Original Research Article

Determinants and Heterogeneity of District Level Financial Inclusion in Rajasthan: Evidence from Swamy's Panel Data Random Coefficient Model

ABSTRACT

This study examines the heterogeneity and determinants of financial inclusion across 30 districts of Rajasthan over the period 1994-2023, with a specific focus on deposit and credit penetration as key dimensions of financial inclusion. This study employs a range of well-established panel data econometric techniques – namely, Pooled Ordinary Least Squares Model, Fixed Effects Model, Random Effects Model, Panel-Corrected Standard Errors, Feasible Generalized Least Squares, Generalized Method of Moments, and Swamy's Random Coefficient Model - to analyze district-level data. In this study, two models are estimated taking per capita deposit and per capita credit as dependent variables. The explanatory variables include the number of bank branches, per capita net district domestic product, manufacturing activity, and population growth. The findings consistently indicate that banking infrastructure and per capita net district domestic product significantly promote financial inclusion, whereas manufacturing activity and population growth exhibit heterogeneous effects across districts. Accordingly, the study advocates for tailored district-specific interventions, with particular emphasis on expanding banking infrastructure and fostering local economic development.

Keywords: District Level Financial Inclusion, Panel Data Analysis, Rajasthan.

JEL Classification: G21, C23, R10, O16, R20.

1. INTRODUCTION

Financial inclusion refers to the process of integrating the marginalized and vulnerable segment of society into the formal financial system. It ensures that disadvantaged groups, such as low-income individuals, have access to timely and adequate credit as well as other financial services at an affordable cost. A well-developed banking infrastructure and an extensive branch network play a crucial role in fostering financial inclusion. In turn, financial inclusion contributes to economic growth, investment expansion, employment generation, and infrastructure improvement (Feldstein and Horioka, 1980; Brunetti et al., 1997; Hartog and Oosterbeek, 1993).

Over the past decade, India's banking sector has undergone substantial growth in both scale and operational complexity. Although considerable progress has been made in financial stability, profitability, and competitiveness, concerns persist that essential banking services have not fully reached marginalized and vulnerable communities. Consequently, policymakers and financial institutions have intensified efforts to promote financial inclusion, recognizing its potential to significantly enhance the economic well-being and living standards of poor and disadvantaged groups (Leeladhar, 2006; Subbarao, 2009; Thorat, 2008).

Financial inclusion is widely recognized as a key driver of sustainable and inclusive economic growth. However, despite economic liberalization and the adoption of a market-driven strategy, India continued to face challenges in achieving the desired level of inclusive growth. One useful indicator for assessing financial exclusion is the indebtedness of agricultural households. Data from the National Sample Survey Office (NSSO) 70th round survey show that 51.9 per cent of agricultural households in India are indebted, with an average outstanding loan amount of ₹47,000. Households that do not hold any debt from formal credit institutions are classified as financially excluded according to the NSSO classification.

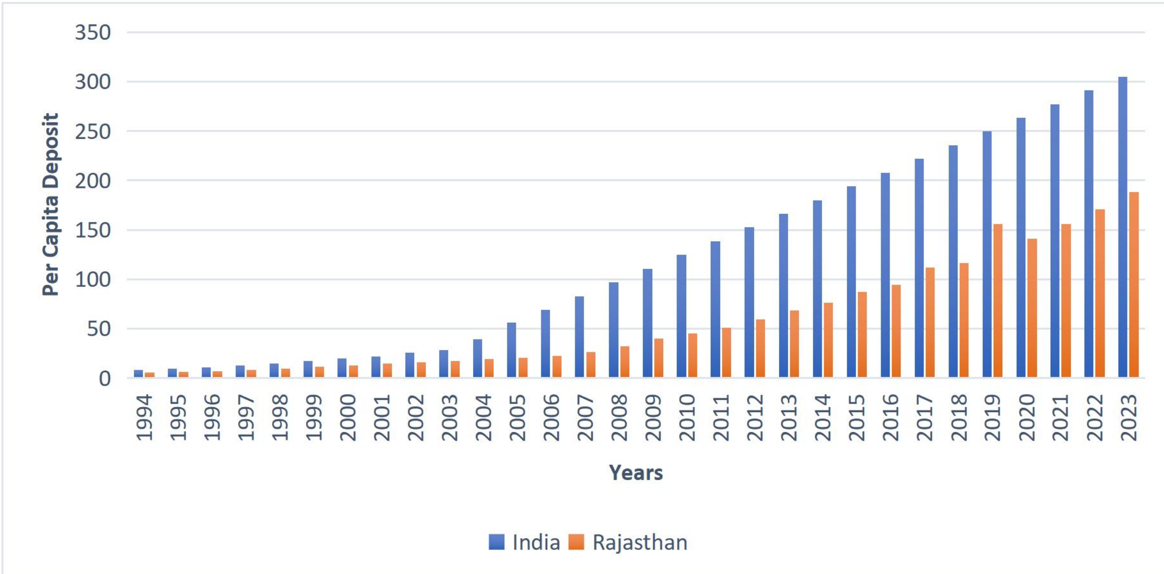
Since 2005, reducing financial exclusion has been a priority for both the Indian government and the Reserve Bank of India, as outlined in the 12th Five-Year Plan. In Rajasthan, where access to basic financial services has historically been limited, the proportion of agricultural households without access to formal credit declined from 47.6 per cent in the NSSO 59th round to 37.6 per cent in the NSSO 70th round. This share further decreased to approximately 25.9 per cent in the NSSO 77th round. However, the Rangarajan Committee (2008) reported that about 14 districts in the state exhibited a substantial credit gap ranging from 95.2 per cent to 97.8 per cent.

Despite the expansion of formal financial institutions, informal lending channels- such as money lenders, friends and relatives- continue to play a significant role in meeting the credit needs of households in Rajasthan. The NSSO 77th round further indicates that approximately 28.5 per cent of rural households and 9.4 per cent of urban households relied on these informal financial channels, highlighting the continued dependence on non-institutional credit, particularly in rural areas.

Although banks have increased their share of institutional finance by 27 per cent over two survey rounds, money lenders have simultaneously expanded their share of non-institutional lending by 31 per cent. Consequently, a substantial number of households, especially those with smaller landholdings, continue to rely on informal sources of credit. According to the NSSO 77th round, 60.3 per cent of agricultural households in Rajasthan were indebted, with an average outstanding loan of ₹113,865 per household. These figures indicate that despite various government initiatives aimed at strengthening financial inclusion, considerable challenges remain.

This study has been conducted taking separate penetration indicators for deposit and credit accounts. This helps avoid the aggregation issues often seen in index construction. Moreover, deposit and credit accounts serve different purposes. Deposit accounts (including savings and term deposits) suit individuals and households with regular incomes, allowing them to save and withdraw funds as needed—especially those in urban areas and the formal sector. By contrast, credit accounts support entrepreneurs and households seeking loans for business or personal needs, and banks generally require proof of financial stability or income to reduce default risk. Given their distinct functions, it is crucial to evaluate deposit and credit products independently.

A comparative analysis of the financial inclusion indicators for India and Rajasthan provides insights into financial penetration over time. These findings, illustrated in Figure 1 and Figure 2, highlight the factors influencing the Financial Inclusion Index (FII) and underscore how the two regions differ in their pace and extent of financial service adoption.



Source. Constructed by authors using DES and DBIE database.

Figure 1. India and Rajasthan per account deposit

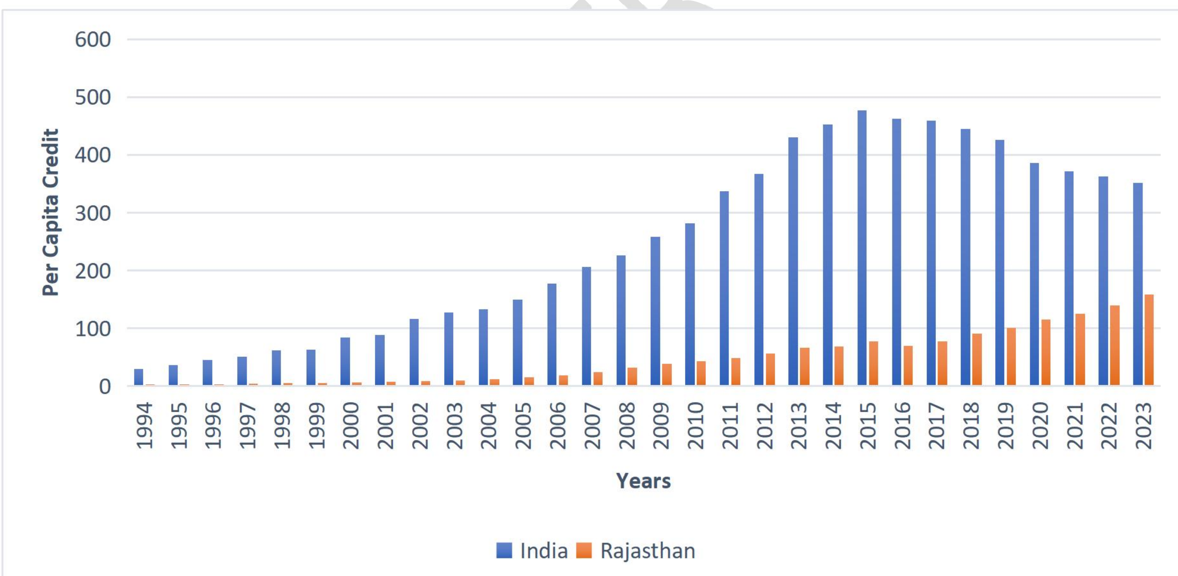


Figure 2. India and Rajasthan per account credit

Source. Constructed by authors using DES and DBIE database.

Both Figure 1 and Figure 2 illustrate a clear upward trend in the average (per account) deposit and credit amounts for both India and Rajasthan from 1994 to 2023, reflecting the steady growth of financial services in both regions. In Figure 1, India consistently shows higher per account deposit values than Rajasthan, indicating stronger deposit mobilization at the national level. However, Rajasthan has shown significant improvement in recent years, gradually narrowing the gap and reflecting increasing access to and usage of formal savings instruments.

Figure 2 shows a similar upward trajectory in per account credit values, with India initially maintaining a substantial lead. Nonetheless, the graph reveals a notable surge in Rajasthan's credit figures in the later years, suggesting an ongoing catch-up in credit penetration. Any persistent gap between the two regions reflects disparities in access to formal credit, possibly driven by differences in infrastructure, income levels, or institutional outreach. Overall, the data highlights a continuous expansion in financial inclusion through deposits and credit across both geographies, while also emphasizing the existing gap in financial penetration that Rajasthan is gradually working to bridge.

Additionally, Figure 3 illustrates the distribution of per account deposit and credit amounts across districts of Rajasthan in 2023, highlighting notable differences in district-wise financial activity. It demonstrates where deposits outweigh credit and vice versa, indicating varying degrees of financial penetration. By including this chart, we can pinpoint districts needing more targeted interventions to balance deposit and credit growth.

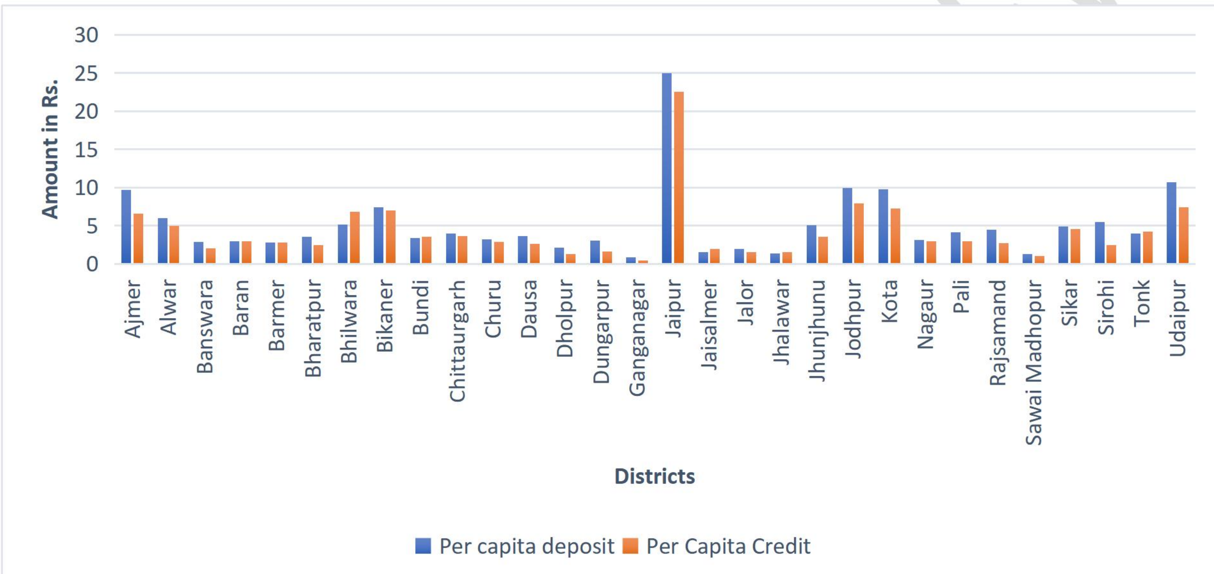


Figure 3. Per account deposit and credit of the districts of Rajasthan in 2023

Source. Constructed by authors using the DES database.

Figure 3 provides a comparative picture of deposits and credits per account across 30 districts of Rajasthan in 2023. The data clearly shows significant inter-district variation in financial activity. Jaipur stands out prominently with the highest values in both deposit and credit amounts, indicating its role as the state's primary financial hub. Ganganagar and Udaipur also exhibit relatively high financial activity, although the gap between deposits and credit is more pronounced in these regions.

In contrast, several districts such as Dholpur, Baran, and Bundi display considerably lower figures, reflecting limited financial penetration and possibly underdeveloped banking infrastructure. Interestingly, in a few districts like Ganganagar and Bharatpur, credit amounts are nearly equal to or exceed deposit amounts, which may point to higher lending intensity or agricultural and business credit dependency. Overall, the figure underscores the uneven distribution of financial resources across districts in Rajasthan, highlighting the need for more balanced regional development and targeted financial inclusion strategies. The disparities call for policy attention to enhance banking access and credit flow in lagging districts while sustaining the growth momentum in financially active regions.

In the light of above discussion, it is pertinent to examine the determinants of financial inclusion in 30 districts of Rajasthan, using data from 1994 to 2020.

The rest of the paper is structured as follows: Section 2 reviews related literature, Section 3 presents the methodology and outlines the data sources and variables, and Section 4 offers analyses to explore the determinants of financial inclusion using district-level data. Section 5 concludes the study, and Section 6 provides suggestions.

2. REVIEW OF LITERATURE

Researchers have used various methods to understand what drives financial inclusion—starting with simple comparisons across regions and gradually moving to more advanced techniques such as dynamic panel models and detailed individual-level analysis.

Bhanot et al. (2012) explored determinants of financial inclusion in rural India using data collected from household surveys. Their econometric analysis emphasized literacy, household income, employment status, and physical proximity to banking services as significant drivers. Notably, households with better literacy and higher income levels showed a stronger inclination to adopt formal financial services, highlighting education and economic empowerment as fundamental catalysts of financial inclusion.

Singh and Tandon (2012) investigated determinants of financial inclusion [measured by an Index of Financial Inclusion (IFI)] at the state level in India. Using Ordinary Least Squares (OLS) regression methods, they found that higher per capita Net State Domestic Product (NSDP) and increased urbanization rates were significantly associated with greater financial inclusion. Conversely, their study indicated that literacy and employment rates had no statistically significant impact on financial inclusion, suggesting economic factors might play a more dominant role than educational ones in promoting financial access.

Kumar (2013) employed a robust analytical approach by examining panel data for 29 Indian states from 1995 to 2008. Using both fixed-effects and Generalized Methods of Moments (GMM) models, Kumar identified employment generation through industrial growth and manufacturing sector expansion as key drivers of financial inclusion. His results emphasized that states having robust industrial activities experienced significantly higher levels of engagement with formal financial institutions, reinforcing the critical role of economic structure and employment opportunities in driving financial inclusion.

Allen et al. (2014) analyzed the determinants of financial inclusion using global cross-country data from the World Bank's Global Findex. Using Probit regression models, they showed that demographic characteristics such as gender, income, education level, age, and rural-urban location significantly affect account ownership and usage of formal financial services. They noted specifically that higher educational attainment and income levels substantially improved financial inclusion, while rural residence and female gender negatively influenced the likelihood of being financially included.

Yadav and Sharma (2016) analyzed factors influencing financial inclusion among Indian states using Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and regression analysis. Their findings identified agriculture's contribution to GDP, literacy rates, population density, infrastructure development, and farmer suicide rates as pivotal determinants. States with robust agricultural sectors and better-developed infrastructure exhibited higher levels of financial inclusion, underscoring the role of structural economic factors alongside social dimensions like literacy.

Ghosh and Vinod (2017) explored state-level determinants of financial inclusion in India, specifically focusing on banking infrastructure, education, urbanization, and internet penetration. Using panel data regression models, they established that urbanization and digital connectivity significantly accelerated financial inclusion. However, they also identified stark regional disparities due to unequal distribution of physical and digital infrastructure.

Demirgüç-Kunt et al. (2018) extensively analyzed determinants of financial inclusion across developing economies using Global Findex data. Their comprehensive global study employed multivariate regression analyses, revealing that income disparity, gender inequality, educational attainment, and institutional quality significantly shaped financial inclusion levels. Higher GDP per capita, better institutional quality, and stronger regulatory environments were positively associated with greater financial inclusion, reinforcing the critical role of governance and macroeconomic stability.

Sharma et al. (2018) examined the influence of infrastructural variables on the effectiveness of India's flagship financial inclusion scheme, Pradhan Mantri Jan Dhan Yojana (PMJDY). Their empirical analysis, using regression methods, demonstrated that infrastructural improvements, notably better road connectivity, positively influenced the number of bank accounts opened under PMJDY. They identified macroeconomic infrastructure, regional economic conditions, and labour market participation as critical determinants, showing that areas with better infrastructure and higher economic activity reported superior outcomes in financial inclusion metrics.

Anarfo et al. (2019) evaluated socio-economic and institutional determinants of financial inclusion across sub-Saharan African countries. Employing dynamic panel data models, the study identified governance quality, education, income levels, and mobile-phone penetration as significant factors influencing financial inclusion. Their analysis underscored that improvements in governance structures and digital infrastructure could dramatically enhance financial inclusion in economically developing regions.

Lal (2019) explored the role of cooperative banks in promoting financial inclusion and rural development. Using primary data collected through structured questionnaires in Jammu and Kashmir, Himachal Pradesh, and Punjab, and analyzing it through Structural Equation Modeling (SEM) and Exploratory Factor Analysis (EFA), he concluded that access to cooperative credit significantly enhanced rural socioeconomic conditions. The study indicated that cooperatives could effectively serve marginalized rural populations, suggesting targeted cooperative initiatives as determinants of financial inclusion.

Dar and Ahmed (2020) analyzed demographic determinants of financial inclusion using the Global Findex Database (2017) data. Using Probit regression models, they showed that age, gender, education, and income significantly influenced financial inclusion measures such as bank account ownership, savings patterns, and the use of digital payment methods. Their findings emphasized that demographic characteristics serve as crucial factors determining the extent and nature of financial inclusion across populations.

Jain and Bishnoi (2024) constructed a multidimensional Financial Inclusion Index (FII) as well as Financial Inclusion Dimension Indices and estimated the impact of financial inclusion on economic growth in Rajasthan using data from 1994 to 2021, employing the linear Autoregressive Distributed Lag (ARDL) and Non-Linear Autoregressive Distributed Lag (NARDL) bounds cointegration techniques. The results of the study show that Financial Inclusion Dimension Indices have a positive impact on growth rate in the long run in Rajasthan. From the NARDL model, it is evident that the coefficients of Financial Inclusion Dimension Indices are asymmetric, indicating that positive and negative changes in the Financial Inclusion Dimension Indices affect the economic growth differently.

The review of literature indicates that although research on financial inclusion has progressed considerably, there is no comprehensive study examining the inter-district heterogeneity in financial inclusion in Rajasthan, as well as the factors affecting it. To address this gap, the study first constructs separate deposit penetration and credit penetration indices. It then estimates their determinants via a sequence of panel models, including Pooled OLS, Fixed Effects and Random Effects Models, with statistical inference conducted through Panel-Corrected Standard Errors (PCSE) and Feasible GLS to account for cross-sectional dependence, autocorrelation, and heteroskedasticity. To address potential simultaneity issues in the model estimation, a system-GMM estimator is employed. Finally, recognizing that districts within Rajasthan may respond differently to the same determinants, Swamy's Random Coefficient Model is applied to capture cross-district heterogeneity in slope effects.

3. METHODOLOGY

3.1 Model Specification

The following models are specified to examine the effects of different determinants on financial inclusion, measured in terms of deposit and credit penetration:

Model I: Deposit Penetration Model

$$LPCDP_t=\beta_0+\beta_1 LBB_t+\beta_2 LPCNDDP_t+\beta_3 LMANP_t+\beta_4 LPOPGR_t+\varepsilon_{\mathrm{it}} \qquad (1)$$

Model II: Credit Penetration Model

$$LPCCR_t=\beta_0+\beta_1 LBB_t+\beta_2 LPCNDDP_t+\beta_3 LMANP_t+\beta_4 LPOPGR_t+\varepsilon_{\mathrm{it}} \qquad (2)$$

In the Deposit Penetration Model, LPCDP is the dependent variable representing the log of per capita deposit, and in the Credit Penetration Model, the dependent variable is LPCCR representing the log of per capita credit. These serve as proxies for financial inclusion, capturing the extent of formal financial service usage in terms of deposits and borrowing.

The independent variables include LBB (log of the number of bank branches), which indicates the availability and accessibility of banking infrastructure within each district. LPCNDDP (log of per capita net district domestic product) serves as a proxy for income levels and local economic prosperity, reflecting the capacity of households to engage with financial institutions. LMANP (log of contribution of manufacturing in gross state domestic product) captures the influence of industrial presence on financial access, as manufacturing hubs often facilitate greater employment and formal financial transactions. Lastly, LPOPGR (log of population growth rate) accounts for demographic pressures that may affect per capita financial service availability and demand. Together, these variables provide a comprehensive framework to assess the structural and socioeconomic determinants of financial inclusion across Rajasthan's districts over time.

Initially, this study applied the Pooled Ordinary Least Squares (POLS) Method, Fixed Effects Method (FEM), and Random Effects Method (REM), to examine the determinants of financial inclusion. Although panel data models generally incorporate temporal and cross-sectional dimensions, they can still be subject to autocorrelation, heteroskedasticity, and cross-sectional dependency. To mitigate these problems and strengthen the validity of the findings, the study employed Panel Corrected Standard Errors (PCSEs) and the Feasible Generalized Least Squares (FGLS) method. However, neither PCSEs nor FGLS is fully capable of resolving endogeneity concerns or addressing the risk of omitted variables. Consequently, the study ultimately adopts the Generalized Method of Moments (GMM) model to overcome these limitations.

Fixed Effects and Random Effects Models account for panel-specific differences by incorporating a set of parameters that effectively assign each panel its own intercept, while maintaining a common set of slope coefficients across panels. In contrast, Random Coefficients Models allow each panel to draw its own slope vector from a shared distribution, offering a more flexible approach. It also provides the best linear unbiased predictors of each panel's specific draws from that distribution. This model is more flexible than Fixed-Effects or Random Effects Models because it permits both intercepts and slopes to differ across panels, rather than forcing all panels to share the same slope coefficients. Under the null hypothesis, all panel-specific slope coefficients are identical. In other words, there is no significant variation in slopes across panels. Rejecting this null hypothesis indicates that at least one panel's slope parameters differ, supporting the idea that a Random Coefficient Model is more appropriate than a model assuming common slopes.

3.2 DATA SOURCES AND VARIABLES

The study uses data from the Directorate of Economics and Statistics (DES), Government of Rajasthan, the Economic and Political Weekly Research Foundation (EPWRF), and the Reserve Bank of India (RBI) for the period 1994–2023.

3.2.1 Description of Endogenous Variables

Sarma (2008) suggested using bank accounts per capita to measure the penetration of the banking system. In line with this approach, our study constructs penetration indicators by calculating the per capita deposit and per capita credit accounts, which serve as dependent variables, namely, LPCDP and LPCCR, respectively. Deposit accounts are ideal for regular income earners, especially in urban areas, to save funds that can be easily withdrawn. In contrast, credit accounts serve business and personal needs, with banks verifying borrowers' financial stability to minimize default risk. Due to these differences, each should be evaluated separately.

3.2.2 Description of Exogenous Variables

Four variables are used in this study as exogenous variables. These are the number of bank branches (BB), per capita net district domestic product (NDDP), manufacturing activity and population growth. The number of bank branches is used to examine the population segment served by banks. Income is measured by per capita net district domestic product at constant 2011-2012 prices. The contribution of manufacturing in gross state domestic product (MANP) serves as a proxy for the level of manufacturing in the state. Additionally, population growth rate(POPGR), which measures the rate at which a region's population increases is used to capture demographic changes and assess how a growing population may affect banking system penetration. All the variables used are converted into natural logarithms to get the values of elasticities directly.

4. DATA ANALYSIS AND RESULTS

4.1 Description Statistics and Correlation Matrix

Descriptive statistics and correlation matrix of selected variables are presented in Table 1.

Table 1. Descriptive statistics and correlation matrix of selected variables

			Descriptive Statistics			
	LPCDP	LPCCR	LBB	LMANP	LPCNDDP	LPOPGR
Mean	-0.2386	-0.7440	4.8582	2.9450	10.4148	0.8065
Median	-0.2758	-0.6283	4.8081	2.9216	10.4807	0.7841
Maximum	3.2191	3.1172	7.2233	4.2147	12.5796	3.8632
Minimum	-3.4112	-4.2687	3.5553	0.9982	7.7275	0.0010
Std. Dev.	1.2140	1.4567	0.6479	0.4549	0.9466	0.4512
Skewness	0.0720	-0.0647	0.5363	-0.0837	-0.0650	2.5468
Kurtosis	2.4093	2.2566	3.6553	3.4498	2.1243	13.9131
Jarque-Bera	13.860	21.3511	59.2524	8.6400	29.3921	5438.970
Probability	0.0010	0.0000	0.0000	0.0133	0.0000	0.0000
Sum	-214.75	-669.63	4372.37	2650.49	9373.31	725.8743

Sum Sq. Dev.	1324.93	1907.47	377.36	186.023	805.5230	182.9873
Observations	900	900	900	900	900	900
Correlation Matrix						
LPCDP	1.0000					
LPCCR	0.9601	1.0000				
LBB	0.6167	0.5983	1.0000			
LMANP	0.0876	0.0754	0.2220	1.0000		
LPCNDDP	0.8903	0.8918	0.4526	-0.1475	1.0000	
LPOPGR	-0.2152	-0.1979	-0.1620	0.0091	-0.1971	1.0000

Source. Calculated by authors.

The descriptive statistics reveal that most variables exhibit negative skewness and positive kurtosis, indicating a departure from normality, a finding supported by the Jarque-Bera test statistics. Specifically, the Jarque-Bera values are all statistically significant, underscoring these deviations. The correlation matrix demonstrates that LPCNDDP and LBB have substantial positive correlations with the dependent variable. LPOPGR shows a modest positive association, whereas LPCCR and LPCDP have slight negative correlations with the dependent variable.

In summary, the correlation analysis highlights significant relationships between indicators of financial penetration (LPCCR, LPCDP, LPCNDDP) and the dependent variable, alongside a moderate correlation with the banking branch presence indicator (LBB). However, variables such as population growth (LPOPGR) and manufacturing (LMANP) exhibit weaker or inconsistent correlations.

4.2 Estimation Results for Credit and Deposit Penetration

Table 2 presents the estimated results for credit penetration model using various methods: POLS, FEM, REM, PCSE, FGLS and System Dynamic Panel and Table 3 presents the estimated results for deposit penetration model using various methods: POLS, REM, FEM, PCSE, FGLS and System Dynamic Panel.

Table 2. Estimations result for credit penetration

Dependent Variable is LPCCR						
	POLS	**FEM**	**REM**	**PCSE**	**FGLS**	**GMM**
LBB	0.421***	0.579***	0.556***	0.677***	0.756***	0.069
	(0.032)	(0.069)	(0.062)	(0.075)	(0.050)	(0.135)
LMANP	0.499***	0.340***	0.344***	0.145***	0.127***	0.039
	(0.042)	(0.035)	(0.035)	(0.038)	(0.022)	(0.024)
LPCNDDP	1.275***	1.230***	1.23***	0.945***	0.962***	0.225**
	(0.022)	(0.025)	(0.023)	(0.065)	(0.026)	(0.089)
LPOPGR	-0.178	-0.121	-0.013	-0.034	-0.027**	-0.044***
	(0.040)	(0.026)	(0.026)	(0.023)	(0.012)	(0.012)
C	-17.534***	-17.368***	-17.345***	-14.316***	-14.783***	
	(0.258)	(0.225)	(0.233)	(0.738)	(0.277)	

*Note. Standard errors are given in parentheses. ***, ** and * represents significant at 1, 5 and 10 per cent level of significance, respectively. Source. Calculated by authors.*

Table 3: Estimation results for deposit penetration

Dependent Variable is LPCDP						
	POLS	FEM	REM	PCSE	FGLS	System Dynamic Panel
LBB	0.389***	0.726***	0.694***	0.605***	0.671***	0.139***
	(0.026)	(0.044)	(0.042)	(0.056)	(0.032)	(0.026)
LMANP	0.432***	0.251***	0.253***	0.102***	0.093***	0.044**
	(0.033)	(0.022)	(0.022)	(0.027)	(0.015)	(0.022)
LPCNDDP	1.046***	0.928***	0.938***	0.781***	0.786***	0.194*
	(0.018)	(0.016)	(0.015)	(0.047)	(0.017)	(0.091)
LPOPGR	-0.059**	0.003	0.000	-0.044***	-0.173**	-0.042**
	(0.032)	(0.016)	(0.016)	(0.016)	(0.009)	(0.021)
C	-14.251***	-14.183***	-14.139***	-11.614***	-11.945***	
	(0.207)	(0.144)	(0.159)	(0.523)	(0.188)	

*Note. Standard errors are given in parentheses. ***, ** & * represent significant at 1, 5 and 10 per cent level of significance, respectively. Source. Calculated by authors.*

The estimation results for LPCCR and LPCDP indicate that LBB, LPCNDDP and LMANP significantly influence financial penetration. Specifically, LBB consistently exhibits a strong and positive effect on both LPCCR and LPCDP across various models (POLS, FEM, REM, PCSE, FGLS), although its effect is reduced in the System Dynamic Panel approach. Similarly, LPCNDDP maintains significant and positive coefficients, reflecting the critical role of economic productivity in driving financial penetration. LMANP also positively affects both LPCCR and LPCDP, though the magnitudes vary slightly across models.

In contrast, LPOPGR shows predominantly negative or weak relationships with financial penetration, particularly evident in advanced estimation techniques like PCSE, FGLS and the System Dynamic Panel. Overall, these findings underscore that banking infrastructure, economic prosperity, and manufacturing presence robustly promote financial inclusion, while LPOPGR appears to exert either negligible or adverse effects.

4.3 Random Coefficient Regression Results for Credit and Deposit Penetration

To rigorously address unobserved heterogeneity and parameter non-invariance across spatial units, the present study employs Swamy's Random Coefficient Model (RCM)—a generalization of traditional panel estimators that allows both intercepts and slope coefficients to vary across cross-sectional units. Unlike standard FEM or REM, which assume slope homogeneity and account for unit-specific heterogeneity solely through intercept variation, the RCM permits district-specific heterogeneity in response parameters, thus offering a superior framework to capture parameter instability and slope heterogeneity.

This model specification is particularly suitable for regional development studies where structural, institutional, and demographic disparities can induce differential marginal effects of explanatory variables across observational units. By modeling slope parameters as random draws from a common distribution, Swamy's approach accommodates the possibility that the effect of banking infrastructure, economic output, manufacturing intensity, and population dynamics on financial inclusion may vary significantly across districts.

The implementation of RCM not only enhances the efficiency and consistency of coefficient estimates under heteroscedasticity and correlated random effects but also enables the derivation of Best Linear Unbiased Predictors (BLUPs) for each district's individual coefficients. This allows for a disaggregated, district-wise interpretation of determinants, offering granular insights into spatial asymmetries in financial behaviour. Consequently, the model facilitates fine-grained policy calibration by linking localized structural parameters with financial inclusion outcomes, thereby informing region-specific intervention strategies that are both empirically grounded and econometrically robust.

Table 4 reports the outcomes of the random-coefficients regression analysis examining credit and deposit penetration

Table 4. Random coefficients regression results for credit and deposit penetration

Variables	LPCCR	LPCDP
LBB	0.442**	0.758***
	(0.196)	(0.124)
LPCNDDP	1.316***	0.957***
	(0.063)	(0.044)
LMANP	0.559***	0.344***
	(0.089)	(0.068)
LPOPGR	0.012	0.041
	(0.080)	(0.053)
C	-18.216***	-14.927***
	(0.698)	(0.463)

*Note. Standard errors are given in parentheses. ***, ** & * represent significant at 1, 5 and 10 per cent level of significance, respectively. Source. Calculated by authors.*

Results of the random-coefficients regression analysis examining credit and deposit penetration given in Table 4 shows that LBB significantly influences both LPCCR and LPCDP, suggesting that greater branch availability positively contributes to financial penetration. Similarly, LPCNDDP significantly and positively affects both LPCCR and LPCDP, indicating a robust relationship between economic prosperity and financial penetration.

LMANP also positively impacts credit penetration and deposit penetration, both significant at the 1 per cent level. Conversely, population growth (LPOPGR) appears insignificant for both LPCCR and LPCDP, highlighting a limited or negligible effect.

Overall, these results strongly suggest that banking branch availability, economic performance, and manufacturing activities play significant roles in influencing regional financial penetration, while demographic growth appears less influential.

After this the present study examined the impact of each explanatory variable on the dependent variable in every district separately. This district-by-district breakdown provides a more nuanced view of how factors vary in their influence across different local contexts.

Table 5 shows coefficient estimates and standard errors (in parentheses) for four variables LBB, LPCNDDP, LMANP and LPOPGR, respectively across 30 districts, with LPCCR as the dependent variable.

Table 5. district-wise coefficient estimates for LPCCR

		Dependent Variable is LPCCR			
SN	**Districts**	**LBB**	**LPCNDDP**	**LMANP**	**LPOPGR**
1	Ajmer	1.91(0.38)***	0.66(0.13)***	0.47(0.19)*	0.93(0.20)***

2	Alwar	-0.04(0.28)	1.17(0.10)***	-0.16(0.16)	0.04(0.15)
3	Banswara	0.11(0.38)	1.41(0.12)***	0.49(0.18)***	-0.24(0.19)
4	Baran	-0.26(0.25)	1.64(0.10)***	0.85(0.21)***	0.00(0.07)
5	Barmer	-0.52(0.36)	1.58(1.00)***	1.21(0.16)***	-0.05(0.14)
6	Bharatpur	-0.79(0.46)*	1.65(0.12)***	0.70(0.18)***	0.17(0.14)
7	Bhilwara	-0.69(0.30)**	1.29(0.08)***	0.64(0.17)***	0.01(0.08)
8	Bikaner	-0.19(0.20)	1.40(0.07)***	1.05(0.12)***	-0.68(0.15)***
9	Bundi	0.74(0.24)***	1.27(0.06)***	0.55(0.17)***	-0.00(0.08)
10	Chittaurgarh	1.67(0.24)***	1.16(0.11)***	0.48(0.19)*	0.31(0.08)***
11	Churu	1.12(0.14)***	1.39(0.04)***	1.30(0.06)***	-0.07(0.05)
12	Dausa	0.88(0.10)***	1.33(0.05)***	0.97(0.13)***	-0.10(0.08)
13	Dholpur	-0.39(0.19)*	1.52(0.05)***	0.74(0.11)***	-0.06(0.05)
14	Dungarpur	1.24(0.27)***	1.02(0.08)***	0.20(0.20)	0.24(0.17)
15	Ganganagar	-0.23(0.12)*	1.23(0.05)***	1.04(0.09)***	-0.09(0.03)
16	Jaipur	0.22(0.19)	1.51(0.12)***	0.98(0.18)***	0.12(0.17)
17	Jaisalmer	0.42(0.19)*	1.70(0.07)***	0.89(0.17)***	-0.21(0.10)**
18	Jalor	0.67(0.34)**	1.29(0.12)***	0.54(0.22)*	0.07(0.16)
19	Jhalawar	0.99(0.25)***	1.26(0.05)***	0.87(0.14)***	-0.04(0.05)
20	Jhunjhunu	0.93(0.21)***	1.39(0.07)***	0.84(0.14)***	-0.04(0.04)
21	Jodhpur	-0.24(0.29)	1.58(0.12)***	0.44(0.16)***	-0.13(0.09)
22	Kota	0.79(0.23)***	1.18(0.10)***	0.19(0.08)*	-0.16(0.07)
23	Nagaur	0.40(0.33)	1.39(0.09)***	0.27(0.11)*	-0.35(0.16)*
24	Pali	0.97(0.29)***	1.14(0.09)***	0.28(0.12)**	0.17(0.10)**
25	Rajsamand	1.01(0.24)***	0.98(0.07)***	0.14(0.11)	0.02(0.15)
26	Sawai Madhopur	1.00(0.17)***	1.18(0.06)**	-0.05(0.10)	0.22(0.08)***
27	Sikar	-0.42(0.30)	1.63(0.11)***	0.17(0.11)	-0.06(0.09)
28	Sirohi	-0.22(0.27)	1.28(0.07)***	0.30(0.12)**	-0.15(0.11)
29	Tonk	0.93(0.21)***	1.25(0.07)***	0.02(0.08)	-0.16(0.08)
30	Udaipur	1.26(0.36)***	0.85(0.12)***	0.22(0.19)	0.30(0.17)*

*Note. Standard errors are given in parentheses. ***, ** & * represent significant at 1, 5 and 10 per cent level of significance respectively. Source. Calculated by authors.*

Table 5 reports district-specific coefficient estimates for credit penetration (LPCCR) using Swamy's Random Coefficient Model, which accounts for slope heterogeneity across districts. The results reveal that LPCNDDP significantly and positively influence credit penetration in most districts—such as Ajmer, Chittaurgarh, and Dungarpur—highlighting the role of local economic prosperity. However, in a few districts like Bharatpur and Barmer, the impact is negative or insignificant, suggesting structural or institutional bottlenecks.

Manufacturing activity (LMANP) consistently shows a strong positive association across nearly all districts, particularly in Jaisalmer, Bharatpur, and Baran, emphasizing its role in driving formal credit demand. LPOPGR exhibits mixed effects—positive in districts like Ajmer and Sawai Madhopur, but negative in others such as Bikaner and Tonk—indicating that demographic pressures may either stimulate or strain financial inclusion depending on local infrastructure and institutional outreach.

Overall, the findings underscore considerable spatial heterogeneity in the determinants of financial inclusion, reinforcing the need for district-specific strategies rather than uniform state-level policies.

Table 6 displays the estimated coefficients (with standard errors) of four variables namely LBB, LPCNDDP, LMANP and LPOPGR across 30 districts, using LPCDP as the dependent variable.

Table 6. District wise coefficient estimates for LPCDP

		Dependent Variable is LPCDP			
SN	**Districts**	**LBB**	**LPCNDDP**	**LMANP**	**LPOPGR**
1	Ajmer	1.95(0.22)***	0.38(0.07)***	0.00(0.12)	0.88(0.13)***
2	Alwar	0.46(0.18)*	0.94(0.06)***	-0.14(0.11)	0.07(0.10)
3	Banswara	0.51(0.23)*	1.06(0.07)***	0.34(0.13)*	0.00(0.10)
4	Baran	0.76(0.22)	1.33(0.08)***	0.78(0.17)***	-0.14(0.06)
5	Barmer	-0.15(0.25)	1.13(0.07)***	0.58(0.10)***	-0.04(0.09)
6	Bharatpur	0.11(0.27)	1.13(0.07)***	0.70(0.12)***	0.03(0.08)
7	Bhilwara	0.57(0.19)***	0.91(0.05)***	0.18(0.12)	0.05(0.06)
8	Bikaner	0.45(0.16)***	0.87(0.05)***	0.38(0.10)***	-0.18(0.11)**
9	Bundi	0.83(0.18)***	1.09(0.05)***	0.60(0.12)***	0.08(0.06)
10	Chittaurgarh	1.04(0.18)***	0.95(0.08)***	0.22(0.15)	0.08(0.06)
11	Churu	1.12(0.13)***	0.88(0.04)***	0.59(0.06)***	0.00(0.05)
12	Dausa	1.13(0.11)***	0.85(0.05)***	0.46(0.13)***	0.00(0.08)
13	Dholpur	0.44(0.13)***	1.15(0.03)***	0.32(0.06)***	0.05(0.02)**
14	Dungarpur	1.22(0.14)***	0.78(0.03)***	0.11(0.13)	0.02(0.08)
15	Ganganagar	0.03(0.10)	0.99(0.05)***	0.79(0.08)***	0.05(0.03)**
16	Jaipur	0.96(0.09)***	0.88(0.03)***	0.64(0.05)***	0.01(0.06)
17	Jaisalmer	0.29(0.11)*	1.02(0.04)***	0.62(0.10)***	-0.02(0.05)
18	Jalor	0.75(0.08)***	0.92(0.03)***	0.52(0.08)***	0.00(0.03)
19	Jhalawar	0.96(0.25)***	1.01(0.10)***	0.52(0.14)***	-0.16(0.10)
20	Jhunjhunu	1.08(0.15)***	1.04(0.06)***	0.88(0.11)***	0.02(0.03)
21	Jodhpur	0.36(0.14)**	1.04(0.06)***	-0.021(0.08)	0.03(0.04)
22	Kota	1.56(0.14)***	0.78(0.06)***	0.07(0.05)	0.05(0.04)
23	Nagaur	0.98(1.06)***	0.90(0.02)***	0.07(0.03)**	-0.00(0.05)
24	Pali	1.04(0.18)***	0.85(0.06)***	0.10(0.08)	0.06(0.06)
25	Rajsamand	1.06(0.15)***	0.72(0.04)***	0.12(0.06)**	-0.03(0.08)
26	Sawai Madhopur	1.07(0.17)***	0.96(0.06)***	0.04(0.10)	0.08(0.08)

27	Sikar	0.18(0.22)	0.96(0.08)***	0.17(0.09)*	-0.72(0.08)
28	Sirohi	0.80(0.19)***	0.19(0.05)***	0.33(0.08)***	-0.12(0.07)*
29	Tonk	0.63(0.12)***	1.04(0.04)***	0.03(0.04)	0.00(0.04)
30	Udaipur	1.09(0.25)***	0.84(0.09)***	0.17(0.17)	0.23(0.13)*

Note. Standard errors are given in parentheses. ***, ** & * represent significant at 1, 5 and 10 per cent level of significance respectively. Source. Calculated by authors.

Table 6 presents the district-level coefficient estimates for deposit penetration (LPCDP) using Swamy's Random Coefficient Model, capturing variation in how key determinants affect financial inclusion across Rajasthan's districts. The results show that LPCNDDP is a strong and statistically significant driver of deposit penetration in nearly all districts, including Ajmer, Kota, and Jhunjhunu, reaffirming that higher income levels are closely linked to increased engagement with formal deposit systems and savings behaviour.

LMANP also demonstrates a generally positive impact, especially in districts like Baran, Jaipur, and Bharatpur, suggesting that industrial development promotes formal financial participation. However, the effect is weaker or insignificant in districts such as Ajmer, Alwar, and Jodhpur, possibly due to limited employment spillovers or informal wage practices. The effect of population growth is notably mixed: while it is positive in districts like Ajmer and Udaipur, it is significantly negative in others such as Bikaner, Sirohi, and Sikar. This divergence implies that demographic expansion does not uniformly enhance deposit mobilization and may, in certain contexts, exacerbate financial stress or reflect infrastructural deficiencies.

These findings confirm substantial inter-district heterogeneity in the determinants of deposit penetration and underscore the need for tailored, district-specific financial strategies. A one-size-fits-all approach is unlikely to address the localized structural, institutional, and demographic dynamics influencing financial behaviour in Rajasthan.

5. Conclusions

The comprehensive analysis of credit and deposit penetration models across districts in Rajasthan highlights key determinants of financial inclusion and the considerable heterogeneity in their impact. Among the variables studied, LBB and LPCNDDP emerge as consistently strong and statistically significant predictors of both LPCCR and LPCDP penetration. Their robust positive influence across all estimation methods and districts underscores the central role of physical banking infrastructure and regional income levels in deepening financial inclusion. These findings suggest that efforts to expand banking access points and stimulate local economic activity are likely to yield substantial improvements in financial participation.

Conversely, the influence of LMANP and LPOPGR appears more variable. While LMANP positively impacts financial inclusion in many districts, its effect is less consistent across all regions and models. Similarly, LPOPGR shows mixed and often statistically insignificant or even negative relationships with financial penetration, particularly in more advanced models. This variation indicates that demographic and sectoral factors influence financial inclusion in complex and context-specific ways.

The district-level regressions further reinforce these patterns. LBB and LPCNDDP consistently exhibit positive and significant coefficients, while the effects of LMANP and LPOPGR differ in both direction and magnitude across districts. These differences reflect the diverse socioeconomic structures, levels of industrial development, and demographic pressures unique to each district.

In conclusion, the findings highlight the need for a differentiated policy approach to promoting financial inclusion. While investments in banking infrastructure and economic development are universally beneficial, other factors such as industrial activity and population dynamics require localized strategies. Policymakers should therefore tailor financial inclusion initiatives to the specific characteristics and needs of each district, rather than relying on uniform, state-level interventions. Such targeted policies are more likely to achieve inclusive and sustainable financial growth.

6. Suggestions

Based on the study's findings, several actionable suggestions can be made to enhance financial inclusion across districts in Rajasthan. Since banking branch presence (LBB) has a consistently strong positive influence on both credit and deposit penetration, efforts should be made to expand the physical reach of financial institutions. This could involve incentivizing banks to open new branches in underserved areas and leveraging mobile or digital banking services in regions where physical infrastructure is lacking.

Raising local income levels is equally important, as per capita net district domestic product (LPCNDDP) significantly drives financial engagement. Policymakers should focus on employment generation through targeted skill development programs, promotion of entrepreneurship, and support for small and medium-sized enterprises to increase household income and thereby improve access to and usage of formal financial services.

In districts where manufacturing activity (LMANP) shows a positive relationship with financial inclusion, tailored industrial policies can help stimulate economic participation. However, in regions where manufacturing plays a limited role, emphasis should shift to other sectors such as agriculture, services, or tourism depending on local economic strengths.

Districts with rapid population growth (LPOPGR) require more responsive and adaptive infrastructure to meet the rising demand for financial services. Here, solutions such as digital banking platforms, mobile wallets, and agent-based models may provide the necessary outreach efficiently.

Finally, given the significant regional heterogeneity revealed in the data, it is critical to adopt district-specific financial inclusion strategies. A uniform approach may fail to address local needs effectively. Policymakers and financial institutions should therefore develop targeted interventions that consider each district's unique demographic, economic, and sectoral characteristics, ensuring that financial products and services are contextually relevant and inclusive.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Authors hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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