. This suggests successful integration efforts, improved operational efficiency, and possibly a higher value contribution per employee.
- **Percentage of Employees receiving Training during the year:** This metric indicates the proportion of the workforce that undergoes training during the year. The percentage of employees receiving training each year has been high but shows a fluctuating trend with a notable decrease in the last year (2020-21: 90% to 2023-24: 80%). While a large portion of employees are still trained, the declining trend might warrant attention to ensure that the workforce remains adequately skilled and adaptable to future challenges, especially in a rapidly evolving banking landscape.
- **Employee Engagement Score % (as per Employee Engagement Survey):** This score reflects the level of enthusiasm, commitment, and involvement employees have towards their work and the organisation. High employee engagement often correlates with higher productivity, lower attrition, and better customer service.The employee engagement score has remained relatively high(2020-21: 74% to 2023-24: 71%), indicating a generally positive work environment, but there was a slight dip in 2023-24. Maintaining and improving employee engagement is vital for sustained organisational performance, particularly in a post-merger scenario where employee morale and alignment are crucial for success.
- **Ratio of Wage Bills to Total Income:** This ratio indicates the proportion of the bank's total income that is spent on employee wages and benefits. After a slight increase in 2021-22, this ratio shows a general declining trend in the latter years (2020-21: 13.72% to 2023-24: 12.44%). This suggests that the

bank is becoming more efficient in managing its wage costs relative to the income it generates, which is a positive sign for profitability.

In summary, the LGP data indicate that theBoB has significantly enhanced its human capital efficiency post-merger, as evidenced by the dramatic increases in business and profit per employee, despite a reduction in total headcount. While the bank has maintained a high level of training and engagement, the recent declines in these areas might need to be monitored to ensure sustained long-term growth and employee development.

5. Discussion

The merger of Dena Bank and Vijaya Bank into BoB aimed to create a larger, more resilient entity capable of achieving economies of scale, improving operational efficiency, and enhancing its capacity for credit disbursement to support economic growth. A holistic assessment using the BSF reveals significant progress across all four perspectives:

A. FP: Strong Recovery and Growth

The financial data indicate a robust and positive trajectory post-merger. BoB has demonstrated:

- **Significant Profitability Growth**: A dramatic and continuous increase in profit, ROE, and ROA, particularly from 2021-22 onwards. This indicates improved financial health and efficient utilisation of both shareholder funds and overall assets.
- **Enhanced Stability and Asset Quality**: A steady increase in the CAR signifies improved financial resilience. Crucially, the NNPANA has seen a continuous and substantial decline, addressing a key challenge faced by PSBs before the merger and reflecting effective asset quality management.
- **Effective Lending and Interest Income**: The increasing CDR suggests effective deployment of deposits into lending, while a generally positive NIM indicates strong profitability from core banking activities.

These financial outcomes strongly align with the merger's strategic objectives of strengthening the financial sector and improving profitability.

B. IBPP: Operational Efficiency and Digital Transformation

The bank has made considerable strides in optimising its internal operations, indicating successful integration and adaptation post-merger:

- **Increased Productivity**: The BPE Growth shows a consistent upward trend, demonstrating enhanced employee productivity and streamlined processes.

- **Cost Management**: A declining CIR indicates improved operational efficiency and effective cost management.
- **Strategic Digital Adoption**: The exponential growth in the total no of new registrations for WA banking and successful end-to-end WAbanking transactions highlights a successful pivot towards digital channels. This is further supported by the strategic reduction in physical ATMs, signifying a move towards a more digitally-centric operating model.
- **Robust Credit Expansion**: Credit Growth shows a strong increase, fulfilling the merger's aim to enhance credit disbursement capacity.

These trends underscore the bank's success in achieving economies of scale and improving operational efficiency through both traditional and digital means.

C. CSP: Stable Engagement with Areas for Focus

Customer-centric metrics show a generally stable and effective approach, though some areas warrant continued attention:

- **Effective Complaint Redressal**: The consistently high percentage of customer complaints redresseddemonstrates a robust and effective system for addressing customer grievances, which is crucial for maintaining customer trust and satisfaction.
- **Varied Deposit Growth**: While percentage growth in savingsbank deposits has seen a decreasing trend, percentage growth in Term depositshas shown significant recovery and growth, indicating varied success in attracting different types of deposits. Demand deposits also show healthy growth.
- **Stable Market Position**: The market share in deposits has remained relatively stable, suggesting the bank is largely maintaining its competitive standing in the deposit market.
- **Priority Sector Lending**: The gradual decline in the ratio of priority sector advances to total advances is an area that might require monitoring to ensure continued adherence to the regulatory mandates of 40 %.

Overall, the bank appears to be effectively serving its customer base, with digital engagement playing an increasingly important role, but continuous focus on specific deposit products and regulatory compliance remains vital.

D. LGP: Enhanced Human Capital Efficiency

The data in this perspective highlights key developments in the bank's human capital and organisational capacity:

- **Increased Employee Productivity and Profitability**: Despite a continuous decline in the number of employees(likely due to workforce optimisation post-merger), theBPE and PPE have shown remarkable and consistent increases. This is a testament to enhanced efficiency and higher value contribution per employee.
- **Efficient Wage Management**: A generally declining ratio of wage bills to total income suggests improved cost efficiency related to human resources.
- **Training and Engagement Monitoring**: While the percentage of employees receiving training each year remains high, a fluctuating trend with a recent decrease, along with a slight dip in the Employee Engagement Score, suggests these areas need continuous monitoring to ensure sustained skill development and employee morale in a dynamic environment.

Synthesising these perspectives, it is evident that the BoB's post-merger performance, as assessed by the BSF, has been largely successful in achieving its strategic objectives.

6. Conclusion

The bank has demonstrated remarkable improvements in its financial health and profitability, driven by significant operational efficiencies and a strong embrace of digital transformation in its internal business processes. While maintaining a generally positive customer satisfaction level and attracting various types of deposits, ongoing attention to priority sector lending and specific deposit growth strategies is warranted. Crucially, the bank has become significantly more productive and profitable per employee, even with a reduced workforce, highlighting successful human capital optimisation. However, continuous investment in employee training and maintaining high engagement levels will be key for sustained long-term success and adaptability in the evolving banking landscape.

The holistic view provided by the BSF confirms that the merger has not only delivered on financial promises but has also fostered internal improvements, adapted to customer needs, and optimised its human capital, positioning the BoB as a more resilient and competitive entity.

7. Limitations of the study and Directions for Future Research

Although it offers a snapshot, the four-year post-merger review may not adequately capture long-term strategic consequences. Only the BoB is included in this analysis. Therefore, it is important to use extreme caution when extrapolating the results of the present study to other bank mergers or the larger Indian banking industry. Additionally, while the current study takes into account a few performance indicators under the four BSF perspectives, it is still possible that some performance indicators under the financial and non-financial metrics would be overlooked. All of the restrictions that come with using secondary data may affect the information that is based on it.

The BSF with solely bank-specific factors—that is, internal factors—was utilised in this study to assess the BoB's performance. Future research can incorporate external factors like RBI regulations, GDP, inflation, interest rates, and digital penetration, among others. Additionally, it can be used as a springboard for further research in this area within the framework of the banking industry's balanced scorecard.

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Financial Distress Prediction using Natural Language Processing: An Empirical Study with Special Reference to the Indian Manufacturing Sector

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Abstract

An increasing number of cases of corporate financial distress have attracted the attention of scholars to examine its possible causes over a long period of time using different approaches. Along with the traditional methods of financial distress prediction, sophisticated techniques using machine learning and artificial intelligence are also in use to predict corporate distress across the globe. In this context, the present study seeks to predict corporate financial distress using Natural Language Processing, which is inherently a machine learning technique. The study is based on the Indian manufacturing sector, specifically from industries such as auto ancillaries, capital goods (both electrical and non-electrical equipment), cement, consumer durables, steel, textiles, casting, forging and fasteners. The 33 bankrupt companies were selected based on the official website of the Insolvency and Bankruptcy Board of India (IBBI) established under the Insolvency and Bankruptcy Code (IBC), 2016. 48 non-distressed firms were selected from the same industries as the distressed firms and were matched based on asset size. Annual reports for the previous year prior to bankruptcy were considered for the study. Annual reports for corresponding non-distressed firms were also taken for the same year. The study applies a Natural Language Processing model, using a Python programming environment to classify and identify firms as distressed or non-distressed. The classification model reached 88% accuracy, with precision, recall and F1-score each at 0.86, demonstrating strong and balanced performance. The confusion matrix further confirmed the model’s reliability, showing only two misclassifications. The word cloud analysis highlighted that distressed firms consistently emphasize terms like loss, dividend, cash flow, provision, bankruptcy and going concern.

Keywords: Financial distress prediction, bankruptcy, Natural Language Processing

1. Introduction:

In simple words, Corporate Distress or Financial Distress is a financial condition where a firm's assets are inadequate to meet its external liabilities, generally seen as the stage before bankruptcy. It is often indicated by weak liquidity, poor solvency, outdated production, declining sales, inefficient administration and adverse economic pressures. Different authorities define it distinctly. ICICI views a company as sick when adverse factors continue to threaten its viability. The RBI (under the MSMED Act, 2006) classifies a Micro or Small Enterprise as sick if any borrowal account remains NPA for over three months or if accumulated losses erode 50% of its net worth. The Companies Act, 2013 allows a firm to be declared sick if secured creditors holding at least 50% of its debt demand repayment and the company fails to comply within 30 days. The Sick Industrial Companies Act, 1985 treats a unit as sick if it has existed for at least five years and its accumulated losses equal or exceed its net worth. Distress is not just about numbers on balance sheets. It reflects a firm's weakening ability to function as a going concern, affecting employees, creditors, investors and the broader economy. Past crises, such as the global financial meltdown of 2008, have shown how interconnected one firm's failure can be to an entire economic system. Thus, corporate distress is not an isolated event, it is a chain reaction that can ripple across industries, markets and economies.

The ability to predict financial distress early on is critical because it allows stakeholders to take corrective action before it escalates into insolvency. For regulators and governments, accurate predictions help to safeguard the stability of financial systems and avoid systemic risks. For managers, it enables timely strategic intervention, whether restructuring debt, securing new investments or cutting evadable costs. Creditors and lending institutions use predictions to assess a company's creditworthiness and mitigate lending risks. Investors use such signals to make informed decisions about where to place their capital. In essence, forecasting corporate distress is a practical necessity for risk management and decision-making in business and policy environments.

Traditionally, predicting distress has focused on financial ratios, such as Altman's Z-score or market-based indicators. These are still useful, but they only tell part of the story. Recent research suggests that words matter too. Qualitative information hidden in financial disclosures can provide signals that numbers alone might miss. Textual analysis looks at the narratives in places like annual reports, Management's Discussion and Analysis (MD&A) sections, chairman's letters or even news articles. The language in these documents often reflects management's tone, sentiment and outlook and can reveal hints about a company's real financial health. For instance, when MD&A sections contain a lot of negative or uncertain words, it has been found to link strongly with a higher chance of distress.

However, extracting insights from text is not as straightforward as working with financial ratios. Because text is unstructured and often messy, this is where Natural Language Processing (NLP) and Machine Learning (ML) play an important role. Modern methods can turn words into numbers using techniques like word embeddings or sentiment scoring, so algorithms can treat them as features. Once in this form, classifiers such as Support Vector Machines, Random Forests, or boosting models can separate financially distressed firms from healthy ones. More advanced methods rely on deep learning models, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs) or hybrid designs, which are able to capture not just the words themselves but also context and linguistic patterns. When these textual signals are combined with traditional numeric data, the models often perform better than older approaches. Recent studies show that tools such as sentiment dictionaries like Loughran-McDonald, thematic analysis and deep embeddings are particularly effective at spotting early warning signs of financial distress.

The primary objective of this study is to explore whether the text in corporate annual reports can be used to predict financial distress among firms. The study focuses on building a dataset of distressed and non-distressed firms, cleaning and preprocessing the extracted content and applying Natural Language Processing (NLP) techniques such as Term Frequency-Inverse Document Frequency (TF-IDF) for vectorisation. The objective is to train predictive models that classify firms as distressed or non-distressed and evaluate their performance using accuracy, precision, recall, F1-score and confusion matrix analysis. The study will also visualise linguistic patterns and commonly used terms in both categories to highlight key differences in their language. Finally, it will test the model on unseen annual reports to measure its real-world value in providing early warning signals of corporate distress.

2. Review of literature:

Financial distress prediction has evolved over decades, originating in classical models like Beaver's univariate ratio analysis (Beaver, 1966, 1968) and Altman's multivariate Z-Score (Altman, 1968). These models leveraged financial ratios to distinguish failing firms. Further developments included logistic regression (Ohlson, 1980), probit models (Zmijski,1984) and survival analysis incorporating time-varying covariates (Shumway, 2001). While these statistical approaches provided interpretability, their effectiveness was limited by assumptions such as normality and linear relationships (Kumar & Ravi, 2007).

The rise of digital disclosures led researchers to explore textual data in annual reports, particularly the Management Discussion and Analysis (MD&A) sections, as rich and forward-looking information sources. Early qualitative studies revealed differences in tone and themes between distressed and healthy firms (Kohut & Segars, 1992; Abraham & Amir, 1996; Bryan, 1997). Narrative analyses linked language styles and themes such as risks and management's outlook to financial outcomes (Smith &Taffler, 2000; Donovan et al., 2018).

Textual disclosures are complementary to financial metrics, providing signals that may precede numeric deterioration (Kearney & Liu, 2014; Du Jardin, 2016). This area aligns with research emphasizing the incremental value of qualitative data in credit risk evaluation, enhancing early warning capacities.

To operationalize text, sentiment dictionaries tailored for finance were developed. One notableone is the Loughran-McDonald (L&M) lexicon, which addresses inadequacies of general-purpose dictionaries by capturing domain-specific word contextuality (Loughran & McDonald, 2011, 2016). Studies demonstrated that the frequency of negative words in disclosures predicts distress probabilities (Gandhi et al. 2019). Additionally, readability metrics and more sophisticated textual features augment forecasting performance (Bonsall et al., 2017).

Recent empirical efforts integrate textual and financial data within predictive frameworks. Mai et al. (2018) applied deep learning models on a large US sample, finding that simple embedding-based architectures (averaging word vectors) outperformed more complex CNNs, highlighting the predictive strength of textual data alone and combined with numeric variables. Nguyen & Huynh (2020) confirmed improved classification accuracy by adding dictionary-derived sentiment features to traditional quantitative models, especially for SMEs. Tang et al. (2020) extended this approach to Chinese firms, demonstrating that textual features derived from MD&A surpass management factors in predictive relevance and that simpler deep learning models outperform more complex variants. Gupta & Banerjee (2023) studied Indian firms under the Insolvency and Bankruptcy Code, confirming that distressed firms exhibit a higher frequency of negative tone in MD&A. Their thematic and quantitative analyses linked key themes i.e. activity, manageability and performance to financial ratios, underscoring the value in adding narrative analysis to prevailing financial distress models.

3. Research Gap:

While textual analysis has gained growing attention in financial distress prediction worldwide, its use in the Indian manufacturing sector remains limited. Most existing research relies heavily on traditional financial ratios and quantitative indicators, often overlooking the qualitative signals embedded in sources such as annual reports, management discussions and market communications. The specific features of the Indian manufacturing industry, shaped by its regulatory environment, market conditions and reporting practices, are yet to be fully examined in this context. This study therefore seeks to build and test models that incorporate textual analysis tailored to this sector, to improve the early identification and understanding of financial distress beyond conventional metrics.

4. Objectives of the Study:

The specific objective of the study is to predict the financial distress of selectedIndian manufacturing sectors using NLP.

5. Data & Methodology:

5.1 Data:

The dataset for this study was developed using publicly available financial documents from Indian firms. Distressed firms were identified through the official website of the Insolvency and Bankruptcy Board of India (IBBI) established under the Insolvency and Bankruptcy Code (IBC), 2016. Distressed firms were selected across different sectors including auto ancillaries, capital goods (both electrical and non-electrical equipment), cement, consumer durables, steel, textiles and casting, forging and fasteners. For these firms, data from the year immediately before the start of bankruptcy proceedings was considered.

To create a fair comparison, non-distressed firms were selected from the Capitaline Corporate Database. These firms belonged to the same industries as the distressed firms and were matched on asset size to ensure similarity. For them, annual reports from the same years as their distressed counterparts were collected so that the comparison reflected the same timeframes.

All annual reports were downloaded in PDF format directly from the official websites of the respective firms. They served as the main source of textual data, containing information such as management discussions, directors' reports, financial reviews and auditor observations.

The raw dataset was organised into two folders: one for distressed firms and another for non-distressed firms. In total, 81 reports were compiled, consisting of 33 distressed and 48 non-distressed firms, which were later processed and used for feature extraction.

5.2 Methodology:

The study applies Natural Language Processing (NLP) model, using Python programming language within the Jupyter Notebook environment to classify and identify firms as distressed or non-distressed. The methodology consists of the following sequential steps:

i. Data collection
ii. Text processing
iii. Features extraction/ Vectorization
iv. Model training
v. Model evaluation
vi. Visualisation of results
vii. Model testing

5.2.i Data collection:

The textual dataset consists of annual reports in pdf formats were stored in two different directories

- 'distressed' for reports of financially distressed firms
- 'non_distressed' for reports of financially healthy firms

5.2.ii Text processing:

Annual reports often contain a large amount of information that is not useful for predicting financial distress. For e.g. long lists of company names, SEBI regulations, introductory messages, legal disclaimersor auditor certifications. The preprocessing step filtered out this noise and retained only the sections that are critical for assessing a company's financial health. Each annual report PDF was opened with the PyPDF2 library but only the first 50 pages were extracted to avoid noise from appendices and other irrelevant sections. The extracted text was then standardised by converting it to lowercase and splitting it into individual lines for easier handling. To remove unnecessary information, rule-based keyword filtering was applied. As a final cleaning step, regular expressions were used to strip out any non-alphabetic characters and to condense multiple spaces into single spaces. The cleaning routine was applied separately to the distressed and non-distressed document folders, with binary labels assigned to each file (1 for distressed, 0 for non-distressed). After processing, the final dataset contained 81 cleaned documents, with the distribution of labels presented in Table 1

Table 1: Distribution of the Distressed and Non-distressed Firms

Class	**Label**	**Count**	**Percentage**
Distressed	1	33	46.91
Non-distressed	0	48	53.09
Total	---	81	100

Source: Author's own

To prepare text data from PDF reports for analysis, a clean_text() Python function was used that:

- ✓ Converts all text to lowercase for consistency.
- ✓ Replaces line breaks with spaces to prevent word fragmentation.
- ✓ Removes non-alphabetic characters (punctuation, numbers, symbols).
- ✓ Eliminates short words (one or two letters) to reduce noise.
- ✓ Normalizes whitespace for a tidy and uniform text.

These steps ensure the text is clean, consistentand ready for reliable analysis.

After saving the cleaned and labeled dataset as a CSV file, it was loaded back into the Python environment for the next phase of processing and model development. The pandas library was used to read the CSV into memoryand the relevant columns were extracted into separate Python lists.

5.2.iii: Features extraction/Vectorization:

Following the preprocessing and storage of the cleaned dataset, the next step involved transforming the unstructured text into numerical features suitable for machine learning models. Since computers can't process raw sentences the way humans do, the text needs to be translated in numbers. In this study, the Term Frequency-Inverse Document Frequency (TF-IDF) method was used to turn the text into features for the model. Simply put, TF-IDF helps highlight the words that really matter in each document while understating the ones everyone uses all the time. If a word pops up often in just one document but isn't common across the whole dataset it gets a higher score. This means the model focuses more on unique and meaningful terms, rather than being distracted by generic words.

5.2.iv: Model training:

After converting the text data into numerical features using TF-IDF, the next step that was pursued to train a classification model to predict whether a firm was distressed or not based on its annual report.

The dataset was divided into two parts to ensure a fair evaluation of the model: an 80% training set, used for learning the underlying patterns in the data and a 20% testing set, reserved to assess performance on previously unseen data.

Table 2: Training and Testing Data

Training set	65	80%
Testing set	16	20%
Total	81	100%

Source: Author's own

Scikit-learn'strain_test_split function was used for this, making sure to keep the same balance of distressed and non-distressed firms in both sets to make sure the model's performance would be realistic and reliable.

For classification, a **Logistic Regression model** was selected. Logistic Regression is widely used in text classification tasks due to its ability to handle high-dimensional sparse feature spaces generated by TF-IDF.

To handle possible class imbalance the parameter class_weight='balanced' was used. This automatically adjusts weights inversely proportional to class frequencies, preventing the model from being biased toward the majority class.

Additionally, max_iter=1000 was specified to allow the optimization algorithm sufficient iterations to converge, since textual datasets are often large and complex.

5.2.v: Model evaluation:

After training the logistic regression model, its performance was evaluated using the reserved test dataset. The evaluation was carried out in two steps:

<u>Measuring Accuracy</u>

The accuracy was calculated to see the overall percentage of firms the model correctly labeled as either distressed or non-distressed. This gave a general sense of how good the model was at making predictions.

Looking at Detailed Metrics

Beyond accuracy, a detailed classification report was generated that included precision, recall and the F1-score. Precision showed how many of the firms the model flagged as distressed were actually distressed. Recall showed how many of the truly distressed firms the model managed to catch. The F1-score provided a balanced overview by combining precision and recall into one measure.

5.2.vi: Visualisation of results:

As part of evaluating the model, a confusion matrix was created to get a clear picture of how well it was performing. The confusion matrix is a table that shows a side-by-side comparison of the model's predictions against the actual outcomes. It breaks down the number of firms the model classified correctly and incorrectly, for both distressed and non-distressed groups.

This helped to see exactly where the model was getting things right and where it was making mistakes, providing a foundation for understanding its overall accuracy and the types of errors it made.

Finally, to get a clearer sense of the language commonly used in reports from distressed firms, a word cloud was generated. All the cleaned text was combined from these firms into one big collection, then a word cloud was used to highlight the most frequently used words. In the word cloud, the size of each word reflects how often it appears. The bigger the word, the more common it is. This made it easy to spot the key themes and financial terms that stand out in the disclosures of distressed companies.

5.2.vii: Model testing:

To evaluate how well the trained model performs in real-world situations, a new set of financial reports was gathered and stored in a folder named 'test_reports.' Each PDF underwent the same preprocessing steps as the training data. Text was extracted page by page, cleaned by removing numbers, punctuation, common stop words and irrelevant sections. This ensured that only the most important financial terms were retained.

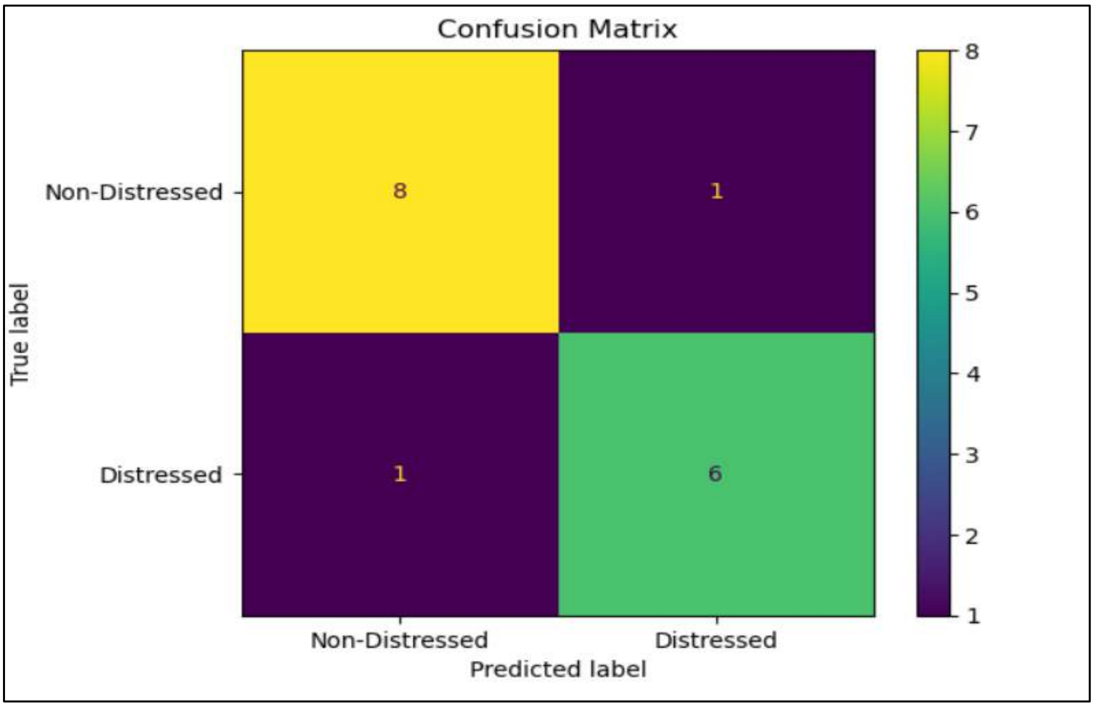
The cleaned text was then transformed into numerical features using the pre-trained TF-IDF vectorizer, ensuring consistency with the training process. A previously trained Logistic Regression model was applied to predict whether each firm was distressed or non-distressed. In addition to categorical predictions, the model produced confidence scores that indicated the certainty of each decision.

The prediction results for every PDF were recorded, providing a basis to evaluate the model's effectiveness on entirely new and unseen data.

6. Results and findings

The confusion matrix presented below summarizes the model's performance in classifying firms into distressed and non-distressed categories.

Figure 1: Confusion Matrix



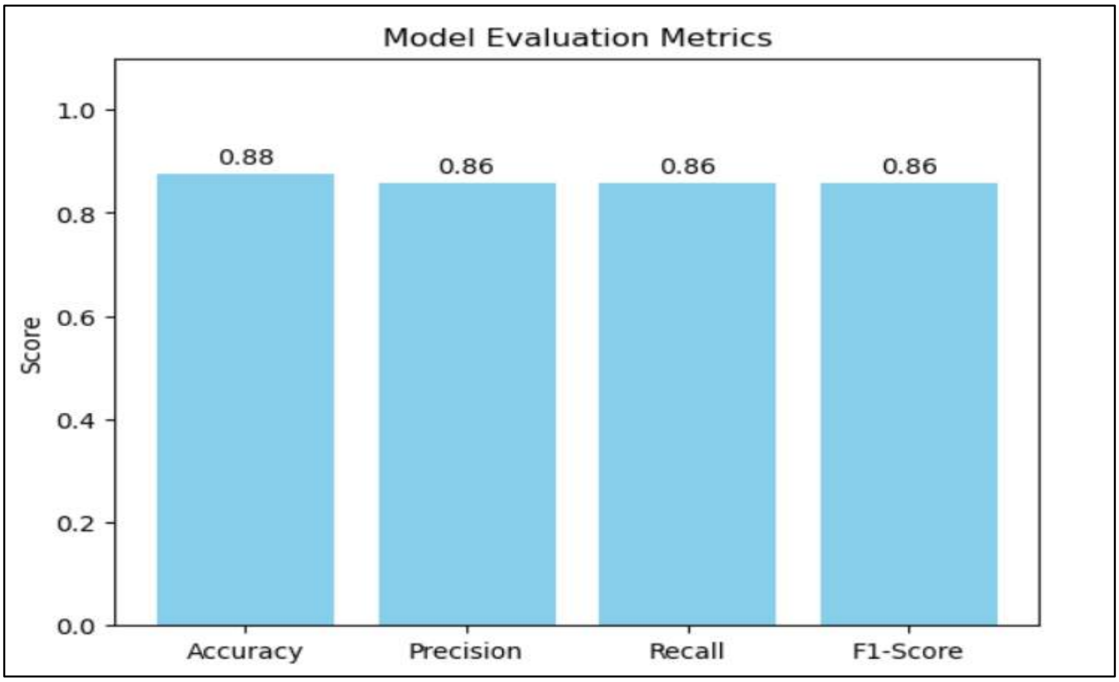
Source: Author's Own

- True Negatives (8 cases): The model correctly identified 8 firms as non-distressed.
- True Positives (6 cases): The model correctly classified 6 firms as distressed.
- False Positives (1 case): One firm was incorrectly classified as distressed despite being non-distressed.
- False Negatives (1 case): One firm was incorrectly classified as non-distressed despite being truly distressed.

Out of 16 total firms, the model misclassified only 2 cases, indicating strong overall accuracy. The balance between false positives and false negatives suggests the model is not overly biased towards one class. Correctly identifying 6 out of 7 distressed firms is especially valuable, as detecting financial distress early is critical in corporate risk management. The model shows high reliability in distinguishing between distressed and non-distressed firms, with a minimal error rate. While improvements can still be made to reduce misclassifications, the current performance indicates that the textual data features used carry significant predictive power.

The evaluation of the trained model was carried out using four key performance metrics: Accuracy, Precision, Recall and F1-Score. The results are summarized below in the bar chart:

Figure 2 Model Evaluation Metrics



Source: Author's own

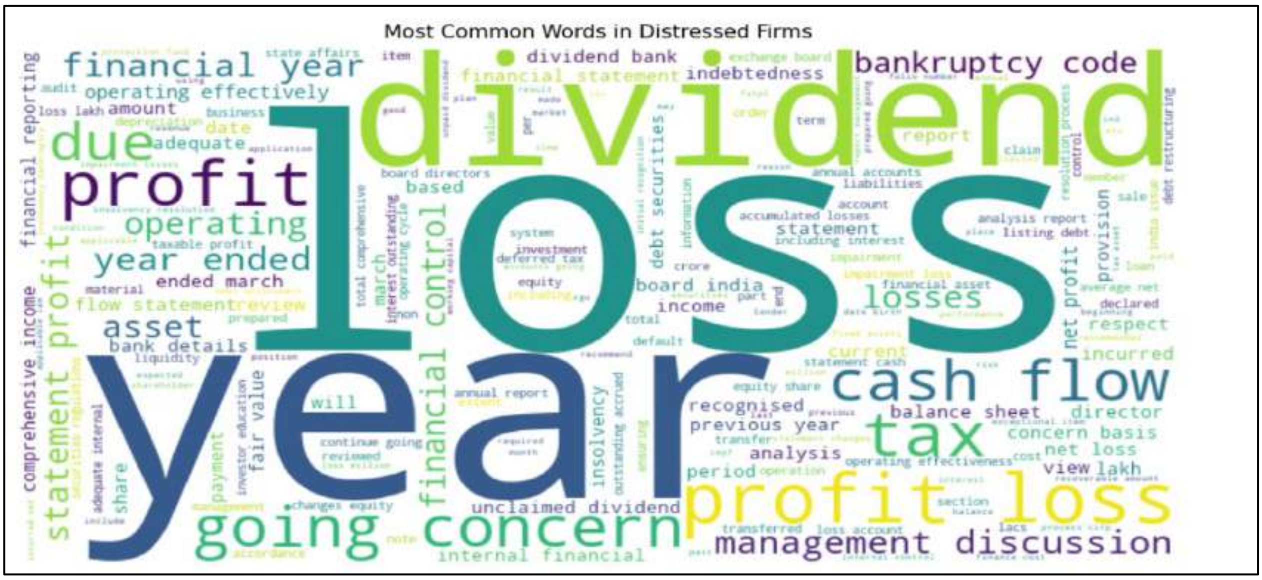
- **Accuracy (0.88):** The model correctly classified 88% of the total cases, reflecting strong overall performance.
- **Precision (0.86):** Of all firms predicted as distressed, 86% were truly distressed, indicating the model has a low false-positive rate.
- **Recall (0.86):** The model successfully identified 86% of all truly distressed firms, showing strong sensitivity to detecting distress.
- **F1-Score (0.86):** The harmonic mean of precision and recall is balanced at 0.86, suggesting the model performs consistently without favoring one metric over the other.

The metrics demonstrate that the model is both accurate and balanced in its predictions. While accuracy is slightly higher, the near-identical values of precision, recall and F1-score highlight that the model maintains a good equilibrium between identifying distressed firms correctly and avoiding misclassification of non-distressed firm

The evaluation confirms that the model is a robust and reliable tool for predicting financial distress. Its balanced performance across metrics makes it suitable for practical applications in corporate risk assessment, regulatory monitoring and early warning systems.

A word cloud was generated to visualize the most frequently occurring terms in the reports of distressed firms. In this visualization, the size of each word represents its relative frequency in the dataset i.e. larger words appear more often while smaller words are less frequent.

Figure 3: Word Cloud



Source: Author’s own

The dominant presence of terms such as “year,” “loss,” “dividend,” “profit,” “due,” and “operating” reflects the recurring emphasis on financial performance and reporting periods in these disclosures.

The prominence of “loss,” “cash flow,” “tax,” and “provision” suggests that distressed firms often face persistent financial challenges, liquidity constraints and tax-related obligations, which are critical issues leading up to bankruptcy. Similarly, terms like “concern,” “management discussion,” “bankruptcy,” and “code” indicate that these firms are frequently compelled to discuss their ongoing viability, compliance requirements and governance-related matters.

Additional recurring words such as “control,” “balance sheet,” “indebtedness,” “asset,” and “going concern” further emphasize the struggle to manage solvency, debt obligations and asset positions. The frequent appearance of “board,” “statement,” and "ended" also reflects the standardized and compliance-driven language often found in corporate disclosures of troubled firms.

Taken together, the word cloud indicates that distressed firms' textual narratives are dominated by themes of losses, financial constraints, compliance reporting and solvency risks. These patterns reinforce that language used in financial disclosures contains strong distress signals, thereby supporting its application in predictive modelling for firm distress.

7. Conclusion:

This study demonstrated that textual disclosures extracted from corporate reports can serve as dependable indicators for predicting financial distress. Textual disclosures in corporate reports can be leveraged as dependable predictors of financial distress. After applying thorough preprocessing steps, the classification model reached 88% accuracy, with precision, recall and F1-score each at 0.86, demonstrating strong and balanced performance. The confusion matrix further confirmed the model's reliability, showing only two misclassifications.

The word cloud analysis highlighted that distressed firms consistently emphasize terms like loss, dividend, cash flow, provision, bankruptcy and going concern. This consistent focus points to recurring themes around profitability, liquidity and sustainability, showing how narrative disclosures can signal financial weakness long before any formal bankruptcy process.

Overall, these results indicate that integrating machine learning with textual analysis offers a valuable supplement to traditional financial ratios. While the study's scope was limited by dataset size, the evidence supports the idea that narrative analysis can strengthen early warning systems for corporate distress. Expanding future research with larger datasets and more advanced NLP approaches could further boost predictive performance and extract deeper insights from disclosure narratives.

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Interplays between Credit and Output: New Empirical Evidence from the Panel of Indian States

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Abstract

A suitable connection between the financial sector (FS) and the real sector (RS) is essential for achieving balanced growth and development in a country, especially for those nations where financial development remains unsaturated. This study assesses the long-run (LR) connections between commercial bank credit and NSDP across Indian states from 2001 to 2023 using a panel data technique. Utilizing the PC and VECM methods, the study reveals that indicators of both sectors are cointegrated, indicating the existence of LR equilibrium relationships. The findings also reveal a demand-following (DF) relationship in the LR and bidirectional interplay between NSDP and credit in the short run (SR). The study advocates for the enhancement of both sectors' developments to ensure their interconnected effects elevate the states to new levels of growth and development.

Keywords: Unit roots, NSDP, credit & VECM.

1. Introduction

There has been debate and discord among two groups of economists over the effect of financial institutions on the RS of the economy. Adam Smith's (1789) group contended that financial institutions exert no influence on the productive activities of the actual sectors and, thus, on a nation's growth. Schumpeter (1911) led another group that posited an opposing argument or that presented the opposite viewpoint. He asserts that the advancement of the FS is crucial for EG. It fosters EG via technological advancements. His argument posits that FD influences EG by supplying adequate funds to enterprises that utilize resources most productively. After much discourse, Patrick (1966) islikely the first to explicitly delineate the direct connection between FD and EG. He contends that the connection between credit and the expansion of domestic products can be explained in two ways. One is the Supply Leading Approach (SLA), while the other is the Demand Following Approach (DFA). Under SLA, the behaviour of credit under SLA is similar to conventional production inputs, suggesting that an increase in credit may result in the growth of a nation's domestic product. Conversely, the DFA framework posits that the development of the RS leads to a nation's financial progress. A nation's credit facilities expand only when its infrastructure develops or its domestic product grows. Patrick posits that the SLA is probably applicable during the early phases of development, while the DFA is more relevant in the later stages. A suitable connection between the sectors is essential for balanced growth and development at both the national and regional levels, especially in nations where FD is not fully realized.Over time, empirical support has been found for the two opposing views on whether the two sectors are interconnected. The existing literature includes studies from both advanced and emerging economies. There are few studies addressing the topic at the sub-national economic level. This paper seeks to explore this arid region with distinct objectives.

2. Survey of Literature

We first discuss several pieces of research that explore the favourable relationship between financial development (FD) and economic growth (EG). In another study, Demetriades and Hussein (1996) demonstrated a bilateral connection between EG and FD in a cohort of sixteen less developed nations. Ahmed and Ansari (1998) identify a robust correlation between FD and EG in a cross-country analysis. Furthermore, their causality findings validate the SLA. The study of Fase (2001) conducts an empirical analysis of the connection between FD and EG. Using aggregated balance sheet data from financial organisations in the Netherlands spanning 1900–2000, Fase demonstrates that financial intermediation fosters EG. In the Indian context, Misra (2003) investigated the credit-output connection by using data from 25 Indian states between 1981 and 2000. The research demonstrated substantial backing for the credit-output relationship in Indian states. Bader and Qarn (2007) observe a two-way causal relationship between FD and EG. They have also highlighted the necessity of accelerating financial reforms to enhance EG. In a separate study, Katircioglu and Benar (2007) assessed the connection between FD and EG in the context of India. Their research demonstrates a bidirectional causation between FD and EG.

Acharya et al. (2009) assessed the financial-growth connection in the Indian states and identified a LR association between two. Kiran et al. (2009) shown that, for 10 emerging nations, including India, from 1968 to 2007, there is a LR connection between FD and EG.

In the Indian context, Bhanumurthy and Singh (2009) demonstrated that financial inclusion, among other factors, has contributed to the country's strong GDP growth. They have demonstrated that branch growth is not an appropriate measure of FD. They also noted a cointegrated link between the SDP ratio and the credit-deposit ratio. In another study, Okyo (2012) looked into how bank credit affected EG in Nigeria and determined that such credit exhibits a significant positive correlation with GDP. The study by Ray (2013) investigates the relationship between FD and EG in India from 1990-91 to 2010-11. The research revealed that FD significantly affected EG. In Turkey, Arac et al. (2014) look into the connection between FD and EG. Their finding demonstrates that the FD and EG indicators have a long-term relationship. Additionally, their findings support both the DF and SL hypotheses in the SR. Gyanwaly (2014) analysed the connection between FD and EG in Nepal, utilising data from 1975 to 2014. The research identified a significant positive connection between FD and EG.

In another study, Sehrawat and Giri (2015) conducted a state-specific study in India that looked at how FD affected the 28 states' growth between 1993 and 2012. Their findings substantiate the SLA in the short run (SR), whereas in the LR, a two-way causality exists between EG and FD. Narayanan (2015) investigates the interplay between India’s agricultural GDP and formal agricultural credit. The research indicates that agricultural input utilization is responsive to credit availability, while agricultural GDP is not affected. Thus, credit appeared to facilitate both agricultural and overall EG. Kaushal and Ghosh (2016) examined the LRconnection between FD and EG in India. Their analysis demonstrated a LR association between financial institutions and EG in India. In their research, Sehrawat and Giri (2017) confirm a LR connection among the FD index, trade openness, and EG in India, with causality tests indicating a uni-directional causality from FD to EG.In a similar study, Helhel (2018) identified a unidirectional causal association from growth to FD.

In another study, Aydın (2019) analyses the relationship between FD and EG among the Fragile Five nations from 1992 to 2016, revealing a strong and significant LR connection between EG and FD.In their research, Gülay and Cowley (2020) reassess the impact of FD on EG in Turkey from 2006 to 2015 and observe a significant positive connection between them.Recent research by Nguyen et al. (2022) utilizing data from 22 nations found that FD had a favourable impact on EG in emerging nations, showing a bidirectional and linear relationship between the two.

Alongside the above-mentioned study that endorses the positive association between FD and EG, there are also studies that present opposing viewpoints regarding a connection between the two. Lucas (1988) found no connection between EG and finance, describing the association between FD and EG as 'overstressed.' Demetriades and Luintel (1996) indicated that India's financial policy adversely affected growth, as the outcomes of such liberalization were significantly contingent upon institutional factors, such as effective governance, which India lacked. In another study, Sarkar (2009) investigates the potential influence of FD on EG. The study concluded that a negative causal relationship occurs from FD to EGwhile a positive causal association s present from EG to FD in the panel. However, based on data sets from each country, the study found that, for the majority of the countries, there is no association between the two, either short-term or long-term. Ince (2011) examined the nexus between FD and EG in Turkey. The study's findings revealed no LR association between economic expansion and FD.

Recent studies indicate that FD is beneficial only to a certain extent, beyond which it impedes growth. The association between the two variables is characterized by a non-linear, inverted U-shape. Cecchetti and Kharroubi (2013) found in their research that the threshold for bank-extended private sector credit is approximately 90% of GDP. Their findings indicate that accelerated growth in the FS correlates with decelerated growth in the whole economy. This study also indicates that extensive and swiftly growing FS can impose considerable costs on the broader economy, as their development depletes existing economic resources.

Bolukoglu (2021) analysed data from one hundred countries between 1995 and 2018 and found that finance and growth are directly related when FD is low, but this relationship is insignificant when FD is high. In another study, Omar and Khalid (2022) investigated the association between EG and FD in forty African economies spanning 1980 to 2019. The results demonstrated that bank credit is insignificant for EG in African economies.

Rationale of the Study

To sum up, the literature assessment indicates that opinions on the relationship between FD and EG are not all in agreement. Contradictions and variations in the findings on the connection between FD and EG suggest a need for a re-examination of this relationship. The study also indicates that the link is contingent upon the selection of FD indicators and the degree of financial inclusion within the economy. Furthermore, in most cases, the literature assessment summarizes the connections between FD and EG at the national level without having many detailed studies at the state level in India. Therefore, the current study looks at the SR and LR connection between commercial bank credit and NSDP across a panel of Indian states between 2001 and 2023 to close the gap in the literature.

3. Data and Methodology

We have obtained state-level data on credit from scheduled commercial banks in India (measured in Rs. lakh) and output data represented by net state domestic products (NSDP) at constant 2011–12 prices (also in Rs. lakh) from the database of the RBI for a panel of 20 Indian states for the period 2001–2023.

Methodology

Panel unit root (UR) test

When panel data includes n cross-sections and m times, conducting individual unit root tests may encounter a power issue, which can result in spurious regression outcomes. We resolve this issue and obtain more powerful results using a panel UR test. This study has primarily focused on panel data analysis.

Levin-Lin-Chu (LLC) (2002) proposed testing method for Panel unit root with homogeneous coefficients (βis) across all units. In contrast, Im et al. (1997, 2003), along with the Fisher type test using ADF and PP tests by Maddala and Wu (MW) (1999)& Choi (2001), addressed cases with heterogeneous coefficients across individual units.

The model by LLC (2002) are represented by the Eq. (1), where $\beta_i s = \beta$:

$$\Delta C_{i,t} = \pi_i C_{i,t-1} + \sum_{j=1}^{p} \hbar_j \Delta C_{i,t-j} + R'_{i,t}\,\lambda_i + \varepsilon_{i,t} \qquad (1)$$

The variable 'C' representing 'credit and NSDP' in the present study, Where, $i = 1, 2, 3, ...N$ (here, N = 20) represents cross-section units like country or states and t = 1, 2, ..., T (here, T = 23), where t indicates time. $C_{i,t}$ is said to have a UR if $\pi_i = 0$ and stationary if $\pi_i < 0$.

In accordance with Fischer's recommendations, MW provided test statistics structured as follows:

$$\chi^2 = -2\sum_{i=1}^{N}(\log \pi_i) \qquad (2)$$

It follows $\chi^2{}_{2N}$.

Panel Cointegration (PC) test

The assessment of cointegration among variables was conducted using the Pedroni test, which is grounded in Engle and Granger's (1987) two-step technique. The following is an outline of the methodologies.

Pedroni expands the Engle-Granger (1987) framework to test the presence of cointegrating relationships in panel data. This test is based on heterogeneous intercepts and trend.Primary and auxiliary regression are shown below

$$C_{i,t} = \beta_i y_{i,t} + e_{i,t} \quad (3)$$

$$e_{i,t} = \rho_i e_{i,t-1} + \sum_{j=1}^{p_i} \Psi_{ij} \Delta e_{i,t-j} + w_{i,t} \qquad (4)$$

To evaluate the null of absence of cointegration (i.e., $\rho_i = 1$), the Pedroni PC test statistic is derived from the residuals of Eq. (4). To evaluate the null (i.e., $\rho_i = 1$), Pedroni derives seven test statistics. Among these, four are derived from within-dimension statistics, while the other three PC statistics are based on between-dimension.

Vector Error Correction (VEC) Mechanism

Upon establishing the presence of the LR equilibrium relationships between the proposed variables, we will proceed to construct the panel VECM to detect the SR adjustment of the variable to its LR.

We consider 2-variables with a single cointegrating equation and without any lagged difference factors that can be specified as follows:

$$C_t = \beta y_t \qquad (5)$$

And the estimated error term is

$$\varepsilon_{t-1} = C_{t-1} - \beta y_{t-1} \qquad (6)$$

Hence, our VEC model

$$\Delta C_t = \lambda_c (C_{t-1} - \beta y_{t-1}) + e_c \qquad (7)$$

$$\Delta y_t = \lambda_y (y_{t-1} - \beta C_{t-1}) + e_y \quad (8)$$

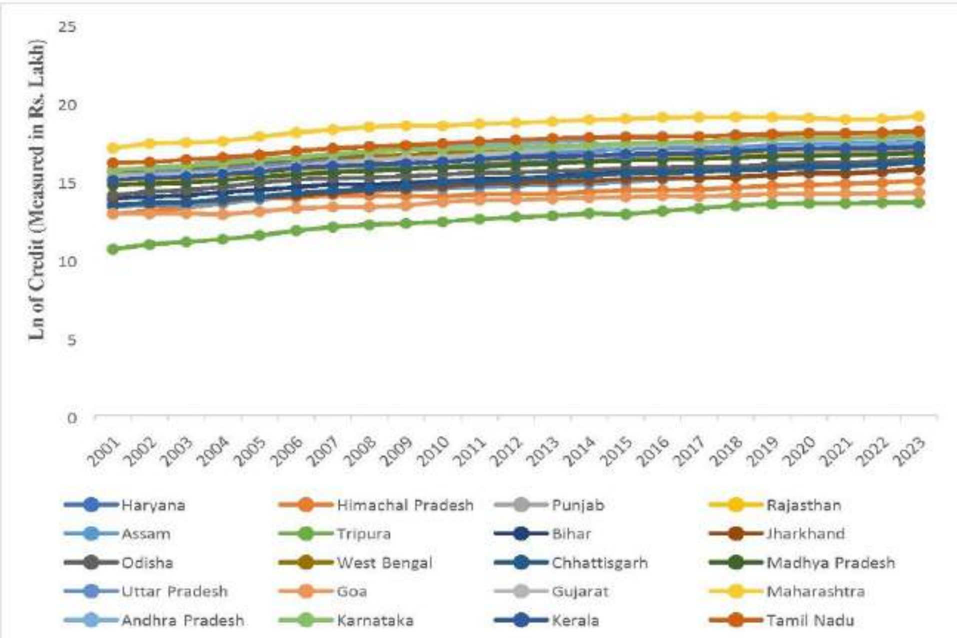
The sole variable on the R.H.S is the EC term. The coefficient 'λ' givesthe speed of adjustment to LR equilibrium. Furthermore, if $\lambda < 0$ & significant, it indicates the existence of the LR causation from either exogenous variable to either endogenous variable.

Finally, the SR causality can be tested in this VEC mechanism framework by employing the Wald test.

4. Results and Discussion

We will first provide a graphical depiction of the natural logarithm values of the two series before performing a quantitative evaluation of our hypothesis regarding the SR and LR relationships between credit and NSDP in Indian states. The charts for lncredit and lnNSDP in the states during the study period are presented in Figures 1 and 2, respectively.

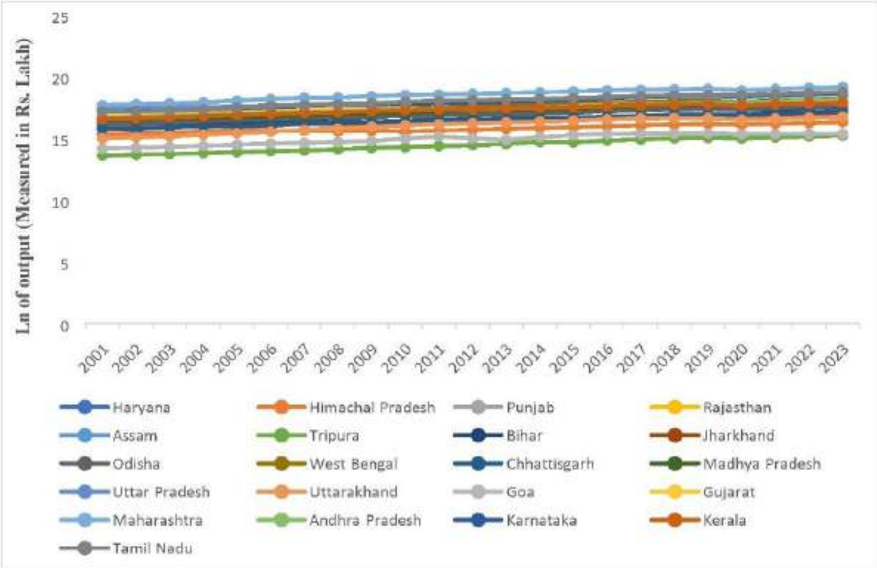
Figure 1. Series for lnCREDIT



Source: Sketch by the author on the basis of RBI data

Fig. 1 shows that all in-credit series have an upward trajectory over the years. Maharashtra has the highest credit level, which is significantly higher than that of the following states, including Tamil Nadu, Karnataka and West Bengal. Tripura is at the bottom of the whole credit sequence.

Figure 2. Series for lnNSDP



Source: Sketch by the author on the basis of RBI data

Figure 2 illustrates that all series of the state's output exhibit upward trends. In the entire lnNSDP series, the state of Maharashtra is at the top of the group. In terms of state NSDP, Tripura has consistently maintained its 20th-place ranking over time, similar to its credit ranking.

4.1. Panel unit root (UR) results

We conducted Panel UR tests under common and individual UR processes, following Eqs. (1) – (2) for the NSDP and credit series of the panel of Indian states. These tests have been conducted both at the level (values not shown) and at the first difference. Table 1 displays the estimated outcomes. It has been noted that the Credit and NSDP series are both non-stationary at their level but stationary at I(1). Therefore, we proceed to examine PC between proposed variables.

Table 1: Panel Unit root test results for Credit and NSDP at their First Differences

Method	First Difference (Prob.)		First Difference (Prob.)	
	Test statistics with considering intercept		Test statistics with incorporating intercept and trend	
	Credit	NSDP	Credit	NSDP
Levin, Lin and Chu	-5.126 (0.00)	-6.248 (0.00)	-7.145 (0.00)	-5.877 (0.00)
Im, Pesaran and Shin	-7.022 (0.00)	-6.562 (0.00)	-8.837 (0.00)	-6.100 (0.00)

MW–ADF–Fisher chi-square	133.317 (0.00)	119.536 (0.00)	152.122 (0.00)	106.952 (0.00)
MW–PP–Fisher chi-square	129.572 (0.00)	235.053 (0.00)	141.410 (0.00)	285.494 (0.00)

Source: The authors.

4.1.1. Panel Cointegration (PC) Results

Now that we have met the main requirement for doing cointegration tests, which is that both series are I(1), we will look for LR relationships between credit and output in the chosen states. The Pedroni test results at various specifications are presented in table 2.

Table 2. Pedroni Residual Panel Cointegration Test

Test Criteria	H_0: Does not have Cointegration	Test	Statistic (Prob.)	Statistic (Prob.) with Weighted
No deterministic trend	AR coefficients (within-dimension)	v rho pp ADF	3.02 **(0.00)** -0.16 (0.43) 0.23 (0.59) -0.90 (0.18)	3.72 **(0.00)** -1.59 **(0.05)** -1.91 **(0.02)** -4.05 **(0.00)**
	AR coefficients (between-dimension)	Rho pp ADF	-0.22 (0.41) -1.79 **(0.03)** -5.35 **(0.00)**	- - -
Deterministic intercept and trend	AR coefficients (within-dimension)	v rho pp ADF	7.94 **(0.00)** -0.57 (0.28) -3.13 **(0.00)** -5.35 **(0.00)**	3.25 **(0.00)** -0.54 (0.29) -2.64 **(0.00)** -5.31 **(0.00)**
	H_1: AR coefficients (between-dimension)	Rho pp ADF	0.81 (0.79) -3.18 **(0.00)** -6.09 **(0.00)**	- - -
No deterministic intercept and trend	H_1: AR coefficients (within-dimension)	v rho pp ADF	0.35 (0.36) -0.82 (0.20) -1.87 **(0.03)** -2.10 **(0.01)**	-1.28 (0.90) 0.25 (0.60) -0.74 (0.22) -1.02 (0.15)
	H_1: AR coefficients (between-dimension)	Rho pp ADF	2.91 (0.99) -0.36 (0.35) -0.76 (0.22)	- - -

Source: The authors.

The Pedroni test findings reveal that out of 11 statistics for the deterministic intercept and trend criteria, 8 show significant results, while 7 out of 11 statistics for the no deterministic trend method also show significant results, supporting the presence of cointegration.

The PC results indicate that the series on credits and NSDP of the Indian states are cointegrated and exhibit a LR equilibrium connection.

4.1.2. VECM Results

Having established the LR association between two variables, the next step is to investigate the panel VEC to see the dynamics after any departures from the LR. The VECM encapsulates this behaviour. Utilizing Equations (5) – (8), we have calculated the EC terms.Table 3 displays the panel VECM results.

Table 3. VECM Results

Dependent Variable	EC term	Errors Corrected?	Remarks
D(CREDIT)	C(1) = -0.0318 (0.000)	Yes	**LR causality from NSDP to CREDIT**
D(NSDP)	C(1) = 0.0177(0.217)	No	No LR causality from CREDIT to NSDP

Source: The authors.

Table 3 demonstrates that the signs of the EC terms are negative and significant when credit is the endogenous variable but positive and insignificant when NSDP is the response variable. Moreover, the VECM outcomes demonstrate a LR causal association from NSDP to CREDIT, but not the reverse. Thus, our results indicate that FD and EG in the LR have a DF relationship.

Table 4. Short-Run Causality Through Wald Test

Dependent Variable	Chi-square	Remarks
D(CREDIT)	232.04 (0.00)	**NSDP $\rightarrow$CREDIT**
D(NSDP)	109.70 (0.00)	**CREDIT $\rightarrow$ NSDP**

Source: The authors.

Finally, the test for SR causality between the variables has been derived from the Wald Test (Table 4). The findings demonstrate a bi-directional causality between the proposed variables. Therefore, the econometric analyses of the panel data of the Indian states indicate a LRconnection between credit and output; however, a unidirectional causality is identified in the LR from EG to FD. Nonetheless, there exist bilateral causal relationships between the two-variable panel in the SR. It also shows that the FS and the actual sectors of the Indian state are interconnected, and both the DF and SL approaches have been effective for the states as a whole.

Thus, in the long run, our results are consistent with the findings of Kandir et al. (2007), Bhanumurthy and Singh (2009), & Helhel (2018). Furthermore, the short-run analysis supports Arac et al. (2014) & Patrick's (1966) claim that both the DF and SLA have been effective for all states.

5. Conclusion and Managerial Implications

We are now on the verge of concluding our analysis of the LR relationships between credit and NSDP in the panel of Indian states. We noted that the series under the panel of states had a unit root at the level but was stationary at I(1). We also infer that the series for credit and NSDP from 2001 to 2023 demonstrate LR connections; however, unidirectional causal linkages are identified in the LR from NSDP to credit. In other words, the findings corroborate the DF pattern in the LR. Furthermore, the outcomes of the SR causality tests reveal bidirectional interplay between proposed variables in the panel. We also conclude that the FS and real sector of the Indian state are interconnected, and both the DF and SL patterns have been effective for the states as a whole in the SR. Since bank credits and the outputs of Indian states have LR linkages, it is suggested that the government and policymakers should prioritize improving credit availability in the banking and FS to enhance long-term EG in India.

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