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Credit Accessibility Across Indian States: Evidence From Club Convergence

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Indian states are immensely heterogeneous in terms of their socioeconomic activities. The economic structure of India is consequently bifurcated too. This study examines, under given heterogeneities, whether credit accessibility among states converges over time, particularly in industrial and agricultural lending. We employ the concept of club convergence and find that substantial heterogeneities and multiple transition paths exist for industrial credit convergence across states, while agriculture credit is relatively less heterogeneous as compared with industry. Therefore, more attention is required to reduce access to banking credit for industries in poorer states.

I. Introduction

Accessibility of credit and economic growth and development are strongly connected, as more access to credit leads to expansion of economic activity. The relationship between these macroeconomic variables fascinates academicians and policymakers. The phenomenon of heterogenous credit distribution across time and space has been widely researched (Hassan et al., 2011; Herwadkar & Ghosh, 2013). Diversified socioeconomic and political conditions characterise the Indian economy. Barrow & Sala-i-Martin (1992), Mankiw et al. (1992) and Sala-i-Martin (1996) empirically examine the mandate of absolute beta-convergence. This implies that irrespective of their initial socioeconomic conditions, economies will converge with one another. The absolute beta-convergence hypothesis favours the theoretical notion of exogenous growth models and assumes global convergence. It is quite possible because of the competitive forces and inter-regional migrations and slowing down of regional inequalities due to factor price equalisation (Paas et al., 2007; Solow, 2000). Against this backdrop, this study examines whether accessibility of credit converges over time and helps in dampening inequality across states.

This study is novel to the previous literature on credit accessibility because we address the issue of credit accessibility among different states in India using club convergence concepts under recently available aggregate and disaggregate datasets from 2004 to 2020. The data used in the analysis are state-wise credit by Scheduled Commercial Banks to agriculture and industry by Scheduled Commercial Banks. Credit inequality among Indian states driven through demand and supply of credit conditional on economic development. This paper will provide better insight into development of credit in different sectors across states.

The rest of the study is presented as follows: the next section discusses the dataset and research methodology. The penultimate section presents our empirical findings. The last section concludes the study.

II. Method and Data

We employ Phillips & Sul (2007) [hereafter referred to as PS] test to attain a club convergence.[1] In a panel framework, it identifies the cluster convergence endogenously and based on a nonlinear time-varying factor model. PS offer the framework for modelling transitional dynamics and long-run behaviour, which takes common and individual-specific components. Our study uses panel data for *credit accessibility* (*CA* hereafter). The CA_{it}, where $i = 1,\ 2,\ \ldots, N$ and $t = 1, 2 \ldots, T$ with *N, T* the number of states and the time, respectively. The PS single-factor model is given below.

$$CA_{it} = \delta_i \mu_t + u_{it} \tag{1}$$

where δ_i shows the idiosyncratic distance between the common factor μ_t and the systematic part of CA_{it}. μ_t refers to the accumulated common behaviour of CA_{it} or any common variable of influence on individual behaviour. u_{it} is an error term. Thus, Equation (1) identifies the progression

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1 Further details can be found in Akram and Rath (2022).

Table 1. Credit to industry by bank

Full Sample	**All States**		**-0.71 (-33.98)**
Club 1	Delhi and Maharashtra		
Club 2	Andhra Pradesh, Gujarat and Tamil Nadu		
Club 3	Haryana, Karnataka and West Bengal		
Club 4	Chandigarh, Chhattisgarh, Kerala, Madhya Pradesh and Odisha		
Club 5	Bihar, Jharkhand, Tripura and Uttarakhand		
Club 6	Assam, Jammu and Kashmir		
Club 7	Goa, Himachal Pradesh and Puducherry		
Club 8	Meghalaya and Nagaland		
The log *t*-test for Club merging		***b***	***t* –stat**
Club 1+2		-0.66	-159.70
Club 2+3		-0.34	-18.35
Club 3+4		-0.38	-11.88
Club 4+5		-0.28	-5.60
Club 5+6		-0.0004	-0.007
Club 6+7		-0.20	-14.83
Club 7+8		-0.245	-8.65
Final Clubs after merge			
Club 1	Delhi and Maharashtra		
Club 2	Andhra Pradesh, Gujarat and Tamil Nadu		
Club 3	Haryana, Karnataka and West Bengal		
Club 4	Chandigarh, Chhattisgarh, Kerala, Madhya Pradesh, Odisha , Punjab, Rajasthan and Uttar Pradesh		
Club 5	Assam, Bihar, Jammu and Kashmir, Jharkhand, Uttarakhand and Tripura		
Club 6	Goa, Himachal Pradesh and Puducherry		
Club 7	Meghalaya and Nagaland		

This table reports results on club convergence of credit to industry by banks across Indian states. It includes full sample convergence test, club formation, merging of clubs and final set of club formation.

of the individual CA_{it} in relation with common factor by means of two idiosyncratic elements, that is, systematic element (δ_i) and the error (u_{it}). Next, the variable CA_{it} is divided into two parts: G_{it} and B_{it} stand for systematic and transitory components respectively.

$$CA_{it} = \left(\frac{G_{it} + B_{it}}{\mu_t} \right) \mu_t = \delta_{it} \mu_t, \quad \forall\, i, t \tag{2}$$

Thus, two components are noticed in Equation (2): μ_t refers to a common steady-state trend function which may have both deterministic and stochastic components, and δ_{it} shows an idiosyncratic element which captures both time and individual specific effects. It measures the distance between CA_{it} and common factor μ_t, which is a common stochastic trend in the panel. Furthermore, coefficients of δ_{it} is the share of a common factor μ_t; each individual in the panel data experiences. The convergence is a dynamic process, therefore, δ_{it} suggests the transition paths, which is checked by examining temporal relative evolution of δ_{it}. The null hypothesis of convergence for all i under specific form of γ_{it}: $H_0 : \delta_i = \delta, \forall\, i$ with $a \geq 0$, whereas the alternative hypothesis: $H_1 : \delta_i \neq \delta, \forall\, i$ with $a \geq 0$ or $a < 0$.

Data for this study is taken from the Reserve Bank of India (RBI) Handbook of Statistics on Indian States. It is only available since 2004. Therefore, we collect data from 2004 to 2020. *State-wise Credit to Industry* and *Agriculture by Scheduled Commercial Banks* are two key components of *total credit* taken in the analysis.

III. Results and Discussion

Looking at the average credit to states, Maharashtra, Delhi, Tamil Nadu, Andhra Pradesh, and Gujarat have better access to credit for industry, whereas Goa, Meghalaya, Puducherry, Tripura, Nagaland have the lowest access to credit for industry. Again, Tamil Nadu, Andhra Pradesh, Uttar Pradesh, Maharashtra, Karnataka have better access to credit for agriculture, while Chandigarh, Puducherry, Tripura, Goa, Meghalaya have the lowest access to credit for agriculture. There is a significant variation in the industry over agricultural credit.

We are primarily concerned with the convergence study on industrial and agricultural lending. Tables 1 and 2 display the results of club convergence tests. The industry and agricultural Log t regression tabulated values (-33.98 and -20.30) are lower than Phillips and Sul's critical value (1.65), indicating convergence in the complete sample (Phillips & Sul, 2007). Therefore, the whole sample convergence can be dismissed, implying club convergence exists. This demonstrates that states' *total credit, agricultural credit*, and *industrial credit* convergence paths vary. Thus, a

Table 2. Credit to Agriculture by Bank

Full Sample	**All States**	**-0.407 (-20.30)**	
Club 1	Andhra Pradesh, Kerala and Tamil Nadu		
Club 2	Assam, Bihar, Karnataka, Madhya Pradesh, Maharashtra, Punjab, Rajasthan and Tripura		
Club 3	Gujarat, Haryana, Jammu and Kashmir and Puducherry		
Club 4	Chhattisgarh, Delhi, Himachal Pradesh, Jharkhand, Odisha Uttarakhand and West Bengal		
Club 5	Chandigarh, Goa and Meghalaya		
Group	Uttar Pradesh		
The log *t*-test for Club merging		**Coeff**	***t*-stat**
Club 1+2		-0.037	-0.686
Club 2+3		0.016	0.329
Club 3+4		0.073	1.89
Club 4+5		-0.423	-37.53
Club 5+ group 6		-0.545	-59.72
Final Clubs after merge			
Club 1	Andhra Pradesh, Kerala and Tamil Nadu, , Jammu and Kashmir, Karnataka, Madhya Pradesh, Maharashtra, Puducherry, Punjab, Rajasthan, Tripura,		
Club 2	Gujarat, Haryana, Jammu and Kashmir and Puducherry		
Club 3	Chhattisgarh, Delhi, Himachal Pradesh, Jharkhand, Odisha Uttarakhand and West Bengal		
Club 4	Chandigarh, Goa and Meghalaya		
Group	Uttar Pradesh		

This table reports results on club convergence of credit to agriculture by banks across Indian states. It includes full sample convergence test, club formation, merging of clubs and final set of club formation.

single financial inclusion policy may fail to minimise state-to-state credit inequality. To address sample non-convergence, panel club convergence employs clustering to form groups. Therefore, the next question is which states are club members and whether the sample contains divergent states.

PS further contends that their methodology for calculating club convergence overestimates the number of clubs compared to the actual number. The clustering technique is used between clubs to measure whether there is evidence in favour of clubs merging into larger clubs. The club merging test for the industry shows that Club 5 can be merged with Club 6. Hence, we finally end up with 7 clubs. This shows substantial heterogeneity and multiple transition paths towards convergence in terms of industrial credit across states. The large disparity across states may be owing to various reasons. First and foremost, it could be due to disparities in industry development across states. Club 4 has the highest number of states, most of which lie in the northern region, but it is not purely the Northern region. Club convergence does not support regional classification. For instance, adjacent states might not, contrary to expectations, fall into the same club. It follows the higher incomes in banking and dependence on banks for credit. There are higher-income states that have similar transition paths and fall into the same clubs, whereas low-income states like Bihar, Jharkhand, and Assam follow similar credit trends over time and similar transition paths towards convergence. The results of *credit to industries* are similar to *total credit* by banks, which also have seven clubs and one group. The result of the club convergence analysis for *total credit* has reported in the appendix. Hence, there is a significant importance of credit to industry in *total credit*. The convergence path in *total credit* is primarily driven by industrial credit. Access to credit by industry should be enhanced in poorer states so that we can reduce regional disparities in terms of development. We also find evidence of non-convergence of the full sample in the case of *credit to agriculture*, implying the existence of club convergence. Initially, we find five clubs and a group in which Uttar Pradesh fall, indicating that Uttar Pradesh is neither converging nor diverging. After doing the club merging test, we find that Club 2 can be merged with Club 3. Therefore, we finally end up with four clubs and a group which is less than the number of clubs in the case of credit to industry. Therefore, agriculture credit is relatively less heterogeneous across states. Club 1 has the most significant number of states, most of which are southern states. Club 2 has primarily northern states, but no clear and distinct sign of categorisation of states aligns with regional or geographical classification. This may have to do with government policy of priority lending to agriculture. In considering credit by Scheduled Commercial Banks, it may be more likely that rural regional banks provide better credit access to agriculture. Unfortunately, the data on credit given by regional rural banks is not available at a disaggregate level. Nevertheless, the results favour the convergence of states in 4 different transition paths. It is a better indication of similarities in agriculture credit across states. Adding credit from regional rural banks might reduce the number of club formations for agriculture credit convergence. Less developed states rely more on regional rural banks offering better coverage than Scheduled Commercial Banks.

Credit expansion among Indian states varies significantly. It depends on a number of factors, including economic and financial growth, mobilisation of deposits, and the banking network. It plays a significant role in forming credit in a given state. This highlights the importance of financial sector development and inclusiveness in credit creation. The heterogeneity of credit distribution among areas attracts great academic and policy interest. While previous research only demonstrates credit variability among Indian states, our primary purpose is to investigate club convergence. Given the significant regional variances in income, financial inclusion, and infrastructural development, India serves as an ideal laboratory for studying heterogeneity. We find the existence of multiple equilibrium paths which validate the regional inequality in terms of access to banking credit.

IV. Conclusion

Credit expansion among Indian states varies significantly. We are concerned about club convergence of industrial and agricultural lending. The results show substantial heterogeneity and multiple transition paths toward convergence of industrial credit across states. Large disparities across states may be owing to various reasons. It could be due to disparities in industry development across the states. *Credit to agriculture* is relatively less heterogeneous across states than *credit to industry*.

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Appendix

Table A1. Total Credit by Bank

Full Sample	All States	-0.45 (-16.98)	
Club 1	Delhi, Gujarat, Maharashtra		
Club 2	Andhra Pradesh, Tamil Nadu		
Club 3	Haryana, Kerala, Madhya Pradesh, Punjab, Rajasthan, Uttar Pradesh, West Bengal		
Club 4	Bihar, Chhattisgarh, Odisha		
Club 5	Assam, Chandigarh, Jammu and Kashmir, Jharkhand, Uttarakhand		
Club 6	Goa, Himachal Pradesh, Puducherry, Tripura,		
Club 7	Andaman & Nicobar Islands, Meghalaya, Nagaland		
Group 8	Karnataka		
The log *t*-test for Club merging		**Coeff**	***t*-stat**
Club 1+2		-0.0798	-1.52
Club 2+3		-0.2756	-6.82
Club 3+4		-0.1955	-4.65
Club 4+5		-0.4331	-23.87
Club 5+6		-0.2036	-5.417
Club 6+7		-0.1345	-2.918
Club 7+ Group 8		-0.4044	-12.58
Final Clubs after merge			
Club 1	Delhi, Gujarat, Maharashtra		
Club 2	Andhra Pradesh, Tamil Nadu		
Club 3	Haryana, Kerala, Madhya Pradesh, Punjab, Rajasthan, Uttar Pradesh, West Bengal		
Club 4	Bihar, Chhattisgarh, Odisha		
Club 5	Assam, Chandigarh, Jammu and Kashmir, Jharkhand, Uttarakhand		
Club 6	Goa, Himachal Pradesh, Puducherry, Tripura		
Club 7	Andaman & Nicobar Islands, Meghalaya, Nagaland		
Group 8	Karnataka		

This table reports results o club convergence of total credit by banks across Indian states. It includes full sample convergence test, club formation, merging of clubs, and final set of club formation.