Spatial Convergence among Indian Districts: An Econometric Evidence

Manish Chauhan[1] Somesh Kumar Mathur[2] Praveen Kulshreshtha[3]

Extended Abstract

Do poorer regions catch up with their richer counterparts? This study revisits convergence concepts at a more granular level while focusing on empirical analysis of India at the district level for the country, for each state, each zone of India, and other bifurcation of districts. Spatial Dependence is an important factor among regional economies for growth and development. We use the Spatial Mankiw Romer Weil model to consider it in the catching-up process, which shows that some districts are catching up with their richer counterparts, while others are diverging in case of unconditional convergence, whereas in case of conditional convergence for the whole country, with and without spatial dependence. Firstly, we established the theoretical underpining of this model by including more variables. Empirical justification will identify the catching-up process by unconditional, conditional, and speed of convergence considering the spatial dependence of the economies. Moran's I and LM and adjusted LM tests confirm the spatial dependence among districts.

The speed of absolute convergence varies from 0.28 percent per year to 2.57 percent per year. At the Zonal level, we have some evidence for unconditional convergence. There is much evidence of conditional convergence for all the districts of India with control factors literacy rate, share of agriculture, industry, services in GDP, the density of population, population growth rate, and financial inclusion having a

[1] Research Scholar, Indian Institute of Technology, Kanpur, India, manishc@iitk.ac.in
[2] Professor, Indian Institute of Technology, Kanpur, India, skmathur@iitk.ac.in
[3] Professor, Indian Institute of Technology, Kanpur, India, pravk@iitk.ac.in
Special thanks to two anonymous referees whose valuable comments have greatly improved this paper. We are also grateful to Prof. Chetan Ghate, IEG Delhi for his insightful comments at the Public Policy Conference held at IIT Kanpur and to Prof. Abhiroop Mukhopadhyay of ISI for his feedback during Research Scholar Day of the Department of Economic Sciences, IIT Kanpur.

significant impact on district growth rate per capita. There is evidence of unconditional convergence for India with spatial dependence with a neighboring initial per capita having a significant impact on all India districts' growth rate per capita. However, there is no evidence of unconditional convergence for India with spatial independence. We accounted for spatial heterogeneity using Geographically weighted regressions and endogeneity using spatial GMM in a spatial error model. The results showed similar patterns of conditional and unconditional convergence as those obtained from spatial regression models. We use data for the time period between 2001 through 2017 based on averages.

Keywords: Unconditional convergence, conditional convergence, speed of unconditional convergence, spatial models, Spatial convergence model, Spatial Mankiw Romer Model

JEL Classification: O47, O40

1. Introduction

Despite the high growth rate, India stood at 130 among 191 countries in UNDP's Human Development Index (2021-22). The diverse path of economic growth across states and districts of India seems to be one of the reasons for the low ranking. As per NITI Ayog's report (2019), BIMARU[4] states are underperforming compared to the national average. The gap between higher States and lower States is increasing. Even within the state, disparity among districts can also be seen. The regions besides the cities are much more developed than the farthest regions. Regional income inequality among states can be seen in the differences in the per capita income of Goa and Bihar. According to the economic survey of India (2019), the per capita income of Goa and Delhi is 10- and 8-times Bihar, whereas Haryana's per capita GDP is six times higher than Bihar's. Similar is the case of Uttar Pradesh in terms of comparing its per capita income with other states.

[4] BIMARU states refer for the Bihar, Madhya Pradesh, Rajasthan, and Uttar Pradesh.

Within-state disparity can also be seen in large if we compare the district with industrial clusters like Ghaziabad, Agra, and Lucknow with districts at the border of India and Nepal like Rampur, Balrampur, and Bahraich. A study by Hanagodimath (2019) also confirms that it's not only inter-state disparities but also intra-state disparities that are increasing in India. They also found a negative association between intra-state differences and per capita state income.

The regional disparities among regions may come down in the regional convergence process. Less developed regions may converge to the regions with the more developed regions. Regional convergence of income means that the poorer region's income converges with the richer counterpart over a period of time. Conditional convergence is a concept related to convergence to its own potential income level, while unconditional convergence is related to districts or regions converging to one common potential income level. The latter implies that the poorer districts catch up with their richer counterpart.

With the spatial externalities, convergence is also the function of what is happening in the neighboring district. The income in the neighboring districts can be far away or very near to the common potential or own potential level of income. Your district's growth rate will grow faster if it is near the potential income level. We are trying to understand the speed of convergence and how the district converges to its potential level or common potential level of income, given that in the neighboring district, the units are either very near to their potential or far away from their potential level of income. If they are near the potential income level, the theory says your economy will grow faster.

Profound literature shows much evidence based on country level and sub-national level. We will study this concept at a more granular level, i.e., at the district level for India. Literature on new economic geography starts with the work of Romer (1986, 1990), Lucas (1988), and Krugman (1991), which give shape to new growth theories with the inclusion of regional disparities. Later, considering the spatial characteristics has shaped the concept of spatial convergence in the literature. Comparing the spatial dependence and spatial independence results also becomes a significant area of research. The main thrust area earlier was the conditional, unconditional, and speed of convergence. Now considering it with spatial character becomes essential because of the theory of space, which states that space (nearness) is a crucial factor in analyzing and evaluating it for the whole growth process or other characters.

The speed of unconditional and conditional convergence under spatial externalities differs with the speed of unconditional and conditional convergence with no spatial features, as in the textbook Solow model. In the former, whether a unit is converging to an ordinary potential level of income or its own potential level of income, and in the latter, the speed also gets influenced by regions operating in its neighborhood. If the neighborhood units are close to their own or common potential income level, their counterpart's income would be higher. For example, Delhi would do well if adjoining districts were doing well. Our results suggest that the performance of the adjoining district is modest and higher than the neighboring counterparts' growth rates. Maybe the core-periphery analysis of Krugman or Hirschman's unbalanced growth analysis can explain India's granular level of development. The theoretical equations of the production function, factor accumulation process, and technological progress with spatial externalities are more critical. These help us derive the unconditional and conditional regression equation under spatial features and an expression for convergence speed under spatial externalities. The Empirics can be done by Luc Anselin's GeoDa software, helping us estimate different spatial regression models like SAR, Spatial Durbin, and Spatial error models. Such models all have theoretical justification mimicking the Solovian growth model with spatial externalities. The Spatial Mankiw Romer Weil model by Fischer (2011) and French economists Ertur and Koch (2007) have done deep and extensive work in spatial convergence with theory and evidence.

The outline of the paper is 1) introduction, 2) literature review, 3) Theoretical Understanding of the Textbook Solow Model and its extension with Spatial Externalities, 4) Variables, data and data source, 5) Methodology, 6) Econometric Models Specifications, and results, and last, 7) Conclusions. References and appendix tables are given at the end.

2. Literature Review

Do poorer regions catch up with their richer counterparts? Enormous literature since 1960 is available to answer this question. According to Solow (1956), the income differences in regional economies go down and converge to a common steady state on the condition that population growth, technology, saving, and investment remain the same. The most apparent reason behind this is the neoclassical assumption of diminishing return to capital. Poorer regions have a higher marginal product of capital than richer regions, allowing them to grow higher than richer regions and converge to richer counterparts.

Romer (1986) and Lucas (1988) come up with the new endogenous growth theory with their argument that human capital and Research & Development (R&D) are the two essential factors that do not allow the marginal product of capital to fall even if a region or countries get richer. This restricts the poorer region from converging with a richer counterpart. So, convergence can only be seen by controlling R&D, education, and the variables that determine capital productivity, like population growth, trade openness, government expenditure, and political stability. Mankiw, Romer, and Weil (1992) have evidence of conditional convergence and divergence in the case of unconditional convergence.

Postiglione et al. (2013) employed the Simulated Annealing (SA) algorithm to identify convergence clubs. Additionally, they introduced another algorithm, the Iterated Conditional Modes (ICM), which serves as a deterministic and computationally faster alternative to SA. These algorithms address the limitations in partitioning geographically-based economic data, which were previously tackled using regression tree approaches by Durlauf and Johnson (1995) and Postiglione et al. (2010).

Durlauf et al. (2005) constitutes a significant study that has identified numerous potential determinants of economic growth. This served as a motivation for our research to expand upon these determinants, including factors such as population growth, migration, and population density.

In the context of India, Cashin and Sahay (1996) confirm the absolute beta convergence and no sigma convergence for the years 1961 to 1991 for 20 states of India. Nagaraj et al. (1998), Trivedi (2002), Adabar (2004), Nayyar (2008), Ghosh (2010), Ghosh et al. (1998) conditional beta convergence with no evidence for sigma convergence at the state level. Thirlwall (2015) does not find evidence for unconditional beta convergence in 32 states. The existing literature does not have much evidence for beta convergence at the district level.

A study by Tewari and Godfrey (2016) found unconditional convergence at the state, district, and city levels via night light intensity data. At the district level, Hazrana et al. (2019) found evidence of not only conditional convergence but also spatial convergence at the district level of India, and Bilal et al. (2020) found the same for Madhya Pradesh. Barro & Sala-i-Martin (1991) and Carlino and Mills (1996) provide evidence for per capita income convergence for US regions. Lim (2016) 's study provides evidence of spatial per capita income convergence for the US.

Aroca et al. 2008 confirm the spatial income convergence and spatial dependence in the case of China. For Japan, Narro (2019) gives evidence for spatial convergence. The spatial parameters also account for the convergence concept, which is now attracting much attention in New Economic Geography (NEG) literature. Our study will incorporate spatial convergence at the district level for each state and all country districts, i.e., We will examine the intra-state spatial convergence and compare it with each state.

We will use the existing income convergence methodology to find empirical evidence on spatial income convergence at the district level.

According to Spatial Mankiw Romer Weil Model (SMRW) given by Fischer (2011), the output of the i^{th} region is influenced by the endowment (mainly physical and human capital) of neighboring regions j. (This process is known as spatial spill over). Ghani et al. (2014), Das et al. (2019), and Datta (2012) confirm that Infrastructural improvement (mainly road network) led to a substantial increase in economic activities, and its growth included higher entry rates, incumbent productivity expansion, and improved allocative efficiency in the manufacturing industries.

Mohanty and Bhanumurthy (2018) incorporated spatial income convergence, including the spatial character at the state level. Their results reveal that richer states showed a different spatial relation than the poor states. They also emphasize that spatial patterns are essential in promoting regional balances for growth.

In their study, Li, Rama, and Zhao (2018) examined growth patterns at various geographical levels, including districts and sub-district areas of India. They primarily relied on household consumption expenditure per capita as a measure of living standards.

Table 1: A summary of the literature on growth convergence within India

Study	Findin g		Dependent Variable	Spatial level (no.)	Time Perio d
	Absolute	Conditional			
Cashin and Sahay (1996)	Convergence	Convergence	Income	State (20)	1961–91
Bajpai and Sachs (1996)	Convergence	Convergence	Income	State (19)	1961–71
	Divergence	Divergence	Income	State (19)	1971–95
Rao, Shand and Kalirajan (1999)	Divergence	Divergence	Income	State (14)	1961–91
Nagaraj, Varoudakis and Veganzones (2000)	Divergence	Convergence	Income	State (17)	1971–91
Aiyar (2001)	Divergence	Convergence	Income	State (19)	1971–95
Sachs, Bajpai and Ramiah(2002)	Divergence		Income	State (14)	1976–95
Datt and Ravallion (2002)	Divergence		Income	State (12)	1992–2000
Bandyopadhyay (2012)	Divergence		Income	State (17)	1965–97
Rodrik and Subramanian (2004)	Divergence		Income	State (20)	1980–99
Baddeley, McNay and Cassen(2006)	Divergence		Income	State (15)	1970–97
Kochhar et al. (2006)	Inconclusive		Income	State (14)	1961–2000
Purfield (2006)	Convergence	Convergence	Income	State (15)	1976–2005
Misra (2007)	Divergence	Convergence	Income	State (14)	1976–2001
Kalra and Sodsriwiboon (2010)	Divergence		Income	State (15)	1960–2003
Das (2012)	Divergence		Income	State (14)	1980–2005
	Divergence		Rural expenditure	State (14)	1980–2005
	Convergence		Urban expenditure	State (14)	1980–2005
	Divergence		Income	State (21)	1993–2009

Kumar and Subramanian (2012)	Divergence		Income	State (21)	2001–09
Ghate and Wright (2013)	Inconclusive	Inconclusive	Income	State (15)	1987–2004
Tripathi (2013)		Inconclusive	Income	City (52)	2001-2005
Nayyar (2014)	Divergence	Convergence	Expenditure	State (17)	1994–2012
Das, Ghate and Robertson (2015)	Divergence	Convergence	Income	District (575)	2001–08
Tewari and Godfrey (2016)	Convergence		Nighttime light intensity	State (33)	1992–2013
	Convergence		Nighttime light intensity	District (618)	1992–2013
	Convergence		Nighttime light intensity	City (479)	1996–2011

Source: Li, Rama, and Zhao (2018) and Kalra and Sodsriwiboon (2010).

The above table shows various studies done on convergence issues using state, districts, and city level data. Our study is primarily on spatial convergence & spatial heterogeneity using granular-level data.

Table 2: Drivers of local growth in the literature and results in India's case

Bucket	Indicator	Results		
		Significantly negative	**Small or inconclusive**	**Significantly positive**
Geography	Temperature		Sridhar (2010) Tripathi (2013)	
	Precipitation		Ghate and Wright (2013)	
	Elevation	Considered in the literature but not in India's case		
Urbanization	Urbanization rate	Tripathi (2013)		Ghate and Wright (2013) Das, Ghate and Robertson (2015)
	Population size or growth		Ghate and Wright (2013)	Tripathi (2013) Abhishek, Jenamani and Mahanty (2017)
	Population density		Tripathi (2013)	

	State capital		Tripathi (2013)	Abhishek, Jenamani and Mahanty (2017)
	Governance quality	Considered in the literature but not in India’s case		
	Revenue, expenditure or debt			
Market access	Nearby economic activity		Das, Ghate and Robertson (2015)	
	Distance to large cities	Sridhar (2010) Das, Ghate and Robertson (2015) Abhishek, Jenamani and Mahanty (2017)	Tripathi (2013)	
	Landlocked	Ghate and Wright (2013)		
	Riverbank or seaport city		Tripathi (2013)	

Bucket	**Indicator**	**Results**		
		Significantly negative	**Small or inconclusive**	**Significantly positive**
Infrastructure	Access to electricity			Das, Ghate and Robertson (2015)
	Electricity losses	Purfield (2006)	Kalra and Sodsriwiboon (2010)	
	Access to roads or road density	Abhishek, Jenamani and Mahanty (2017)	Purfield (2006) Sridhar (2010) Das, Ghate and Robertson (2015)	
	Railways stations or railways density	Considered in the literature but not in India’s case		
	Transportation costs			
	Telephone lines			Kalra and Sodsriwiboon (2010)
	Irrigated land	Das, Ghate and Robertson (2015)		
	Housing supply	Considered in the literature but not in India’s case		
	Private investment		Baddeley, McNay and Cassen (2006)	Rao, Shand and Kalirajan (1999) Aiyar (2001) Purfield (2006) Kalra and Sodsriwiboon (2010)
	Development expenditure		Ghate and Wright (2013) Tripathi (2013)	Rao, Shand and Kalirajan (1999) Baddeley, McNay and Cassen (2006) Kalra and Sodsriwiboon (2010)

Economic structure	Agricultural productivity			Baddeley, McNay and Cassen (2006)
	Share of agriculture	Bajpai and Sachs (1996) Purfield (2006) Ghate and Wright (2013)	Baddeley, McNay and Cassen (2006)	
	Share of manufacturing or industry	Purfield (2006) Ghate and Wright (2013)		Sridhar (2010)
	Share of services			Kalra and Sodsriwiboon (2010)
	Diversification index	Considered in the literature but not in India's case		
	Specialization index			
	Mineral production capacity			

Bucket	Indicator	Results		
		Significantly negative	Small or inconclusive	Significantly positive
Employment structure	Share of small, medium or large firms	Considered in the literature but not in India’s case		
	Employment rate		Baddeley, McNay and Cassen (2006)	
	Private sector employment share		Kalra and Sodsriwiboon (2010)	
	Unemployment rate	Considered in the literature but not in India’s case		
	Self-employment share			
	Wage-employment share			
Human capital	Birth rate		Kalra and Sodsriwiboon (2010)	
	Literacy rate		Purfield (2006) Kalra and Sodsriwiboon (2010) Das, Ghate and Robertson (2015) Tripathi (2013)	Aiyar (2001) Sridhar (2010) Ghate and Wright (2013)
	Primary education		Tripathi (2013) Abhishek, Jenamani and Mahanty (2017)	Sridhar (2010)
	Secondary education		Tripathi (2013)	Baddeley, McNay and Cassen (2006)
	Tertiary education	Considered in the literature but not in India’s case		
	Years of schooling			
Social inclusion	Access to finance		Das, Ghate and Robertson (2015)	
	Land inequality	Considered in the literature but not in India’s case		
	Female educational disadvantage		Purfield (2006)	Baddeley, McNay and Cassen (2006)
	Rural income inequality			Baddeley, McNay and Cassen (2006)
	Urban income inequality		Baddeley, McNay and Cassen (2006)	
	Overall income inequality	Considered in the literature but not in India’s case		
	Social heterogeneity or segregation			

(Continued)

Bucket	Indicator	Results		
		Significantly negative	Small or inconclusive	Significantly positive
Governance	Crime rate		Rao, Shand and Kalirajan (1999)	Baddeley, McNay and Cassen (2006)
	Labor rigidity	Ghate and Wright (2013)	Purfield (2006)	
	Land market distortions		Sridhar (2010)	

Source: Li, Rama, and Zhao (2018)

The above table shows a host of factors impacting growth at a granular level. Our study has been able to take a subset of the exhaustive list due to the spatial nature of the variable

The inclusion of economic structure (share of the agricultural, manufacturing, and services sector) as a determinant of growth is mainly motivated by Ghate and Wright (2013), Purfield (2006), and Baddeley, McNay , and Cassen (2006). Durlauf et al. (2005) motivated us to include factors like population growth, migration, and population density.

Our study incorporates the inter-state, within-state (district-wise), and inter-country level analysis on catching up processes by incorporating spatial spillover factors and taking care of endowments of regions. Although, Hazrana et al. (2019) and Bilal et al. (2020) found strong spatial linkages in economic growth at the district level (only for Madhya Pradesh), leading to a significant acceleration in its speed of convergence. But still, there is a scope to show how it varies across other states spatially and to know how it varies if we divide the district according to their economic potential.

This study would give a theoretical justification for convergence equations where poorer regions catch up with their richer counterpart and to their own potential income level under no spatial externality and spatial externality assumption. We consider extended production function and technology being modeled through the following variables: share of Manufacturing, Agriculture, Services in district GDP, Health infrastructure, health indicator of the district, migration rate, population density, and among others in a spatial setting. The inclusion of economic structure (share of the agricultural, manufacturing, and services sector) as a determinant of growth is mainly motivated by Ghate and Wright (2013), Purfield (2006), and Baddeley, McNay , and Cassen (2006).

Durlauf et al. (2005) motivated us to include factors like population growth, migration, and population density.

In the empirical portion, our addition to the exiting literature would be to give state-wise, zone-wise, and categorized district-wise comparisons (at the district level) of convergence with and without spatial externalities.

3. Theoretical Understanding of Textbook Solow Model and its extension with Spatial Externalities

3.1. Textbook Solow Model

Let's first build the understanding Neo-Classical growth model propounded by Robert Solow in 1956, and later it was furthermore developed by considering the human capital in production function by Mankiw Romer Weil (1992).

$$Y = AK^{\alpha_K} H^{\alpha_H} P^{\alpha_P} (L)^{(1-\alpha_K-\alpha_H-\alpha_P)} \qquad (1)$$

Where Y (0utput) is the function of K (stock of physical capital), H (stock of human capital), A (level of technological knowledge), and L (labor). α_K α_H and α_P represent the output elasticities with respect to physical capital, health, and human capital, respectively. The proportion of income invested in human capital is assumed to be s_H , proportion that is invested in physical capital and health infrastructure assumed as $s_K \; and \; s_P$. The regional economy evolves according to the following differential equation.

$$\dot{k} = s^K y - (n+\delta)k$$

$$\dot{h} = s^H y - (n+\delta)h$$

$$\dot{p} = s^P y - (n+\delta)p$$

Where, $y = Y/AL, k = K/AL$, and $h = H/AL$. The dot above the variable mentioned above represents the derivation regarding time. n and g are the growth rate of labor and technology, respectively. So, production function in terms of per effective labor will be as follow:

$$\tilde{y} = \tilde{k}^{\alpha_k}\tilde{h}^{\alpha_H}\tilde{p}^{\alpha_P}$$

At steady state, $\dot{\tilde{k}} = 0$, $\dot{\tilde{h}} = 0$, $\dot{\tilde{p}} = 0$ and noting $\tilde{y} = \tilde{k}^{\alpha_k}\tilde{h}^{\alpha_H}\tilde{p}^{\alpha_P}$, we get $0 = s_k\tilde{k}^{\alpha_k}\tilde{h}^{\alpha_H}\tilde{p}^{\alpha_P} - (n+g+\delta)\tilde{k}$ and $0 = s_H\tilde{k}^{\alpha_k}\tilde{h}^{\alpha_H}\tilde{p}^{\alpha_P} - (n+g+\delta)\tilde{h}$

$$\tilde{k} = \left(\frac{s_k\tilde{h}^{\alpha_H}\tilde{p}^{\alpha_P}}{n+g+\delta}\right)^{1/(1-\alpha_k)}, \quad \tilde{h} = \left(\frac{s_h\tilde{k}^{\alpha_K}\tilde{p}^{\alpha_P}}{n+g+\delta}\right)^{1/(1-\alpha_H)}, \tilde{p} = \left(\frac{s_p\tilde{h}^{\alpha_H}\tilde{k}^{\alpha_K}}{n+g+\delta}\right)^{1/(1-\alpha_P)}$$

There is a diminishing return to aggregate capital (including physical, human, and health) i.e. $\alpha_k + \alpha_H + \alpha_P < 1$, then the region converges to it steady state[5]:

$$\tilde{k}^* = \left(\frac{s_k^{(1-\alpha_H-\alpha_P)}s_h^{\alpha_H}s_p^{\alpha_P}}{(n+g+\delta)}\right)^{\left(\frac{1}{(1-\alpha_P-\alpha_K-\alpha_H)}\right)}$$

$$\tilde{h}^* = \left(\frac{s_H^{(1-\alpha_K-\alpha_P)}s_P^{\alpha_P}s_K^{\alpha_k}}{n+g+\delta}\right)^{\left(\frac{1}{(1-\alpha_P-\alpha_H-\alpha_K)}\right)}$$

$$\tilde{p}^* = \left(\frac{s_P^{(1-\alpha_H-\alpha_K)}s_K^{\alpha_K}s_h^{\alpha_H}}{(n+g+\delta)}\right)^{\left(\frac{1}{(1-\alpha_P-\alpha_H-\alpha_K)}\right)}$$

Therefore, the potential level of income is as follows.

$$\tilde{y} = \left(\frac{s_K^{\alpha_K}s_H^{\alpha_H}s_P^{\alpha_P}}{(n+g+\delta)}\right)^{\frac{(\alpha_K+\alpha_H+\alpha_P)}{(1-\alpha_K-\alpha_H-\alpha_P)}}$$

Substituting the value of $\tilde{k}^*$, $\tilde{h}^*$ and $\tilde{p}^*$ Into the production function and taking the log, we find that steady state income per capita is as follows:

$$\ln\left[\frac{Y(t)}{L(t)}\right] = \ln A(0) + gt - \frac{\alpha_K+\alpha_H+\alpha_P}{1-\alpha_K-\alpha_H-\alpha_P}\ln(n+g+\delta) + \frac{\alpha_K}{1-\alpha_K-\alpha_H-\alpha_P}\ln(s_k) + \frac{\alpha_H}{1-\alpha_K-\alpha_H-\alpha_P}\ln(s_h) - \frac{\alpha_P}{1-\alpha_K-\alpha_H-\alpha_P}\ln(s_P)$$

[5] Solving for this is describe with each little step in Appendix B1

Dealing with the dynamism around the steady-state level of income[6] following Mathur et al. (2015), we get

$$\frac{\dot{\tilde{y}}}{\tilde{y}} = \lambda(\log \tilde{y}^* - \log \tilde{y})$$

Where $\lambda = -(1 - \alpha_k - \alpha_H - \alpha_P)(n + g + \delta)$, λ is the speed of convergence defined as $-\frac{d\left(\frac{\dot{\tilde{y}}}{\tilde{y}}\right)}{d\,\mathrm{lo}\ \tilde{}}$

$$\frac{d \log \tilde{y}}{dt} + \lambda \log \tilde{y} = \lambda \log \tilde{y}^*$$

Solving this differential equation we get,

$$\log \tilde{y} - \log \tilde{y}(0) = -\log \tilde{y}\,(0)\left(1 - e^{-\lambda}\ \right) + \log \tilde{y}^*\left(1 - e^{-\lambda t}\right) \tag{2}$$

$$\log y_t - \log \tilde{y}(0) = -\left(1 - e^{-\lambda}\ \right)\log \tilde{y}(0) + c_i \tag{3}$$

This is the equation for unconditional convergence where c_i is the term consist of other portion of potential level of income.

Thus, by putting the value of the potential level of income in the above equation, we get the equation of conditional convergence:

$$\ln\big(y(t)\big) - \ln\big(y(0)\big) = \left(1 - e^{-\lambda t}\right)\frac{\alpha_k}{1 - \alpha_K - \alpha_H - \alpha_P}\ln(s_K) + \left(1 - e^{-\lambda t}\right)\frac{\alpha_H}{1 - \alpha_K - \alpha_H - \alpha_P}\ln(s_H) + \left(1 - e^{-\lambda t}\right)\frac{\alpha_H}{1 - \alpha_K - \alpha_H - \alpha_P}\ln(s_P) - \left(1 - e^{-\lambda t}\right)\frac{\alpha_k + \alpha_H + \alpha_P}{1 - \alpha_K - \alpha_H - \alpha_P}\ln(n + g + \delta) - \left(1 - e^{-\lambda t}\right)\ln\big(y(0)\big) \tag{4}$$

3.2. Solovian Model with Spatial Externalities

Tobler's law[7] emphasizes that spatial relationships are stronger among nearby features. This is why spatial dependence, whether from variables, covariates, or omitted factors, plays a crucial role in growth models. Spatial dependence can help to capture within-country and state variations in GDP and their proximity impact.

Examining a system of N similar regions, variations emerge due to diverse endowments and allocations, contributing to the total output Y(t). This arises from an aggregate Cobb Douglas production function demonstrating constant returns to scale in labor and capital.

---

[6] Dynamism around steady state is solved in Appendix B2
[7] Tobler (1950)

In equation (1), we have includes five variables: Manufacturing M_{it}, Agriculture G_{it} and Health infrastructure R_{it}, health indicator of the region F_{it} and services S_{it}. We have added migration P_{it} and population density D_{it} to account for economic agglomeration and clustering. Therefore, our Cobb Douglas production function will become as follows:

$$Y_{it} = A_{it}K_{it}^{\alpha_K}H_{it}^{\alpha_H}M_{it}^{\alpha_M}G_{it}^{\alpha_G}R_{it}^{\alpha_R}F_{it}^{\alpha_f}S_{it}^{\alpha_S}P_{it}^{\alpha_P}D_{it}^{\alpha_D}\ (L_{it})^{(1-\alpha_K-\alpha_H-\alpha_M-\alpha_G-\alpha_r-\alpha_J-\alpha_s-\alpha_P-\alpha_D)} \qquad (5)$$

Th exponent α_K signifies output elasticity to physical capital, while other exponents do the same for respective variables. The final factor in the production of output is the level of technological knowledge available in region i at time t. In accordance with Ertur and Koch (2007) and Fischer (2010), we model A_{it} as

$$A_{it} = \Omega_t e^{g_t}\, k_{it}^{\theta}h_{it}^{\phi}m_{it}^{\psi}g_{it}^{\omega}r_{it}^{\Phi}f_{it}^{\upsilon}S_{it}^{\tau}P_{it}^{\xi}D_{it}^{\kappa}\prod_{j\neq i}^{N}A_{jt}^{\rho W_{it}} \qquad (6)$$

The last term on the right-hand side of Eq. 6 formalizes the spatial extent of this dependence by mean of the so-called spatial weight term W_{ij} That represents spatial connectivity between region i and j for j=1,…, N. The Manufacturing can explain the level of technology in Eq.5 as M_{it}, Agriculture G_{it} and Health infrastructure P_{it}, health indicator of the region J_{it}, services S_{it}, migration P_{it} and population density D_{it}. The additional variables added in the A_{it} are the steppingstone for our theoretical model and contribute to the additional variables that have spatial spillover impact.

The technological interdependence among the regions can be analyzed as an interdependent system. Therefore, we can write equation (6) in the matrix form as

$$A = \boldsymbol{\Omega} + \theta\boldsymbol{k} + \phi\boldsymbol{h} + \psi\boldsymbol{m} + \omega\boldsymbol{g} + \Phi\boldsymbol{r} + \upsilon\boldsymbol{f} + \tau\boldsymbol{s} + \xi\boldsymbol{p} + \kappa\boldsymbol{d} + \boldsymbol{\rho W A} \qquad (7)$$

Where A is the vector of the logarithmic of the level of technology having dimension $(N \times 1)$. On the right side of the equation first ten are the variable vectors with dimension $(N \times 1)$ and the coefficient is attached to each variable as a scaler. W is the having dimension as $(N \times N)$ Which is termed a Markov matrix with the property of non-negative elements of the matrix and having the sum of each column vector equal to 1. This property is required for row standardization for spatial weight matrix W. We can resolve the equation (5) for A, where $\rho \neq 0$ and $1/\rho$ is not an eigen value of W.

$$A = (1-\rho W)^{-1}\boldsymbol{\Omega} + \theta(1-\rho W)^{-1}\boldsymbol{k} + \phi(1-\rho W)^{-1}\boldsymbol{h} + \psi(1-\rho W)^{-1}\boldsymbol{m} + \omega(1-\rho W)^{-1}\boldsymbol{g} + \Phi(1-\rho W)^{-1}\boldsymbol{r} + \upsilon(1-\rho W)^{-1}\boldsymbol{f} + \tau(1-\rho W)^{-1}\boldsymbol{s} + \xi(1-\rho W)^{-1}\boldsymbol{p} + \kappa(1-\rho W)^{-1}\boldsymbol{d}$$

According to the SMRW model, the expression of capital-output ratios at steady state into the per worker production function and taking the logarithm, gives an equation of the output per worker of region i at steady state:

$$A_{it} = \Omega_t^{\frac{1}{1-\rho}} k_{it}^{\theta} h_{it}^{\phi} m_{it}^{\psi} g_{it}^{\omega} r_{it}^{\Phi} f_{it}^{\upsilon} s_{it}^{\tau} p_{it}^{\xi} d_{it}^{\kappa} \prod_{j\neq i}^{N} \begin{matrix} k_{jt}^{\theta\sum_{r=1}^{\infty}\rho^r (W^r)_{ij}} & h_{jt}^{\phi\sum_{r=1}^{\infty}\rho^r (W^r)_{ij}} & m_{jt}^{\psi\sum_{r=1}^{\infty}\rho^r (W^r)_{ij}} \\ g_{jt}^{\omega\sum_{r=1}^{\infty}\rho^r (W^r)_{ij}} & r_{jt}^{\Phi\sum_{r=1}^{\infty}\rho^r (W^r)_{ij}} & f_{jt}^{\upsilon\sum_{r=1}^{\infty}\rho^r (W^r)_{ij}} \\ s_{jt}^{\tau\sum_{r=1}^{\infty}\rho^r (W^r)_{ij}} & p_{jt}^{\xi\sum_{r=1}^{\infty}\rho^r (W^r)_{ij}} & d_{jt}^{\kappa\sum_{r=1}^{\infty}\rho^r (W^r)_{ij}} \end{matrix}$$

Here, the level of technology does only depend on its own physical capital per worker or other factors determining income but also on the neighborhood's physical capital per worker or other factors taken in the model. Where, $(W^r)_{ij}$ is the $(i,j)th$ element of W^r. By normalizing the production function given in equation (5) by L_{it} And inserting the above value of technology in production, we can get the foundation of the theoretical model.

$$y_{it} = \Omega_t^{\frac{1}{1-\rho}} k_{it}^{a_{ii}} h_{it}^{b_{ii}} m_{it}^{c_{ii}} g_{it}^{z_{ii}} r_{it}^{\mathrm{n_{ii}}} f_{it}^{q_{ii}} s_{it}^{l_{ii}} p_{it}^{o_{ii}} d_{it}^{x_{ii}} \prod_{j\neq i}^{N} k_{jt}^{a_{ij}} h_{jt}^{b_{ij}} m_{jt}^{c_{ij}} g_{jt}^{z_{ij}} r_{jt}^{\mathrm{n_{ij}}} f_{jt}^{q_{ij}} s_{jt}^{l_{ij}} p_{jt}^{o_{ij}} d_{jt}^{x_{ij}} \tag{8}$$

3.2.1. Dynamism Around Steady State for the Solovian Spatial Externality model

The basic dynamic equations of the Solow model, which govern the evolution of output per worker in region i is as follow.

$$\dot{k_{it}} = s_i^K y_{it} - (n_i + \delta) k_{it}$$

The per-worker production function exhibits diminishing returns for the mentioned factors. Output in regions i=1…N converges to a steady state define by

$$y_{it}^{*} = \Omega^{\frac{1}{(1-\rho)(1-a_{ii}-b_{ii}-c_{ii}-m_{ii}-n_{ii}-q_{ii}-l_{ii}-o_{ii}-x_{ii})}}$$

$$\left[\frac{\left(s_i^K\right)^{a_{ii}} + \left(s_i^H\right)^{b_{ii}} + \left(s_i^M\right)^{c_{ii}} + \left(s_i^G\right)^{m_{ii}} + \left(s_i^R\right)^{n_{ii}} + \left(s_i^F\right)^{q_{ii}} + \left(s_i^S\right)^{l_{ii}} + \left(s_i^P\right)^{o_{ii}} + \left(s_i^D\right)^{x_{ii}}}{(n+g+\delta)^{a_{ii}+b_{ii}+c_{ii}+m_{ii}+n_{ii}+q_{ii}+l_{ii}+o_{ii}+x_{ii}}}\right]^{\frac{1}{(1-a_{ii}-b_{ii}-c_{ii}-m_{ii}-n_{ii}-q_{ii}-l_{ii}-o_{ii}}}$$

$$\prod_{j=i}^{N}\left(k_{jt}^{*a_{ij}} h_{jt}^{*b_{ij}} m_{jt}^{*c_{ij}} g_{jt}^{*m_{ij}} r_{jt}^{*\mathrm{n_{ij}}} f_{jt}^{*q_{ij}} s_{jt}^{*l_{ij}} p_{jt}^{*o_{ij}} d_{jt}^{*x_{ij}}\right)^{\frac{1}{(1-a_{ii}-b_{ii}-c_{ii}-m_{ii}-n_{ii}-q_{ii}-l_{ii}-o_{ii}-x_{ii})}} \qquad (9)$$

With a balance growth rate

$$g = \frac{\mu}{(1-\rho)\left(1-\alpha_K-\alpha_H-\alpha_M-\alpha_G-\alpha_r-\alpha_J-\alpha_s-\alpha_P-\alpha_D\right)-\theta-\phi-\psi-\omega-\Phi-\upsilon-\tau-\xi-\kappa}$$

Where * used in the superscript of the variable means the steady-state levels for $y, k,$ and h. Therefore, the factor-output ratios of region i are constant. Thus,

$$\frac{k_{it}^{*}}{y_{it}^{*}} = \frac{s_i^K}{n_i+g+\delta}$$

Similarly, we have factor output ratio for all other factors. These expressions of factor-output ratio at steady state are a substitute for the per-worker production function and take the logarithm. This gives us the following:

$$lnY_i^{*}(t) = \frac{1}{1-\eta} ln\Omega(0) + \frac{\alpha_K+\theta}{1-\eta}\ln s_i^K + \frac{\alpha_H+\phi}{1-\eta}\ln s_i^H + \frac{\alpha_M+\psi}{1-\eta}\ln s_i^M$$

$$+\frac{\alpha_G+\omega}{1-\eta}\ln s_i^G + \frac{\alpha_R+\Phi}{1-\eta}\ln s_i^R + \frac{\alpha_F+\upsilon}{1-\eta}\ln s_i^F + \frac{\alpha_S+\tau}{1-\eta}\ln s_i^S$$

$$+\frac{\alpha_P+\xi}{1-\eta}\ln s_i^P + \frac{\alpha_D+\kappa}{1-\eta}\ln s_i^D - \frac{1}{1-\eta} ln(n_i+g+\delta) - \frac{\alpha_K}{1-\eta}\rho\sum_{\substack{j=1\\ j\neq i}}^{N} W_{ij}\ln s_j^K$$

$$-\frac{\alpha_H}{1-\eta}\rho\sum_{\substack{j=1\\j\neq i}}^{N}W_{ij}\ln s_j^H-\frac{\alpha_M}{1-\eta}\rho\sum_{\substack{j=1\\j\neq i}}^{N}W_{ij}\ln s_j^M-\frac{\alpha_G}{1-\eta}\rho\sum_{\substack{j=1\\j\neq i}}^{N}W_{ij}\ln s_j^G$$

$$-\frac{\alpha_R}{1-\eta}\rho\sum_{\substack{j=1\\j\neq i}}^{N}W_{ij}\ln s_j^R-\frac{\alpha_F}{1-\eta}\rho\sum_{\substack{j=1\\j\neq i}}^{N}W_{ij}\ln s_j^F-\frac{\alpha_S}{1-\eta}\rho\sum_{\substack{j=1\\j\neq i}}^{N}W_{ij}\ln s_j^S$$

$$-\frac{\alpha_P}{1-\eta}\rho\sum_{\substack{j=1\\j\neq i}}^{N}W_{ij}\ln s_j^P-\frac{\alpha_D}{1-\eta}\rho\sum_{\substack{j=1\\j\neq i}}^{N}W_{ij}\ln s_j^D$$

$$-\frac{\zeta}{1-\eta}\rho\sum_{\substack{j=1\\j\neq i}}^{N}W_{ij}\ln(n_i+g+\delta)+\frac{1-\zeta}{1-\eta}\rho\sum_{\substack{j=1\\j\neq i}}^{N}W_{ij}\ln Y_{jt}^{*}$$

(10)

Where, $\eta = \alpha_K+\alpha_H+\alpha_M+\alpha_G+\alpha_R+\alpha_F+\alpha_S+\alpha_P+\alpha_D+\theta+\phi+\psi+\omega+\Phi+\upsilon+\tau+\xi+\kappa$. and $\zeta = \alpha_K+\alpha_H+\alpha_M+\alpha_G+\alpha_R+\alpha_F+\alpha_S+\alpha_P+\alpha_D$

Equation for spatial convergence

$\ln y_t(t\,)-\ln y_i(0) = \Delta_i-\left(1-e^{-\lambda_t t}\right)\ln y_i(0)+\left(1-e^{-\lambda_i t}\right)\frac{\eta}{1-\eta}s_i^K+\left(1-e^{-\lambda_i t}\right)\frac{\eta}{1-\eta}s_i^H+\left(1-e^{-\lambda_i t}\right)\frac{\eta}{1-\eta}s_i^M+\left(1-e^{-\lambda_i t}\right)\frac{\eta}{1-\eta}s_i^G+\left(1-e^{-\lambda_i t}\right)\frac{\eta}{1-\eta}s_i^R+\left(1-e^{-\lambda_i t}\right)\frac{\eta}{1-\eta}s_i^F+\left(1-e^{-\lambda_i t}\right)\frac{\eta}{1-\eta}s_i^S+\left(1-e^{-\lambda_i t}\right)\frac{\eta}{1-\eta}s_i^P+\left(1-e^{-\lambda_i t}\right)\frac{\eta}{1-\eta}s_i^D+\left(1-e^{-\lambda_i t}\right)\frac{1-\zeta}{1-\eta}\sum_{\substack{j=1\\j\neq i}}^{N}w_{ij}\ln y_j(0)-\left(1-e^{-\lambda_i t}\right)\frac{\alpha_K\gamma}{1-\eta}\sum_{\substack{j=1\\j\neq i}}^{N}w_{ij}\ln s_j^K-\left(1-e^{-\lambda_i t}\right)\frac{\alpha_H\gamma}{1-\eta}\sum_{\substack{j=1\\j\neq i}}^{N}w_{ij}\ln s_j^H-\left(1-e^{-\lambda_i t}\right)\frac{\alpha_M\gamma}{1-\eta}\sum_{\substack{j=1\\j\neq i}}^{N}w_{ij}\ln s_j^M-\left(1-\right.$

$$e^{-\lambda_i t}\Big)\frac{\alpha_G\gamma}{1-\eta}\sum_{\substack{j=1\\ j\neq i}}^{N} w_{ij}\ln s_j^G - \Big(1-e^{-\lambda_i t}\Big)\frac{\alpha_R\gamma}{1-\eta}\sum_{\substack{j=1\\ j\neq i}}^{N} w_{ij}\ln s_j^R - \Big(1-$$

$$e^{-\lambda_i t}\Big)\frac{\alpha_F\gamma}{1-\eta}\sum_{\substack{j=1\\ j\neq i}}^{N} w_{ij}\ln s_j^F - \Big(1-e^{-\lambda_i t}\Big)\frac{\alpha_S\gamma}{1-\eta}\sum_{\substack{j=1\\ j\neq i}}^{N} w_{ij}\ln s_j^S - \Big(1-$$

$$e^{-\lambda_i t}\Big)\frac{\alpha_P\gamma}{1-\eta}\sum_{\substack{j=1\\ j\neq i}}^{N} w_{ij}\ln s_j^P - \Big(1-e^{-\lambda_i t}\Big)\frac{\alpha_D\gamma}{1-\eta}\sum_{\substack{j=1\\ j\neq i}}^{N} w_{ij}\ln s_j^D + \Big(1-$$

$$e^{-\lambda_i t}\Big)\frac{\zeta\gamma}{1-\eta}\sum_{\substack{j=1\\ j\neq i}}^{N} w_{ij}\ln\big(n_j+g+\delta\big) + \Big(1-e^{-\lambda_i t}\Big)\frac{(1-\zeta)\gamma}{1-\eta}\sum_{\substack{j=1\\ j\neq i}}^{N}\frac{1}{\big(1-e^{-\lambda_i t}\big)} w_{ij}\big[\ln y_j(t) -$$

$$\ln y_j(0)\big] \qquad (11)$$

Unconditional Spatial Externality Model Equation

$$\begin{aligned}\ln y_t(t\ ) - \ln y_i(0) &= \Delta_i - \big(1-e^{-\lambda_t t}\big)\ln y_i(0) + \big(1-e^{-\lambda_i t}\big)\frac{1-\zeta}{1-\eta}\sum_{j=i}^{N} w_{ij}\ln y_j(0) \\ &+ \big(1-e^{-\lambda_i t}\big)\frac{(1-\zeta)\gamma}{1-\eta}\sum_{j=i}^{N}\frac{1}{\big(1-e^{-\lambda_j t}\big)} w_{ij}\big[\ln y_j(t) - \ln y_j(0)\big] \qquad (12)\end{aligned}$$

Following Ertur and Koch (2007), the speed of convergence considering spatial externalities is given by:

$$\frac{d\ln\ y_i(t)}{dt} = \frac{\mu}{1-\gamma} - \lambda_i[\ln\ y_i(t) - \ln\ y_i^*]$$

Where the speed of convergence is:

$$\lambda_i = \frac{\sum_{j=1}^{N}\ a_{ij}\frac{1}{\Phi_j}\big(n_j+g+\delta\big)}{\sum_{j=1}^{N}\ a_{ij}\frac{1}{\Phi_j}} - \sum_{j=1}^{N}\ a_{ij}\frac{1}{\Theta_j}\big(n_j+g+\delta\big)$$

This convergence speed is valid for the production function consisting of only physical capital, but in our case, the production function has many variables. Therefore, the above expression for the speed of convergence will include more variables that not only have a_{ij} but also for other variables mentioned in equation (6). Thus, the speed of convergence is as follows.

$$\lambda_i = \sum_{u}^{u=[a,b,c,z,n,q,l,o,x]]} \frac{\sum_{j=1}^{N} u_{ij} \frac{1}{\Phi_j}(n_j + g + \delta)}{\sum_{j=1}^{N} u_{ij} \frac{1}{\Phi_j}} - \sum_{j=1}^{N} u_{ij} \frac{1}{\Theta_j}(n_j + g + \delta)$$

4. Variables, Data and Data Source

Our analysis is based on the districts of India. Spatial units are the districts of 36 States and Union Territories of India. First and foremost, the object of the study is to test for district-level unconditional spatial convergence. For this purpose, we have used the data of the annual growth rate of the districts averaged over the period from 2001-02 to 2017-18 and the initial level of GDP at the constant price level of 2004-05 (i.e., the district GDP as of 2001-02).

Table 3: Variable Description and Sources of Data

Variable	Description	Source of Data	Hypothesis
Growth of Income	Growth of GDP per Capita in each district	IIM Ahmedabad	Negative in Spatial Regression
Literacy Rate	Proxy for Human Capital	Population Census	Positive
Financial Inclusion	means the ability to access necessary financial services in an appropriate form.	RBI database	Positive
Health Index	Health Index indicates the health of the district. More is the index, less well of the district is in the case of Health status	NFHS[8] and Population Census data	Negative
Health Infrastructure	Score indicating infrastructure development	DLHS-4[9]	Positive
Share of Agriculture, Manufacturing and Services (three variables)	Share of Agriculture, Manufacturing or Services in GDP of particular district	IIM Ahmedabad	Positive for all three variables
Population Density	Density of Population per thousand Km of district	Population Census	Positive

[8] National Family Health Survey (NFHS)
[9] District Level Household Survey (DLHS)

Migration rate	Population migrated from the district	Census	Positive

4.1. Data sources

The source of GDP data IIM Ahmedabad's district GDP database. Migration, population growth, and density data are from the 2001 and 2011 censuses. The RBI's website provides the data for financial inclusion which comprising deposit and credit indicators along with the bank count at district level. Health data is obtained from NFHS-4 and DLHS-4. Refer to Table 3 for data sources and variable details.

4.2 Financial Inclusion Index

Levine (1997) discovered that financial functions like resource allocation, corporate governance, savings mobilization, and trade facilitation act as conduits for capital accumulation, consequently propelling economic growth. King and Levine (1993) observed strong and consistent correlations between various factors—such as the size of the formal financial intermediary sector relative to GDP, the significance of banks compared to the central bank, the allocation of credit to private firms, and the credit-to-GDP ratio for private firms—and both growth and physical capital accumulation rates. These findings encourage the use of a comprehensive financial inclusion index as a proxy for physical capital.

Financial inclusion means the ability to access necessary financial services in an appropriate form. As per the Rangarajan committee, financial inclusion as *the process of ensuring access to financial services and timely and adequate credit where needed by vulnerable groups, such as the weaker sections and low-income groups, at an affordable cost.*

Since this index needs to include the number of variables used by literature in context of India, we mainly have three variables that will compose this index for district-level computation of this index. The first one is the number of banks[10]per thousand population, the second one consists of the amount of aggregate deposits in banks, and the last one includes the aggregate amount of credit the banks

[10] Banks here means the scheduled commercial banks

give. We will use the multidimensional approach for creating an index used by Sarma 2008. This approach will help us consider the availability and usage of financial resources. We also adjust the variability of the district by dividing all three variables mentioned above by population. Then these variables are converted into the dimension index d_i for i^{th} district at one particular point in time, whose formula would be given by:

$$d_i = \frac{x_i - \min(x_i)}{\max(x_i) - \min(x_i)} \tag{13}$$

Where, x_i is the actual value of the variable, $\max(x_i)$ is the maximum value of x_i and $\min(x_i)$ is the minimum value of x_i. Thus, the formula of d_i ensure its value lies between zero and one. Thus, we can say, $D_i = (d_1, d_2, d_3)$ is the three-dimensional cartesian space. Where, $O = (0,0,0)$ represents the worst situation, and $I = (1,1,1)$ represents the highest achievement among all districts. For computing the index of the financial inclusion index FI_i for the i^{th} district, there is a need to normalize the Euclidean distance of D_i from its ideal point $I = (1,1,1)$. This gives us the complete formula for financial inclusion:

$$FI_i = 1 - \frac{\sqrt{(1-d_1)^2 + (1-d_2)^2 + (1-d_3)^2}}{\sqrt{n}} \tag{14}$$

4.3 Health Index and Health Infrastructure

Health infrastructure significantly influences economic growth and development in various facets, enhancing overall population well-being, thereby impacting regional economies. Rivera and Luis (1999) emphasized health's pivotal role in economic growth among OECD countries. Similarly, Bloom et al. (2001) and Agu (2015) highlighted health index and infrastructure as vital growth determinants. These studies contribute to understanding the importance of health-related factors in fostering economic growth.

For the index's composition, we have taken mainly three domains, namely elderly health, adult heath, and child health. We have followed Mohanty et al. (2019) to formulate the index. Adult health was measured using the body mass index (BMI), hypertension and diabetes (among women of age between 15 and 49 and for men aged between 15 and 54), and moderate and severe anemia (among women aged 15–49). Elderly health is measured using a percentage of disability among the 60+ population. Child health is calculated by using stunting, diarrhea, and under-five mortality. The database for this index is NFHS-4 which is for 2015-16. For elderly health, we have used the Census of India 2011.

For health infrastructure, we use primary health care infrastructure which has used the primary health center's (PHC) quality to indicate the mean physical infrastructure (MPI) score for taking proxy for health infrastructure. MPI of a PHC is simply the average of variables based on the type of building, the primary source of water supply, duration of power supply, availability of toilet facility, availability of labor room, and medical officer residing in the quarters attached to the PHC. For this also, we have followed Mohanty et al. (2019). Data base for this index is DLHS-4.

4.4 District's Cohorts

The primary motivation behind creating EPI groups is the recognition that convergence outcomes can exhibit variations across regions. This phenomenon is exemplified by the Mankiw Romer Weil (1992) study, where convergence results differed across different countries. In the context of Indian states, Cherodian and Thirlwall's (2015) research also demonstrated disparate results among various groups of states. In line with these research findings, we categorized districts into groups based on the Economic Potential Index (EPI) obtained from Robert (2016).The EPI classifies Indian districts into five distinct groups using five key indicators: market access, economic density, urbanization rate, human capital availability, and local transport connectivity.

We have also taken the aspirational districts marked by the government of India based on their poor performance. The program ranks the districts according to the composite score, which focuses on five main themes – Health & Nutrition, Education, Agriculture & Water Resources, Financial Inclusion & Skill Development, and Basic Infrastructure with the weight of 30%, 30%, 20%, 5%, 5%, and 10% respectively.

Northeastern Zone consists of Arunachal Pradesh, Assam, Manipur, Meghalaya, Mizoram, Nagaland, and Tripura. In contrast, Southern Zone has Andaman and Nicobar, Andhra Pradesh, Karnataka, Kerala, Lakshadweep, Tamil Nadu, and Telangana. We have Dadra and Nagar Haveli in Western Zone, Daman and Diu, Goa, Gujarat, Maharashtra, and Rajasthan. Central Zone comprises Bihar, Jharkhand, Orissa, Sikkim, West Bengal, Chhattisgarh, Madhya Pradesh, Uttar Pradesh, and Uttaranchal. And lastly, Northern Zone consists of Chandigarh, Delhi, Haryana, Himachal Pradesh, Jammu and Kashmir, Puducherry, and Punjab.

5. Methodology

5.1. Spatial Dependence

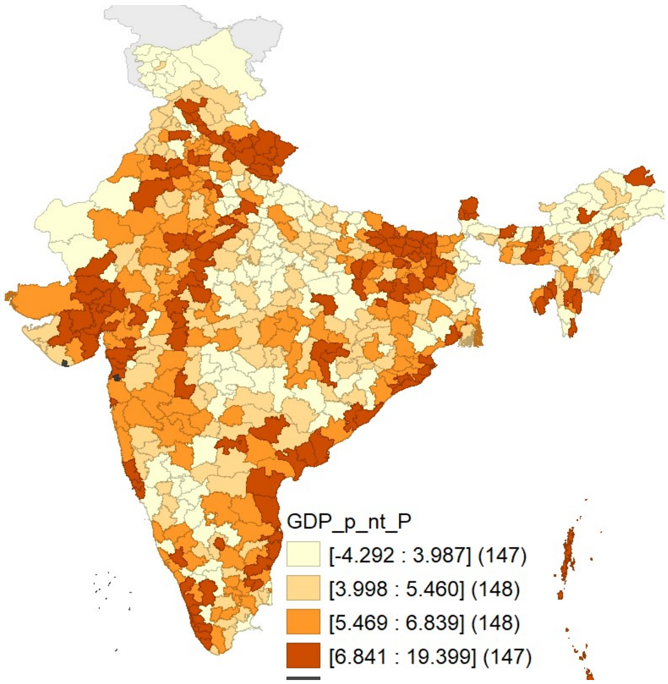
First, we test for the spatial correlation among units which will be diagnosed by Moran's I statistics. This process needs to create the spatial weight matrix based on contiguity, which weighs all regions, but the nearest regions or adjacent regions are shown more. In the contiguity-based spatial weight matrix, we gave weight as one to adjacent regions that share common boundaries and zero to other areas. Afterward, we do row standardization in this matrix.

We use queen contiguity-based neighbors, which consider polygons sharing a common border or vertex, as opposed to rook contiguity that considers polygons sharing a common boundary[11].

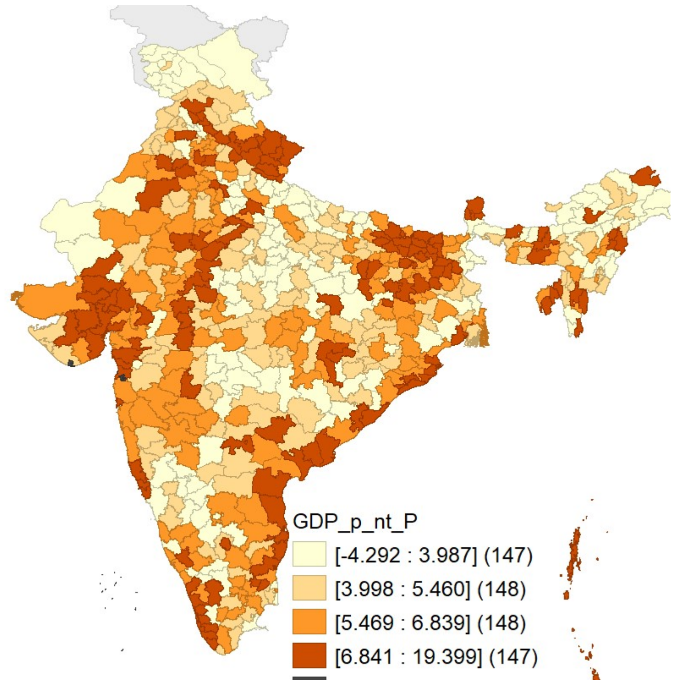
Working of Spatial Analysis: The spatial regression and spatial dependence test need to create the spatial weighted matrix. According to the contiguity, the weights need the shape file at the district level for India. The source of the shapes files is diva-gis.org. We have used the GeoDa software to read the shape file and merge our data with the shape file. Further, we used this merged file for spatial regression in R software. The state-wise comparison of convergence requires the shape file of different states. We have used the Q-GIS software to split the district-level shape file of India into district-level shape files of other states.

[11] Website of Luc Anselin whose URL is the following :
https://geodacenter.github.io/workbook/4a_contig_weights/lab4a.html#fn1

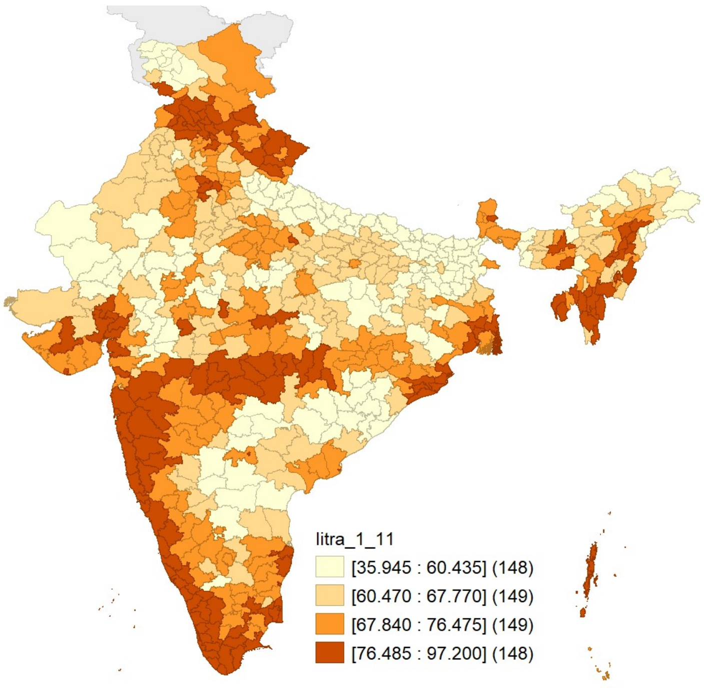
Figure 1: Spatial Distribution of Selected Variables Among Indian Districts for the Time Period Averaged from 2001 to 2017



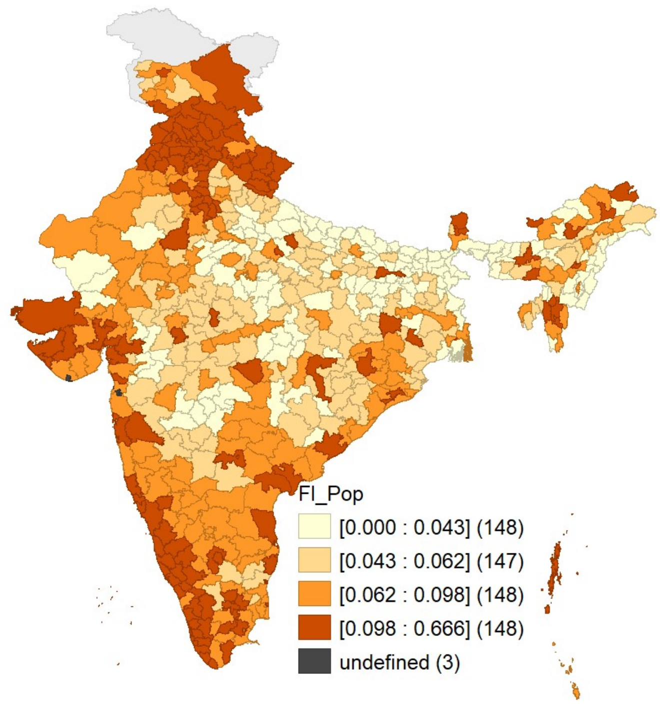
(a) Growth Rate of GDP per Capita of Indian Districts



(b) Log of Initial GDP per Capita of Indian Districts



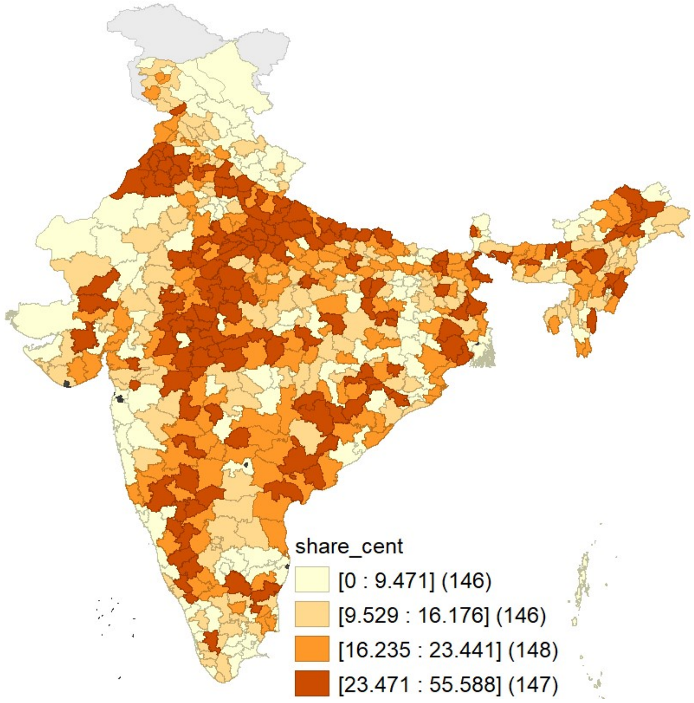
(c) Literacy Rate of Indian Districts



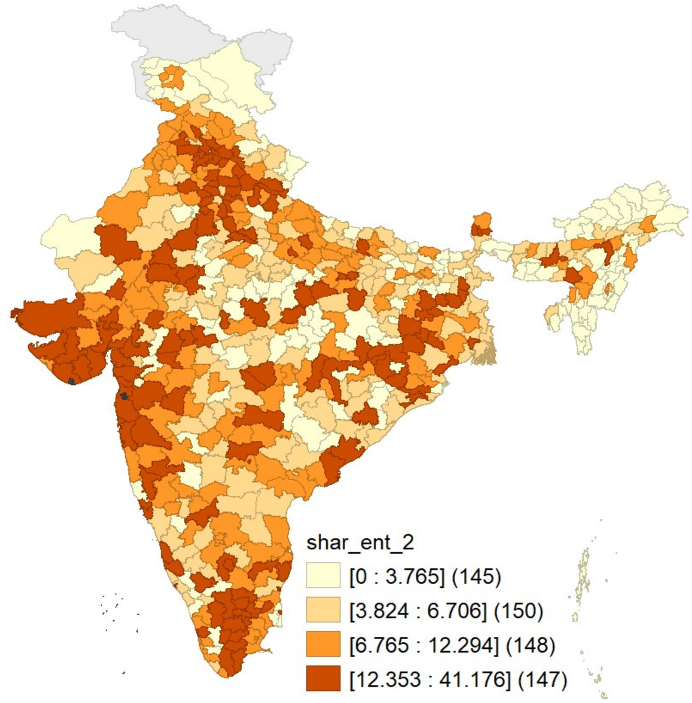
(d) Financial Inclusion Index of Indian Districts

Source: Author's Calculation Based on Work in GeoDa

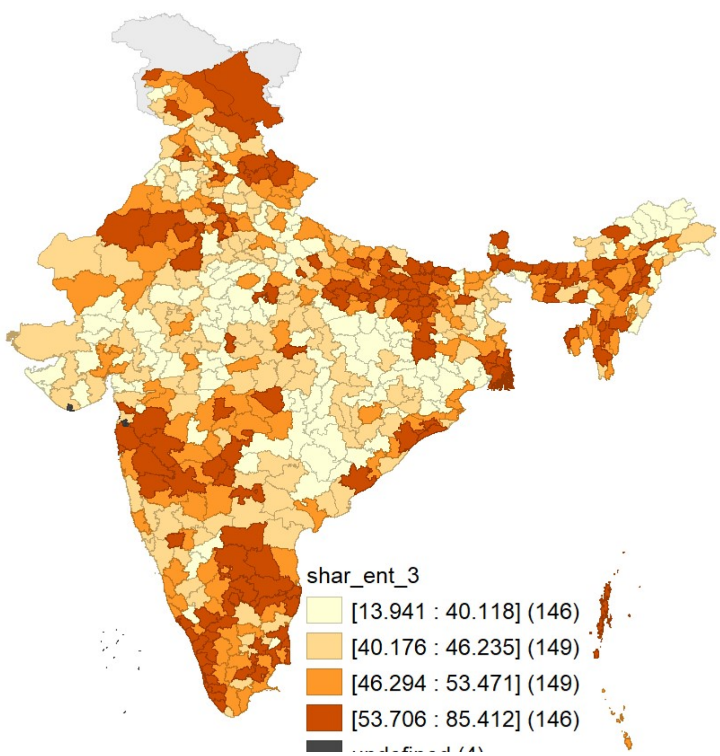
Figure 2: Spatial Distribution of Sector Share in GDP and Population Density Among Indian Districts



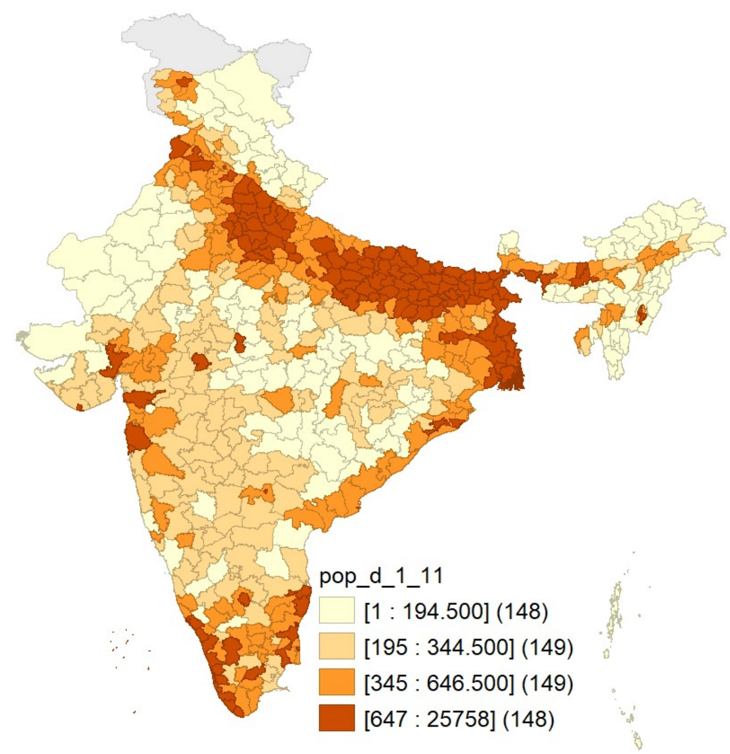
(a) Share of Agricultural Sector in GDP of Indian Districts



(b) Share of Manufacturing Sector in GDP of Indian Districts



(c) Share of Services Sector in GDP of Indian Districts



(d) Population density of Indian Districts

Source: Author's Calculation Based on Work in GeoDa

Figures 1 and 2 depict the spatial distribution among India's districts. The spatial correlation between district-level initial GDP and growth is readily apparent in Figure 1(a) and (b), where similar patterns of colored districts are clustered together. In Figure 1(c), districts with high literacy rates are concentrated in Tamil Nadu, Kerala, Maharashtra, and Punjab. Conversely, districts in Uttar Pradesh, Bihar, Jharkhand, and Chhattisgarh exhibit lower literacy rates. Figure 1(d) illustrates a high pattern of financial inclusion among districts in Punjab, Haryana, Uttarakhand, Gujarat, Kerala, Andhra Pradesh, Telangana, and Karnataka. In contrast, districts in Uttar Pradesh, Bihar, Jharkhand, and Madhya Pradesh exhibit lower levels of financial inclusion.

The districts that lag behind in terms of literacy rate, financial inclusion, and GDP per capita, as shown in Figure 1, exhibit high population density in Figure 2(d) and a high dependency on the agriculture sector in Figure 2(a). The concentration of the Manufacturing sector, as depicted in Figure 2(b), is particularly pronounced around Delhi, Gujarat, Maharashtra, Tamil Nadu, and parts of Jharkhand. The concentration of the Service sector in Figure 2(c) is prominently centered around metropolitan cities.

Moran's I Statistics:

$$I = \frac{\sum_i \left(\sum_j w_{ij} y_j \times y_i\right)}{\sum_i y_i^2} \tag{15}$$

w_{ij} represents the weight assigned to each region's connection with other regions. y_{ij} denotes the dependent variable, specifically the growth rate of GDP per capita at constant prices. For a more specific assessment of spatial dependence, in addition to considering the results of the econometric specification, we have also incorporated the spatial dependence test based on the Lagrange Multiplier principle, as developed by Anselin (1996).

Table 4: Value of Moran's I for District-Level Variable in India

Variable	Moran's I Value
Initial level of GDP	0.523***
Literacy Rate	0.678***
Financial Index	0.339***
Share of Agriculture Sector in GDP	0.333***
Share of Manufacturing Sector in GDP	0.274***
Share of Service Sector	0.398***
Migration rate	0.633***
Population Density	0.067***
Population Growth rate	0.453***

Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

The highest value of Moran's I among the variables listed in Table 4 is associated with the literacy rate. Moreover, significant Moran's I values are also evident for the migration rate, initial GDP level, and the share of the service sector in GDP. These findings indicate a robust spatial correlation for these variables. Similarly, the share of Agriculture and Manufacturing in GDP, along with the population growth rate, also display spatial correlation.

5.2 Spatial Weighted Matrix

The spatial contiguity matrix can be constructed using a weight function that adheres to contiguity criteria (Anselin (1988)). For a universe of n elements within the region, the spatial contiguity matrix, denoted as C can be expressed as follows :

$$C = \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1n} \\ c_{21} & c_{22} & \cdots & c_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ c_{n1} & c_{n2} & \cdots & c_{nn} \end{bmatrix}$$

$$W = \frac{C}{C_0} = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & \cdots & w_{nn} \end{bmatrix}$$

Where c_{ij} is a measurement used to compare and judge the degree of nearness or the contiguous relationships between region i and region j.

C_{ij} can be defined as 1 if region i is a neighbor of j or otherwise zero. Where $C_0 = \sum_{j=0}^{n} c_{ij}$. Row-standardization takes the given weights w_{ij} and divides them by the row sum: $w_{ij} = c_{ij}/\sum_j c_{ij}$. So, when add up the numbers in each row of the adjusted weights, the total is always one.

5.3 Non-Spatial Unconditional & Conditional Income Convergence and Speed of Convergence

The foundation of income convergence lies in the vast literature on economic growth and new economic geography, which emerged with lots of empirical and theoretical research focused on the traditional models of exogenous growth developed by Solow (1956) and Swan (1956). The primary focus on income convergence was given by Mankiw, Romer, and Weil (1992) and Barro & Sala-i-Martin (1995). Cherodian & Thirlwall 2015 has the following equation for the unconditional beta convergence.

$$g_{gdp} = \alpha + \beta(\text{log initial } PC\_GDP\ ) + \varepsilon_r \qquad (16)$$

Where g_{gdp} is the growth of GDP per capita, α is the constant and ε_r is the error term. In this equation, β is the coefficient of initial log GDP per capita, which exhibit the convergence of income of the poorer region with the richer counterpart. If β is negative, it gives evidence of unconditional convergence and otherwise divergence. For the unconditional convergence, we have taken the district-level data of India averaged over the time of 2001-02 to 2017-18. The dependent variable is

GDP growth per capita, and the independent variable is the initial value of per capita GDP. We would like to see unconditional convergence with considering spatial interaction's impact. We will also use the spatial growth regression by following Rey and Le Gallo (2009)[12].

For conditional convergence we will add more variables to equation (16) and which is the econometric specification equation of our solovian model of section 2.1 and equation (4) with addition of more variables the we mentioned earlier.

In the growth theory Barro-Salai-Martin, the convergence speed can be calculated by following the equation.

$$Y_{\mathrm{i},,\mathrm{T}} = \mathrm{a} - \left(1 - \mathrm{e}^{-\lambda_s}\right) * \log \mathrm{Y}_{\mathrm{i}0} + \mathrm{u}_{\mathrm{t}} \qquad (17)$$

where $Y_{\mathrm{i},,\mathrm{T}}$ is the average annual growth rate of gross domestic product per capita of Indian States between time period t and $t + T \cdot \log \mathrm{y}_{\mathrm{t}}$ is the log (natural) of per capita gross domestic product at time period t. U_{t} is the error term. λ_s is the speed of convergence implying the speed at the which actual income is reaching its common steady state level of income (potential level of income) in a year. We will use Non-linear least square method of estimation for calculating the speed of convergence. Equation (17) above gives the speed of conditional convergence (This is the same equation (3) that we have worked out in section 3). In future work, we will be working out the speed of conditional convergence under no spatial externality and with spatial externality.

5.4 Spatial Unconditional & Conditional Income Convergence

For spatial conditional and unconditional income convergence, we will estimate the equations (12) and (13). The econometric specification of these equations in matrix form is as follow:

$$\boldsymbol{y} = \boldsymbol{t}_N \beta_0 + \boldsymbol{X\beta} + \boldsymbol{WX\theta} + \rho \boldsymbol{Wy} + \boldsymbol{\varepsilon} \qquad (18)$$

Where y is N-by-1vector of observations on growth of GDP per capita of each region. X is N-by-Q matrix which consists of q number of variables that we have in our model. β is vector of regression

[12] Palgrave Handbook of Econometrics

parameter which is associated with independent variables. W is the matrix of N-by-N which is described in section 5.2. $\boldsymbol{\theta}$ is the vector of spatial association of independent variables and ρ is parameter associated with the spatial dependence of dependent variable.

For the unconditional convergence we have only one variable in $\boldsymbol{X}$ matrix that is log of initial level of GDP per capita. In case of conditional convergence, we will include more variables mentioned in the model. We have also used various spatial regression model mentioned below for all type of spatial relations.

Different Models of Spatial Regression

Model	**:**	**Specification**
OLS	:	$y = X\beta + \varepsilon$
SLX: Spatial Lagged X	:	$y = X\beta + WX\theta + \varepsilon$
SAR: Spatial Lag Model	:	$y = \rho Wy + X\beta + \varepsilon$
SEM: Spatial Error Model	:	$y = X\beta + u, \qquad u = \lambda Wu + \varepsilon$
SDEM: Spatial Durbin Error Model	:	$y = X\beta + Wx\theta + u, \qquad u = \lambda Wu + \varepsilon$
SDM: Spatial Durbin Model	:	$y = \rho Wy + X\beta + WX\theta + \varepsilon$
Manski All-inclusive Model	:	$y = \rho Wy + X\beta + WX\theta + u, \quad u = \lambda Wu + \varepsilon$

In the above-mentioned spatial regression models, y is the vector of the dependent variable, X is the matrix of the covariates. θ, ρ and λ are spatial dependence parameters. W is the weight matrix of the relation of one region to another based on queen contiguity. u is the error term.

5.5 GWR to deal with Spatial Heterogeneity

Geographically weighted regression (GWR) enables the coefficients of regression to vary across space. It can account for spatial heterogeneity, the spatial variation in the relationship between the regressand and regressors. GWR addresses spatial heterogeneity by applying a weighted approach in regression. This weighting prioritizes observations that align with predicted values, reducing the impact of outliers or data points that don't represent the spatial pattern.

Anselin (2010) characterizes continuous heterogeneity as a phenomenon in which regression coefficients exhibit variations over space. This can be assessed by calculating local estimation processes, which can be effectively estimated using the GWR model proposed by Fotheringham et al. (2002).

GWR relies on acquiring separate regression equations for each geographical region, in which a kernel centered on the area is adapted so that adjoining areas are weighted according to a distance decay function. Following Fotheringham et al. (2003), the model to estimate is:

$$Y = (\beta \otimes X)1 + \epsilon$$

Y is having dimension $\mathrm{n} \times 1$, and X is a matrix of dimension $\mathrm{n} \times (\mathrm{k}+1)$ k is the number of independent variables and a column of all 1s, and 1 is a vector of $(\mathrm{k}+1) \times 1$ observations of all 1s. The model's coefficients β can be expressed:

$$\beta = \begin{pmatrix} \beta_0(u_1, v_1) & \cdots & \beta_k(u_1, v_1) \\ \vdots & \ddots & \vdots \\ \beta_0(u_n, v_n) & \cdots & \beta_k(u_n, v_n) \end{pmatrix}$$

A weighted least squares estimate is made using the weight matrix $W(u_i, v_i)$ to weight observations decreasing with distance to the point of interest.

The least-square estimates of $\beta_i(\widehat{\beta_i})$ and their variances are:

$$\widehat{\beta_i} = (X^T W_i X)^{-1} X^T W_i Y$$

$$Var(\hat{\beta}_i) = (X^T W(u_i, v_i) X)^{-1}$$

$W(u_i, v_i)$ is an n-by-n weighting matrix with diagonal elements representing geographical weighting and off-diagonal elements set to zero.

$$W(u_i, v_i) = \begin{pmatrix} w_1(u_1, v_1) & 0 & \cdots & 0 \\ 0 & w_2(u_2, v_2) & & 0 \\ \vdots & & \ddots & \vdots \\ 0 & & \cdots & w_n(u_n, v_n) \end{pmatrix}$$

The choice of W i depends on the selection of kernel function, which may be in the form of fixed (i. e., fixed bandwidth) or adaptive kernels (i. e., varying bandwidths). A typical kernel for W i is given below:

$$w = \exp\left[-\frac{d_{ij}^2}{2b^2}\right]$$

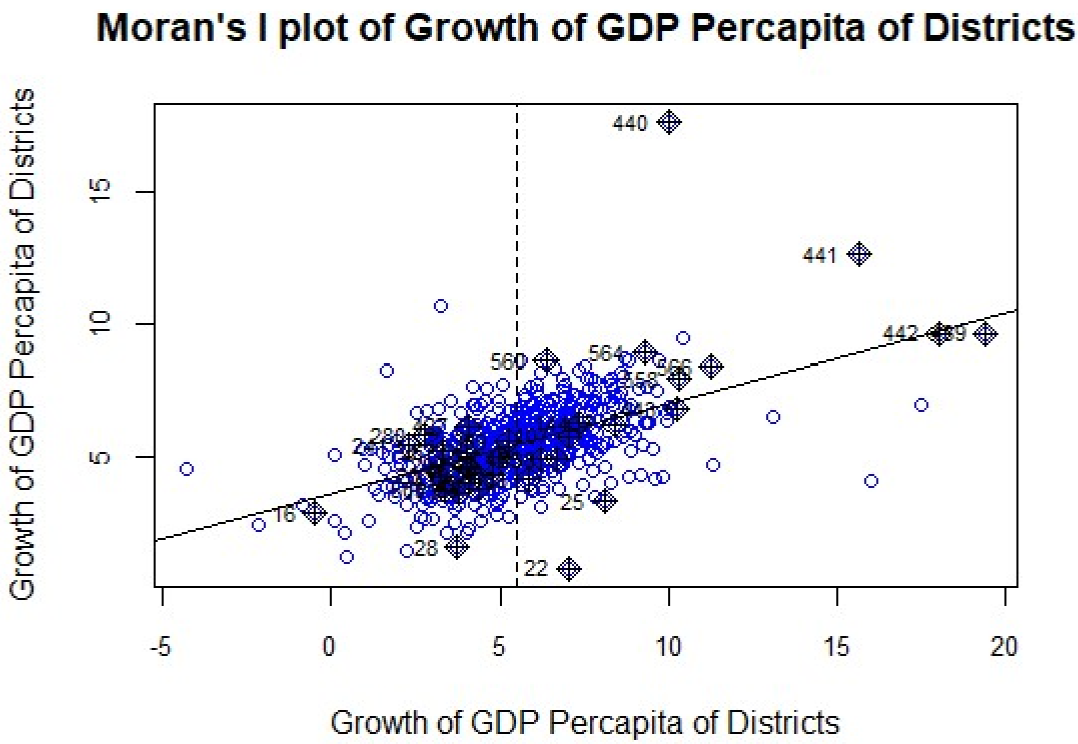
Where b is the bandwidth and d_{ij} is the distance between centers of spatial regions i and j.

6. Econometric Models Specifications and Results

6.1. Spatial Dependence Test

6.1.1. Moran's I

Figure 3: Moran's I Value and Plot



Source: Author's Calculation based on working in R

Moran's I is the simplest measure of spatial dependence. We have calculated it for dependent variable which is growth rate of GDP percapita of each district. It works out to be 0.336 with 1% level of significance. This clearly shows the presence of spatial dependence. Here, we have taken the weight matrix created out of queen contiguity method. We have also used the LM test for diagnosing spatial dependence.

6.1.2. LM test for Spatial Dependence

Table 5: Results of LM test for Spatial Dependence

Test	**Statistics**	**p-value**
LM test for error dependence (Lmerr)	167.64,	p-value < 2.2e-16
LM test for a missing spatially lagged dependent variable (Lmlag)	145.76,	p-value < 2.2e-16
Robust LM test for error dependence (Lmerr)	28.773,	p-value = 8.14e-08
Robust LM test for a missing spatially lagged dependent variable (Lmlag)	6.8929,	p-value = 0.008654

Source: Author's Calculation based on working in R

The results of the LM test and their robust part show the spatial unit's dependence, which can be seen in Table 5 after considering the value of statistics and the p-value. To consider spatial dependence in the growth equation we have run a spatial regression model for understanding spatial growth convergence or convergence under spatial externalities. We have applied seven types of regressions.

6.2. Results of Pan India at the District level

Table 6: Results of Spatial Beta Convergence at District level data of India

	OLS	SLX	SAR	SEM	SDM	SDEM	Manski
Log (Initial Per Capital Income)	0.208	0.356*	0.125	0.025	0.381	0.022	-0.013
	(0.177)	(0.191)	(0.157)	(0.199)	(0.166)	(0.198)	(0.189)
W*Log (Initial Per Capital Income)		-0.308**			-0.543**	-0.327*	-0.015
		(0.149)			(0.131)	(0.137)	(0.144)
Constant	3.482**	5.034**	1.492	5.433***	4.112**	8.604***	9.816**
	(1.738)	(1.89)	(1.549)	(1.968)	(1.661)	(2.366)	(2.394)

Rho			0.518***		0.547***		0.645***
			(0.046)		(0.044)		(0.097)
Lambda				0.563***		0.566***	0.848***
				(0.563)		(0.044)	(0.033)
Observations	590	590	590	590	590	590	590
R^2	0.002	0.01					
Adjusted R^2	0.001	0.006					
Note:	*** p < 0.001; ** p < 0.01; * p < 0.05.						

Source: Author's Calculation based on working in R

The spatial convergence results in Table 6 of India at the district level show the divergence, but the coefficient is insignificant. The critical point in the above table is the result of the Manski Model, which includes spatial dependence at all levels. Hereafter considering the impact of spatial dependence at all levels, we can see the convergence but with an insignificant coefficient. The SLX, SDM, and SDEM models show interesting results signifying that lower income in the neighboring district promotes growth in the said district.

Table 7: Results of Spatial Conditional Convergence at District Level

	OLS	SLX	SAR	SEM	SDEM	SDM	Manski
(Intercept)	20.8145***	22.1209***	16.3511***	19.0890***	23.9518***	18.0799***	22.7713***
	(2.7974)	(3.0414)	(2.6013)	(2.8134)	(3.0899)	(2.7409)	(2.9704)
Log (Initial GDP PC)	-1.9755***	-1.8320***	-1.7088***	-1.8938***	-1.9702***	-1.5980***	-1.7769***
	(0.2999)	(0.3105)	(0.2753)	(0.2850)	(0.2830)	(0.2750)	(0.2710)
Literacy rate	0.0644***	0.0682**	0.0553***	0.0734***	0.0638***	0.0661***	0.0611***
	(0.0126)	(0.0213)	(0.0116)	(0.0154)	(0.0170)	(0.0186)	(0.0157)
Financial Inclusion	19.5480***	21.3743***	16.1218***	19.8130***	22.1205***	19.7978***	21.3975***
	(2.9907)	(3.4579)	(2.7679)	(3.0286)	(2.9674)	(3.0321)	(3.0598)
Share of Agri in GDP	0.0437**	0.0968***	0.0413***	0.0754***	0.0918***	0.1044***	0.0841***

	OLS	SLX	SAR	SEM	SDEM	SDM	Manski
	(0.0134)	(0.0167)	(0.0123)	(0.0139)	(0.0137)	(0.0146)	(0.0134)
Share of Manufacturing in GDP	0.0539**	0.0838***	0.0446**	0.0716***	0.0819***	0.0883***	0.0672***
	(0.0172)	(0.0193)	(0.0157)	(0.0165)	(0.0165)	(0.0168)	(0.0172)
Share of Services in GDP	0.0130	0.0148	0.0051	0.0008	0.0105	0.0128	0.0107
	(0.0146)	(0.0160)	(0.0133)	(0.0139)	(0.0137)	(0.0140)	(0.0142)
Migration rate 2011	0.3327	0.6904	1.3093	1.3267	1.2887	1.6769	0.2845
	(1.3127)	(1.8357)	(1.1946)	(1.4513)	(1.4746)	(1.6033)	(1.4578)
Population Density	-0.0001	-0.0000	-0.0001	-0.0001	-0.0000	-0.0001	0.0001
	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Population Growth rate	0.0118	0.0176	0.0156	0.0160	0.0137	0.0163	0.0163
	(0.0093)	(0.0126)	(0.0084)	(0.0100)	(0.0101)	(0.0110)	(0.0098)
Health Index	-6.0075**	-4.3124	-5.0997**	-5.5287*	-4.2303	-2.9218	-3.6076
	(2.0388)	(2.7540)	(1.8567)	(2.2736)	(2.2777)	(2.4090)	(2.2587)
Health Infra Score	0.0474	0.0187	0.0178	-0.0334	-0.0010	-0.0189	0.0015
	(0.0549)	(0.0529)	(0.0499)	(0.0463)	(0.0496)	(0.0463)	(0.0513)
W*Log(Initial GDP PC)		-0.2163			-0.2514	-0.1197	-0.3333
		(0.3291)			(0.3393)	(0.2876)	(0.3974)
W*Literacy rate		-0.0177			-0.0041	-0.0321	0.0374
		(0.0291)			(0.0285)	(0.0255)	(0.0331)
W*Financial Inclusion		1.7851			0.0640	-5.0789	7.2819
		(4.8231)			(5.5621)	(4.2466)	(7.2283)
W*Share of Agri in GDP		-0.1027***			-0.0921***	-0.1250***	-0.0390
		(0.0256)			(0.0272)	(0.0225)	(0.0336)
W*Share of Manufacturing in GDP		-0.0673*			-0.0815*	-0.0966***	-0.0576
		(0.0306)			(0.0341)	(0.0267)	(0.0417)

	OLS	SLX	SAR	SEM	SDEM	SDM	Manski
W*Share of Services in GDP		0.0123			0.0097	-0.0134	0.0157
		(0.0248)			(0.0273)	(0.0218)	(0.0330)
W*Migration rate 2011		-1.4546			-2.1064	-1.0803	-3.4024
		(2.6370)			(2.7703)	(2.3022)	(3.3774)
W*Population Density		0.0002			-0.0001	0.0000	-0.0001
		(0.0005)			(0.0005)	(0.0004)	(0.0007)
W*Population Growth rate		-0.0160			-0.0080	-0.0126	0.0062
		(0.0197)			(0.0207)	(0.0172)	(0.0240)
W*Health Index		-3.1187			-1.8978	-1.1647	-3.1368
		(3.6512)			(3.9403)	(3.1894)	(4.8763)
W*Health Infra Score		0.4693^{***}			0.2643	0.2601^{*}	0.2070
		(0.1379)			(0.1543)	(0.1209)	(0.1656)
Rho			0.4281^{***}			0.4997^{***}	-0.5233^{***}
			(0.0494)			(0.0473)	(0.1071)
Lambda				0.5949^{***}	0.5530^{***}		0.8149^{***}
				(0.0444)	(0.0470)		(0.0415)
R^2	0.1828	0.2684					
Adjusted R^2	0.1653	0.2363					
Number of Observations	525	525	525	525	525	525	525

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Source: Author's Calculation based on working in R

The results of conditional convergence with and without spatial externalities are shown in Table 7. Our study has the Literacy rate as a proxy for Human capital. We used the financial inclusion index as a proxy for physical capital. Other covariates in the specification of conditional convergence are the share of agricultural, industries, and services sectors; health index, health infrastructure; migration rate; population density, and population growth rate.

The results of conditional convergence are different from those of unconditional convergence. Both the spatial and non-spatial regression results show evidence of conditional convergence. This means poorer districts are converging to their own potential income level. In other words, conditional convergence is a concept related to convergence to its potential level of income. Our study has evidence of district economies converging to their own potential level. At the same time, unconditional convergence is related to districts converging to one's common potential income level for which we do not have significant evidence at a non-spatial level. The coefficient of conditional convergence, i.e., the coefficient of log of initial GDP per capita of a district, is negative and significant. The impact of spatial convergence can be seen in the values of the coefficients in spatial regression, which has dropped marginally across the spatial regression models. The main reason for this drop is considering the impact on other's districts or nearer districts with the help of spatial regressions. The impact of other regions is negative but insignificant.

Financial inclusion has a positive and significant impact on growth. Share of Agriculture and manufacturing has a positive and significant impact. The share of services also has a considerable impact but does not have a significant coefficient—migration and population growth rate impact negative growth. Further, population density has a positive impact for two models, and for the other two, it is negative, but both are insignificant. The positive value has a reason for the agglomeration and clustering of industries which impact income growth.

The health index has a negative and significant coefficient, implying that health is also essential in determining income growth. A negative sign means that the harmful health status would be impacted negatively. Health infrastructure has a positive impact in many regression models, but for two, it has a negative sign with an insignificant coefficient. The positive sign explains that good health infrastructure would drive growth.

The necessary coefficients to be noted are the spatial dependent parameters. ρ and λ are significant, clearly showing the spatial dependence in the case of the dependent variable and the spatial error dependence. Spatial dependence in the independent variable is vital in the case of the share of the agriculture and manufacturing sector in GDP. This clearly says that if the share of these two sectors of the nearer region increase, it would negatively impact the observed region.

For calculating the speed of convergence (λ_s), we have used equation (1) by applying a nonlinear regression equation. The speed of convergence at all India levels comes out to be -0.18 based on 594 districts but is statistically insignificant. For the states, Karnataka, Maharashtra, Telangana, and West Bengal show the divergence path with significant results. Bihar, Chhattisgarh, Gujarat, Haryana, Jammu & Kashmir, Madhya Pradesh, Manipur, Mizoram, Orissa Punjab, Tamil Nadu, Uttar Pradesh, and Uttarakhand have a positive speed of convergence, but they have insignificant coefficients. We have also done the convergence analysis for all the districts for major states and five zones of India.

6.3. Results of Major States at the Districts level

The beta convergence (conditional) results in Table 5 show much evidence for the convergence of poorer districts with the richer counterpart at the district level for the whole country. But we did this exercise for major states, disclosing different pictures. Assam, Jharkhand, and Rajasthan have shown clear evidence of beta convergence with significant coefficients. Twelve states are leading the beta convergence with insignificant coefficients. Those states are Andhra Pradesh, Bihar, Chhattisgarh, Gujarat, Haryana, Himachal Pradesh, Jammu & Kashmir, Meghalaya, Nagaland, Tamil Nadu, Uttar Pradesh, and Uttarakhand. Three states show evidence of divergence with significant coefficients: Karnataka, Maharashtra, and Telangana. And the states like Arunachal Pradesh, Madhya Pradesh, Manipur, Mizoram, Odisha, and Punjab show the divergence with insignificant coefficient.

Table 8: Results of Unconditional Convergence for OLS and Spatial Models for districts belonging to each State

States	OLS	SLX	SAR	SEM	SDEM	SDM	Manski
Andhra Pradesh	-2.449 (1.99)	-2.945 (2.25)	-2.44 (1.526)	-2.968 (1.584)	-2.989 (1.605)	-3.014 (1.593)	-2.9 (1.685)
Arunachal Pradesh	2.282 (1.318)	3.035* (1.114)	2.291 (1.231)	4.596*** (0.977)	2.992*** (0.876)	3.772*** (0.86)	3.355** (1.051)
Assam	-2.577* (1.18)	-0.967 (1.736)	-3.086** (1.145)	-2.817*** (0.767)	-1.111 (1.65)	-1.256 (1.497)	-1.189 (1.979)

Bihar	-0.412 (0.68)	-0.398 (0.689)	-0.451 (0.633)	-0.492 (0.616)	-0.388 (0.667)	-0.433 (0.632)	-0.418 (1.088)
Chhattisgarh	-0.359 (0.701)	-0.787 (0.954)	-0.343 (0.655)	-0.34 (0.65)	-0.785 (0.87)	-0.776 (0.869)	-0.786 (1.252)
Gujarat	-0.852 (0.725)	-0.905 (0.735)	-0.785 (0.688)	-0.759 (0.685)	-0.883 (0.691)	-0.853 (0.689)	-0.82 (0.754)
Haryana	-0.718 (0.89)	-0.725 (1.136)	-0.55 (0.811)	-0.64 (0.904)	-0.669 (0.936)	-0.677 (0.997)	-0.675 (1.589)
Himachal Pradesh	-2.314 (1.619)	-1.604 (1.6)	-1.692 (1.408)	-1.58 (1.497)	-1.53 (1.357)	-1.369 (1.403)	-1.396 (2.139)
Jammu and Kashmir	-0.45 (0.77)	-0.459 (0.795)	-0.475 (0.711)	-0.538 (0.707)	-0.494 (0.703)	-0.509 (0.702)	-0.514 (0.901)
Jharkhand	-1.948* (0.715)	-1.748205	-1.955** (0.635)	-1.764** (0.573)	-1.378034	-1.933** (0.696)	-1.890** (0.642)
Karnataka	1.665** (0.521)	1.711** (0.552)	1.654** (0.506)	1.653** (0.506)	1.688** (0.518)	1.691** (0.52)	1.690* (0.704)
Kerala	-1.919 (2.237)	-3.088 (2.041)	-1.818 (2.068)	-2.179 (2.086)	-7.249633	-2.844 (1.845)	-4.700** (1.578)
Madhya Pradesh	0.549 (0.995)	0.422 (1.031)	0.402 (0.893)	0.322 (0.919)	0.415 (0.942)	0.328 (0.918)	0.364 (1.204)
Maharashtra	2.420*** (0.612)	2.269* (1.001)	1.781*** (0.538)	2.473*** (0.635)	2.467*** (0.663)	2.456** (0.749)	2.456** (0.954)
Manipur	1.167 (6.13)	1.193 (6.601)	1.521 (5.28)	1.723 (5.251)	1.415 (5.286)	1.614 (5.233)	1.602 (8.812)
Meghalaya	-1.081 (1.165)	-0.656 (1.311)	-0.052 (0.593)	0.544 (0.538)	-0.217 (0.781)	0.267 (0.592)	0.1 (0.946)
Mizoram	1.725 (3.646)	1.557 (4.368)	2.315 (2.964)	2.345 (2.582)	1.22 (3.687)	1.802 (3.171)	1.493 (6.667)
Nagaland	-1.07 (1.124)	-0.945 (0.982)	-0.853 (0.866)	-0.359 (0.854)	-0.923 (0.778)	-0.944 (0.828)	-0.902 (2.239)
Odisha	1.554 (1.209)	1.145 (1.374)	0.82 (0.99)	0.889 (1.088)	0.877 (1.089)	0.867 (1.109)	0.769 (1.041)
Punjab	1.547 (0.892)	1.184 (0.979)	1.243 (0.784)	1.22 (0.842)	1.217 (0.826)	1.089 (0.852)	1.148 (1.641)
Rajasthan	-1.927* (0.851)	-1.974* (0.822)	-1.934* (0.82)	-2.074* (0.808)	-1.922* (0.778)	-1.985* (0.783)	-2.377*** (0.668)
Sikkim	-3.248 (6.804)	2.749 (8.207)	-1.196 (1.892)	-0.285 (2.305)	1.841*** (0)	1.841 (0)	1.841 (0)
Tamil Nadu	-0.48 (0.996)	-1.365 (1.111)	-0.693 (0.921)	-1.221 (0.978)	-1.434 (0.85)	-1.97808	-1.168 (1.077)
Telangana	2.561* (1.043)	1.062 (1.35)	3.228*** (0.855)	3.266*** (0.659)	1.755 (0.956)	1.809* (0.913)	2.129** (0.696)

Tripura	-2.582 (10.811)	-72.87 (24.091)	-1.884 (6.866)	-4.036 (9.481)	-68.986*** (9.88)	-95.635*** (5.899)	NA
Uttar Pradesh	-0.25 (0.502)	-0.228 (0.597)	-0.256 (0.495)	-0.253 (0.488)	-0.243 (0.588)	-0.237 (0.584)	-0.24 (0.546)
Uttarakhand	-0.923 (2.63)	-0.392 (2.619)	-0.584 (2.339)	-0.072 (2.375)	-0.785 (2.116)	0.312 (2.149)	-0.281 (2.641)
West Bengal	1.791 (0.894)	1.655 (0.89)	1.481* (0.736)	1.41 (0.74)	1.447 (0.779)	1.474* (0.745)	1.135 (0.704)

Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Source: Author's Calculation based on working in R

The spatial model for unconditional convergence in Table 8 shows evidence that Kerala and Tripura districts are also catching up with their richer counterparts. The speed of absolute convergence varies from 0.28 percent per year to 2.57 percent per year. There is evidence of unconditional convergence for India with spatial dependence with a neighboring initial per capita having a significant impact on the growth rate per capita of all India districts. However, there is no evidence of unconditional convergence for India with spatial independence.

Table 9: Results of State wise WX log of Initial level of Income

States	SLX	SDEM	SDM	Manski
Andhra Pradesh	2.121 (3.895)	-0.19 (2.63)	2.454 (2.808)	1.433 (13.727)
Arunachal Pradesh	4.684* (1.724)	4.276*** (1.273)	6.428*** (1.321)	5.772** (2.051)
Assam	-2.798 (2.239)	-2.278 (1.962)	-3.672 (2.038)	-3.133 (7.144)
Bihar	0.475 (1.333)	0.568 (1.419)	0.659 (1.221)	0.615 (2.065)
Chhattisgarh	-2.059 (3.038)	-2.068 (2.76)	-2.042 (2.755)	-2.069 (3.459)
Gujarat	1.397 (1.843)	1.239 (1.703)	1.207 (1.729)	1.356 (1.99)
Haryana	0.017 (1.665)	0.195 (1.506)	0.333 (1.468)	0.325 (9.544)
Himachal Pradesh	-4.74 (3.178)	-4.732 (2.782)	-4.285 (2.885)	-4.426 (5.654)

Jammu and Kashmir	0.567 (1.154)	0.539 (0.999)	0.638 (1.037)	0.608 (4.254)
Jharkhand	1.227 (1.609)	0.089 (1.363)	-0.106 (1.493)	-0.13 (1.723)
Karnataka	-0.267 (0.886)	-0.229 (0.84)	-0.331 (0.937)	-0.316 (14.515)
Kerala	8.247 (3.868)	11.453*** (2.733)	8.504* (3.384)	10.465*** (2.94)
Madhya Pradesh	1.051 (1.968)	0.89 (2.064)	0.621 (1.757)	0.788 (3.176)
Maharashtra	0.321 (1.665)	0.042 (1.52)	-1.582 (1.29)	-0.906 (67.52)
Manipur	4.301 (21.446)	6.711 (17.045)	6.348 (17.003)	7.161 (27.889)
Meghalaya	1.706 (2.075)	1.337 (1.068)	1.24 (0.91)	1.6 (0.887)
Mizoram	0.72 (7.589)	2.637 (5.929)	2.747 (5.567)	2.902 (17.749)
Nagaland	1.98 (1.163)	1.997* (0.913)	1.978 (1.066)	1.941 (4.006)
Odisha	1.742 (2.669)	-0.31 (2.461)	-0.23 (2.163)	-0.707 (2.488)
Punjab	-2.118 (2.297)	-1.748 (2.012)	-1.196 (2.056)	-1.351 (7.424)
Rajasthan	3.06 (1.715)	2.961 (1.676)	3.178 (1.637)	3.641** (1.176)
Sikkim	42.729 (37.263)	32.127*** (0)	20.486 (0)	20.486 ()
Tamil Nadu	3.844 (2.367)	6.573** (1.999)	5.469** (1.987)	6.390** (2.152)
Telangana	7.957 (5.05)	5.811* (2.952)	8.807* (3.553)	1.874 (2.371)
Tripura	-122.742 (41.202)	-115.574*** (16.744)	-160.282*** (10.032)	NA
Uttar Pradesh	-0.066 (0.957)	-0.029 (0.928)	-0.058 (0.937)	-0.336 (1.058)

Uttarakhand	8.338 (6.987)	10.086* (4.633)	10.064 (5.553)	11.449* (5.659)
West Bengal	2.373 (1.97)	0.238 (2.012)	0.541 (1.713)	0.59 (1.422)

Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Source: Author's Calculation Using R

Table 9 shows the coefficient of the W X log of the initial income level. Most of the states have this positive and insignificant coefficient. Those states are Andhra Pradesh, Bihar, Gujarat, Haryana, Jammu & Kashmir, Jharkhand, Madhya Pradesh, Maharashtra, Manipur, Meghalaya, Mizoram, Nagaland, Odisha, Rajasthan, Sikkim, Tamil, Nadu, Telangana, Uttarakhand, and West Bengal. The coefficients are negative for Chhattisgarh, Punjab, Tripura, Uttar Pradesh, Karnataka, and Himachal Pradesh. Arunachal Pradesh, Kerala, and Tamil Nadu's coefficients are positive and significant. Our theoretical model has the negative coefficient mentioned in equation (7).

Table 10: Results of Speed of Unconditional Convergence based on Non Linear Least Square

States	Constant	Speed of Convergence (+)/ Divergence (-)	Number of Observations
Bihar	10.661 (6.025)	0.531 (1.156)	37
Chhattisgarh	9.042 (6.706)	0.445 (1.093)	16
Gujarat	15.790* (7.345)	1.91 (4.895)	25
Haryana	13.871 (9.261)	1.267 (3.161)	19
Jammu & Kashmir	7.365 (7.448)	0.597 (1.398)	14
Karnataka	-12.256* (5.183)	-0.980*** (0.195)	27
Madhya Pradesh	-0.126 (9.578)	-0.438 (0.642)	48

Maharashtra	-19.124** (6.152)	-1.230*** (0.179)	34
Manipur	-7.962 (59.861)	-0.773 (2.829)	9
Mizoram	-11.645 (36.611)	-1.003 (1.338)	8
Orissa	-9.838 (11.668)	-0.938 (0.473)	30
Punjab	-11.451 (9.223)	-0.935* (0.35)	17
Tamil Nadu	10.848 (9.996)	0.654 (1.916)	30
Telangana	-19.907 (10.517)	-1.270** (0.293)	10
Uttar Pradesh	6.488 (4.733)	0.288 (0.67)	70
Uttarakhand	18.174 (26.053)	2.57 (34.37)	13
West Bengal	-13.116 (8.839)	-1.026** (0.32)	19

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$

Source: Author's Calculation based on working in R

The Table 10 above shows the speed of unconditional convergence (absolute convergence) for different state of India varies from 0.28 percent per year to 2.57 percent per year and the speed of divergence varies from 0.44 percent per year to 1.27 percent per year.

6.4. Results of All Zones at the Districts level

For zones, we see a divergence in the speed for four zones: Central, Southern, Western, and Northern. We find their coefficients show negative value and significance at 1 % level. The Eastern and Northeastern zone shows convergence, but the coefficients are insignificant.

Table 11: Unconditional Convergence for each Zones

Zones	Constant	Log of Initial GDP per capita	R^2	Adj. R^2	Number of Observations
Central Zone data	-4.694 (4.455)	1.022* (0.466)	0.032	0.025	147
Northeastern Zone data	11.041 (6.358)	-0.65 (0.646)	0.014	0	74

North Zone data	0.318 (3.753)	0.488 (0.371)	0.018	0.008	96
Southern Zone data	-3.467 (4.829)	0.923 (0.479)	0.037	0.027	100
Western Zone data	-9.789 (5.367)	1.575** (0.53)	0.13	0.115	61
Eastern Zone data	10.789* (4.444)	-0.478 (0.472)	0.009	0	112

Source: Author's Calculation based on working in R

Table 12: Results of Speed of Convergence for each Zone

Zones	Constant	Speed of Convergence	Number of Observation
Central Zone	-4.694 (4.455)	-0.704** (0.231)	147
Northeastern Zone	11.041 (6.358)	1.05 (1.845)	74
North Zone	0.318 (3.753)	- 0.398 (0.249)	96
Southern Zone	-3.467 (4.829)	-0.654* (0.249)	100
Western Zone	-9.789 (5.367)	-0.946*** (0.206)	61
Eastern Zone	10.789* (4.444)	0.651 (0.905)	112

Source: Author's Calculation based on working in R

We do not have strong evidence of unconditional spatial and non-spatial convergence at the zonal level. This can be deduced from Table 11 and Table 30. The Eastern, North-Eastern, and Northern zone coefficients are negative but insignificant. This shows weak evidence of unconditional convergence. The coefficient of W X log of initial per capita is positive for all zones except southern zones, where in northern and central zone's coefficients are significant. Southern zones have negative and significant coefficient. Table 18 through 27 in the appendix give the coefficients of the complete regression model pertaining to conditional and unconditional convergence across India district defining different states.

The speed of convergence at Zonal level shown in Table 12. The speed of convergence works outs to be positive for Eastern and Northeastern Zone and negative for other zones.

Table 23 to 32 in Appendix A shows the conditional convergence results for each zone and all six spatial regression models. The results clearly show the conditional convergence for each zone with and without spatial dependence. The coefficient of covariates of the above four tables shows almost similar behavior as of all India district-level conditional convergence results in Table 8.

When we see the impact of spatial interconnectedness of these districts, the results of Moran's I, LM test, and Adjusted LM test have given evidence of spatial relations of the districts. In the spatial econometric specifications, we have values of ρ and λ, statistically significant to strengthen our claim of spatial dependence. Signs of covariates of our model were also significant coefficient where the lag values of those covariates are negative.

6.5. Results of Categorized Districts

Table 13: Results of Beta Unconditional Convergence for Aspirational Districts and other Bifurcated district according to their Economic Potential

VARIABLES	All Districts	Aspirational Districts	Very High EPI Score	High EPI Score	Medium EPI Score	Low EPI Score	Very Low EPI Score
Log of Initial GDP Per Capita	0.208	-0.761	1.286**	1.688**	-0.310	-1.336*	-0.293
	(0.177)	(0.465)	(0.558)	(0.723)	(0.250)	(0.742)	(0.790)
Constant	3.482**	12.73***	-6.764	-11.44	8.489***	17.98**	8.258
	(1.738)	(4.415)	(5.860)	(7.377)	(2.422)	(6.950)	(7.698)
Observations	590	103	49	82	323	81	23
R-squared	0.002	0.026	0.101	0.064	0.005	0.039	0.006

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Source: Author's Calculation based on working in R

Another bifurcation of the district is according to the economic potential of each district. In this grouping, the result of Table 13 does not have evidence of unconditional convergence for all district levels. The only unconditional convergence evidence comes from the low EPI score group of districts. The high and very high groups have significant divergence across the district. The clear distinction on high and low-score districts is that the results show significant divergence for the higher economic potential group. In contrast, medium and low-score districts (Including aspirational districts) converge to their common potential level.

Table 14: Results of Beta Conditional Convergence for Aspirational Districts and other Bifurcated districts according to their Economic Potential

VARIABLES	All Districts	Aspirational Districts	Very High EPI Score	High EPI Score	Medium EPI Score	Low EPI Score	Very Low EPI Score
Log (Initial GDP PC)	-1.976***	-1.788**	-2.027*	-0.868	-2.197***	-5.540***	0.443
	(0.300)	(0.712)	(1.066)	(1.002)	(0.384)	(1.332)	(2.066)
Literacy rate	0.0644***	0.0435	-0.0356	0.0832	0.0392**	0.0707	0.0205
	(0.0126)	(0.0282)	(0.0682)	(0.0707)	(0.0155)	(0.0445)	(0.0805)
Financial Inclusion	19.55***	27.26*	5.171	12.42*	28.51***	81.90***	-11.24
	(2.991)	(15.14)	(3.810)	(6.259)	(5.175)	(19.16)	(22.62)
Share of Agri in GDP	0.0437***	0.0535*	-0.0243	0.127**	0.0285*	0.156***	0.0251
	(0.0134)	(0.0315)	(0.0719)	(0.0617)	(0.0172)	(0.0455)	(0.0992)
Share of Manufacturing in GDP	0.0539***	0.0879**	0.0604	0.181***	0.0379	0.0984	0.606*
	(0.0172)	(0.0421)	(0.0422)	(0.0616)	(0.0255)	(0.0732)	(0.309)
Share of Services in GDP	0.0130	-0.0432	0.0399	0.0647	-0.00461	-0.0403	0.0283
	(0.0146)	(0.0361)	(0.0428)	(0.0593)	(0.0207)	(0.0497)	(0.0712)
Migration rate 2011	0.333	-4.775	9.360***	-0.754	-1.057	-10.32	-5.129
	(1.313)	(4.312)	(2.781)	(3.444)	(2.130)	(8.140)	(9.504)
Population Density	-7.85e-05	0.00137	-0.000215	2.11e-05	-0.000215	-0.000264	0.00422
	(0.000262)	(0.00111)	(0.000279)	(0.000922)	(0.000502)	(0.00148)	(0.00487)
Population Growth rate	0.0118	0.0404	-0.0345	0.0235	0.0274**	-0.0414	-0.0471
	(0.00926)	(0.0354)	(0.0363)	(0.0532)	(0.0114)	(0.0571)	(0.0574)
Health Index	-6.007***	1.641	8.846	-16.70**	-0.466	-9.344	16.16
	(2.039)	(5.028)	(6.349)	(7.390)	(2.563)	(6.224)	(15.90)
Health Infra Score	0.0474	-0.0402	-0.639*	-0.0538	0.445*	1.804***	0.492
	(0.0549)	(0.0628)	(0.340)	(0.0624)	(0.239)	(0.471)	(0.648)
Constant	20.81***	17.92***	18.41	12.05	19.68***	49.41***	-14.05
	(2.797)	(6.689)	(11.67)	(12.04)	(3.648)	(12.76)	(24.83)
Observations	525	94	39	71	299	75	23
R-squared	0.183	0.297	0.629	0.395	0.172	0.433	0.558

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Source: Author's Calculation based on working in R

The most important results are conditional convergence for districts grouped according to the potential economic index. Table 14 shows clear evidence of conditional convergence for all groups. The results are like the conditional convergence result of all districts of India except for a few variations. Financial inclusion, literacy rate, manufacturing sector, agricultural sector, the health index, and health infrastructure positively and significantly impact the per capita GDP growth rate.

Our results have an explanation that points toward Krugman's (1991) and Hirschman's (1958) models. These models have a different paths of growth for core and periphery regions. Core help the other adjoining region's growth and development. Core regions will reap the benefit of the periphery's cheap labor cost. Here the uneven growth of nearer regions also matters for the growth of the particular region (in our case, the district).

6.6 Result for Spatial Heterogeneity Model: GWR

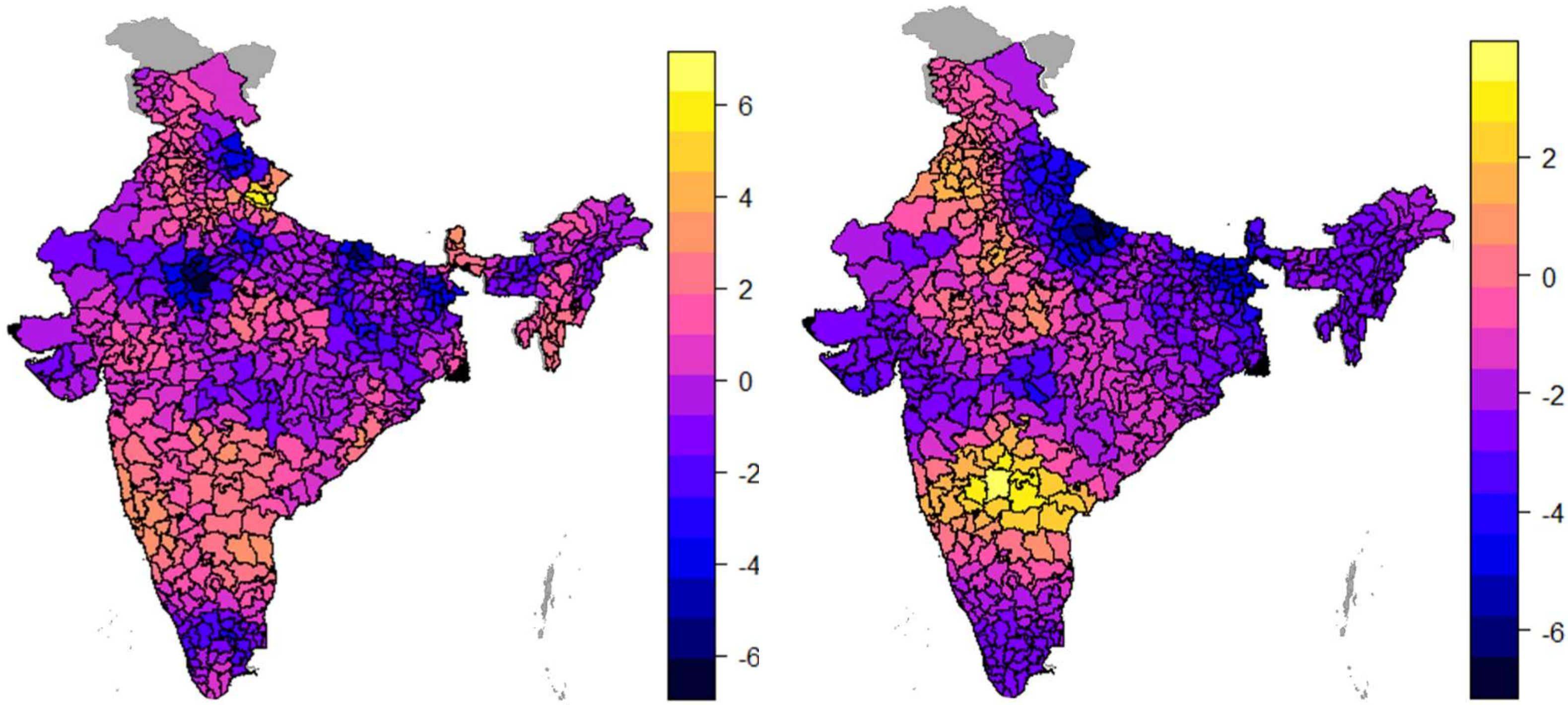
We have applied GWR in conditional and unconditional convergence and got the following results in the Table 15 and Figure 4 given below:

Table 15: Beta Unconditional and Conditional Convergence using GWR

Coefficient for levels	Beta Coefficients of Log of Initial GDP percapita	
	Unconditional Convergence	Conditional Convergence
Global	0.142**	-1.838***
10th Percentile	-1.932	-3.540
Median	0.123	-2.235
90th Percentile	2.214	0.256

The results align with the categorized districts. Low EPI districts show convergence, with the 10th percentile coefficient indicating this trend, while high EPI districts display divergence, as demonstrated by the 90th percentile coefficient, in the case of both unconditional and conditional convergence specifications. We have beta convergence result for all the districts.

Figure 4 : Coefficients of Log of Initial GDP Percapita of GWR model



(a) Unconditonal Beta Convergence with GWR Model (b)Conditonal Beta Convergence with GWR Model

Source: Authors' Calculations in R

We present the results of conditional and unconditional convergence using the GWR model in Figure 4 for each district. Part (a) illustrates the coefficients of the log of initial GDP per capita for each district under unconditional convergence, while Part (b) represents conditional convergence.

The findings from the analysis of conditional convergence indicate that more than three-fourths of the districts in India are experiencing convergence in their per capita GDP. However, it is important to note that some districts are still exhibiting divergence in this aspect. Specifically, certain districts in Punjab, Haryana, Madhya Pradesh, Delhi, Karnataka, and Andhra Pradesh are showing a divergence in their per capita GDP, while all other districts are demonstrating convergence with their more affluent counterparts.

On the other hand, when examining unconditional convergence, we observe that districts in Haryana, Punjab, Madhya Pradesh, Maharashtra, Karnataka, Andhra Pradesh, Arunachal Pradesh, Mizoram, Tripura, Telangana, and Ladakh are experiencing divergence in income. In contrast, districts in Himachal Pradesh, Uttarakhand, Rajasthan, Gujarat, Jharkhand, and Chhattisgarh are showing signs of income convergence. Districts in West Bengal, Jammu and Kashmir, and Madhya Pradesh exhibit mixed results, with some districts demonstrating convergence while others exhibit divergence.

6.7 Endogeneity Issues via the GMM model

We assess the presence of endogeneity in both unconditional and conditional convergence specifications by employing the Spatial Hausman test for endogeneity within the framework of the spatial error model and spatial Durbin error model. The findings are presented in Table 16.

Table 16: Hausman test for Endogeneity in Spatial Error Model

Specification	Model	Spatial Hausman Test Statistics	p-value
Unconditional	SEM	1184.5	2.2E-16
	SDEM	-0.38197	0.9439
Conditional	SEM	37.528	4.59E-05
	SDEM	16.633	0.6147

In the SEM model, we identified the presence of endogeneity. Consequently, we employed the spatial GMM (Generalized Method of Moments) model within the SEM framework, and the outcomes are reported in Table 17. The results indicate that the coefficients' signs and significance levels in the spatial GMM model align closely with those in the SEM model. Thus, our findings and analyses remain consistent. Additionally, the coefficient representing spatial dependence (lambda) retains its statistical significance in the GMM model.

Table 17 : GMM Estimates of Unconditional Convergence with SER model

	Unconditional Specification			Conditional Specification		
	OLS	SEM	GMM	OLS	SEM	GMM
(Intercept)	3.71351*	5.75771**	5.5481	19.69927***	18.82292***	18.948***
	(1.72904)	(1.95374)	(1.937)	(2.52218)	(2.49385)	(2.5105)
Log (Initial Per Capital Income)	0.18249	-0.01634	0.0035	-1.93964***	-2.02006***	-2.017***
	(0.17631)	(0.19822)	(0.196)	(0.26064)	(0.24711)	(0.2504)
Literacy rate				0.06802***	0.07114***	0.071***
				(0.01172)	(0.01370)	(0.0135)
Financial Inclusion				16.34934***	19.70321***	19.286***

	Unconditional Specification			Conditional Specification		
	OLS	**SEM**	**GMM**	**OLS**	**SEM**	**GMM**
				(2.48738)	(2.45732)	(2.476)
Share of Agri in GDP				0.05359***	0.08421***	0.0806***
				(0.01235)	(0.01272)	(0.0128)
Share of Manufacturing in GDP				0.08341***	0.08733***	0.0863
				(0.01449)	(0.01404)	(0.142)
Share of Services in GDP				0.01652	0.01309	0.0133
				(0.01313)	(0.01241)	(0.0126)
Migration rate 2011				0.00000	0.00000	0.00741
				(0.00000)	(0.00000)	(0.000123)
Population Density				-0.00012	-0.00024***	-0.00222***
				(0.00006)	(0.00006)	(0.000598)
Population Growth rate				0.01030	0.01931*	0.0186*
				(0.00856)	(0.00906)	(0.0091)
Health Index				-5.23568**	-4.18456*	-4.273**
				(1.87006)	(2.01588)	(2.0142
lambda		0.56443***	5.548***		0.60555***	0.5364***
		(0.04416)	(1.937)		(0.04167)	(0.0988)
R^2	0.00182			0.21523		
Adj. R^2	0.00012			0.20163		
Num. obs.	588	588	588	588	588	

Note: 1) The dependent variable is the Average of the Annual growth rate of the GDP percapita.
2) *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

7. Conclusions

The study shows no statistical evidence of unconditional convergence among the Indian districts. This concludes that districts are not converging to their common potential income level. The unconditional regression model with spatial externality, however, shows that the lower the income of the neighboring district, the higher the district's per capita growth rate. The explanation can be due to the core-periphery and unbalanced growth hypothesis given by Krugman (1991) and

Hirschman (1958), respectively, unlike the balanced growth hypothesis of neoclassical growth models.

After accounting for various determinants influencing economic growth, distinct from the initial income levels, our findings provide compelling evidence of convergence towards their respective potential income levels. The control variables incorporated into our analysis encompass literacy rate, financial inclusion, the contribution of agriculture, manufacturing, and services sectors to GDP, migration rate in 2011, population density, population growth rate, health index, and health infrastructure.

Our analysis extends to multiple geographical levels, including individual districts, states, geographic zones, aspirational districts, and, notably, in alignment with EPI (Economic Potential Index) groups given by Robert's (2016).

We have very little evidence of unconditional convergence for any group of districts. However, for all districts, we have clear evidence of conditional convergence. Another important result would be the evidence of unconditional convergence for low and medium EPI score districts, whereas it shows significant divergence for high and very high EPI score districts. By incorporating the GWR model to address spatial heterogeneity, our findings remain consistent: Low EPI districts converge (10th percentile coefficient), while high EPI districts diverge (90th percentile coefficient). Addressing endogeneity using Spatial GMM models, our findings align closely with Spatial regressions (specifically SEM model)

Financial inclusion positively influences growth, while a greater share of manufacturing and agriculture in GDP significantly boosts per capita GDP in districts. The services sector shows varied effects, negatively impacting certain zones but insignificantly positively impacting all districts. In contrast, it has a negligible negative impact on low and medium EPI score districts. The importance of good health for growth is evident.

In conclusion, we find that districts with lower economic endowments converge with their wealthier counterparts when accounting for district characteristics and spatial interdependence."

Declaration

- Competing interests : NO
- Funding: NO
- Ethical Approval: NA
- Consent to Participate: YES
- Consent to Publish: YES

8. References

Aayog, N. I. T. I. "Healthy States." Progressive India: Report on the Ranks of States and Union Territories| NITI Aayog,(National Institution for Transforming India), Government of India.

Adabar, Kshamanidhi. "Economic growth and convergence in India." Institute for Social and Economic Change (ISEC) (2004).

Agu, Chukwuma. Poverty: global challenges, role of inequality and reduction strategies. Nova Publishers, 2015.

Anselin, Luc, and Raymond JGM Florax. "Small sample properties of tests for spatial dependence in regression models: Some further results." In New directions in spatial econometrics, pp. 21-74. Springer, Berlin, Heidelberg, 1995. Nadaraya, Elizbar A. "On estimating regression." Theory of Probability & Its Applications 9, no. 1 (1964): 141-142.

Anselin, Luc, Anil K. Bera, Raymond Florax, and Mann J. Yoon. "Simple diagnostic tests for spatial dependence." Regional science and urban economics 26, no. 1 (1996): 77-104.

Anselin, Luc. "Lagrange multiplier test diagnostics for spatial dependence and spatial heterogeneity." Geographical analysis 20, no. 1 (1988): 1-17.

Anselin, Luc. "Thirty years of spatial econometrics." *Papers in regional science* 89, no. 1 (2010): 3-25.

Aroca, Patricio A., Dong Guo, and Geoffrey JD Hewings. "Spatial convergence in China: 1952-99." In Inequality and growth in modern china. Oxford University Press, 2008.

Baddeley, Michelle, Kirsty McNay, and Robert Cassen. "Divergence in India: Income differentials at the state level, 1970–97." *The Journal of Development Studies* 42, no. 6 (2006): 1000-1022.

Bandyopadhyay, Sanghamitra. "Chapter 8 Convergence Club Empirics: Evidence from Indian States'." Inequality, Mobility and Segregation: Essays in Honor of Jacques Silber (Research on Economic Inequality, Volume 20). Emerald Group Publishing Limited (2012): 175-203.

Barro, Robert Joseph, Robert J. Barro, Xavier Sala-i-Martin, and I. Xavier. Economic growth. MIT press, 2004.

Brunsdon, Chris, A. Stewart Fotheringham, and Martin E. Charlton. "Geographically weighted regression: a method for exploring spatial nonstationarity." Geographical analysis 28, no. 4 (1996): 281-298.

Carlino, Gerald A., and Leonard Mills. "Testing neoclassical convergence in regional incomes and earnings." Regional Science and Urban Economics 26, no. 6 (1996): 565-590.

Chang, Koyin, and Yung-Hsiang Ying. "Economic growth, human capital investment, and health expenditure: a study of OECD countries." Hitotsubashi Journal of Economics (2006): 1-16.

Cashin, Paul, and Ratna Sahay. "Regional economic growth and convergence in India." Finance & Development 33, no. 1 (1996): 49-52.

Cherodian, Rowan, and Anthony Philip Thirlwall. "Regional disparities in per capita income in India: convergence or divergence?." Journal of Post Keynesian Economics 37, no. 3 (2015): 384-407.

Cowell, Frank. Measuring inequality. Oxford University Press, 2011.

Dinopoulos, Elias, and Peter Thompson. "Reassessing the empirical validity of the human-capital augmented neoclassical growth model." In Economic Evolution, Learning, and Complexity, pp. 245-264. Physica, Heidelberg, 2002.

Durlauf, Steven N., Paul A. Johnson, and Jonathan RW Temple. "Growth econometrics." *Handbook of economic growth* 1 (2005): 555-677.

Durlauf, Steven N., and Paul A. Johnson. "Multiple regimes and cross-country growth behaviour." *Journal of applied econometrics* 10, no. 4 (1995): 365-384.

Durlauf, Steven N., and Danny T. Quah. "The new empirics of economic growth." Handbook of macroeconomics 1 (1999): 235-308.

Eckey, Hans-Friedrich, Reinhold Kosfeld, and Matthias Türck. "Regional convergence in Germany: a geographically weighted regression approach." Spatial Economic Analysis 2, no. 1 (2007): 45-64.

Ertur, Cem, and Wilfried Koch. "Growth, technological interdependence and spatial externalities: theory and evidence." Journal of applied econometrics 22, no. 6 (2007): 1033-1062.

Fischer, Manfred M. "A spatial Mankiw–Romer–Weil model: theory and evidence." The Annals of Regional Science 47, no. 2 (2011): 419-436.

Fotheringham, A. Stewart, Chris Brunsdon, and Martin Charlton. Geographically weighted regression: the analysis of spatially varying relationships. John Wiley & Sons, 2003.

Gerolimetto, Margherita, and Stefano Magrini. "Nonparametric regression with spatially dependent data." Dipartimento di Scienze Economiche, Università Ca'Foscari Venezia: Veneza, Italy (2009).

Ghate, Chetan, and Stephen Wright. "Why were some Indian states so slow to participate in the turnaround?." *Economic and Political Weekly* (2013): 118-127.

Ghani, Ejaz, Arti Grover Goswami, and William R. Kerr. "Highway to success: The impact of the Golden Quadrilateral project for the location and performance of Indian manufacturing." The Economic Journal 126, no. 591 (2016): 317-357.

Ghosh, M. (2010), regional Economic Growth and Inequality in India During Pre- and PostReform Periods, The Journal of Income and Wealth, 32(2), pp.71-88.

Hembram, Sulekha, and Sushil Kr Haldar. "Beta, sigma and club convergence: Indian experience from 1980 to 2015." Indian Economic Review 54, no. 2 (2019): 343-366.

Hembram, Sulekha, Souparna Maji, and Sushil Kr Haldar. "Club convergence among the major indian states during 1982–2014: does investment in human capital matter?." South Asia Economic Journal 20, no. 2 (2019): 184-204.

Hemmer, Hans-Rimbert, and Andreas Lorenz. Grundlagen der Wachstumsempirie. München: Vahlen, 2004.

Hirschman, Albert O. The strategy of economic development. No. HD82 H49. 1958.

Kant, Chander. "Income convergence and the catch-up index." The North American Journal of Economics and Finance 48 (2019): 613-627.

Krugman, Paul. "Increasing returns and economic geography." Journal of political economy 99, no. 3 (1991): 483-499.

Le Gallo, Julie, and Bernard Fingleton. "Regional growth and convergence empirics." *Handbook of regional science* (2021): 679-706.

Li, Yue, Martin Rama, and Qinghua Zhao. "States diverge, cities converge: Drivers of local growth catch-up in India." *World Bank Policy Research Working Paper* 8660 (2018).

Lim, Up. "Regional income club convergence in US BEA economic areas: a spatial switching regression approach." The Annals of Regional Science 56, no. 1 (2016): 273-294.

Lucas Jr, Robert E. "On the mechanics of economic development." Journal of monetary economics 22, no. 1 (1988): 3-42.

Mankiw, N. Gregory, David Romer, and David N. Weil. "A contribution to the empirics of economic growth." The quarterly journal of economics 107, no. 2 (1992): 407-437.

Mathur, Somesh K., Rahul Arora, Ishita Ghoshal, and Sarbjit Singh. "Domestic energy consumption and country's income growth: A quantitative analysis of developing and developed countries using panel causality, panel VECM, panel cointegration and SURE." Journal of Quantitative Economics 14, no. 1 (2016): 87-116.

Mohanty, Sanjay K., Udaya S. Mishra, and Rajesh K. Chauhan. "The Demographic and Development Divide in India." *Springer Nature Singapore Pte Ltd. https://doi. org/10* 1007 (2019): 978-981.

Monterubbianesi, Pablo Daniel, Martín Grandes, and Carlos Dabús. "New evidence of the health status and economic growth relationship." Panoeconomicus 64, no. 4 (2017): 439-459.

Nagaraj, Rayaprolu, Aristomène Varoudakis, and M-A. Véganzonès. "Long-run growth trends and convergence across Indian States." Journal of International Development: The Journal of the Development Studies Association 12, no. 1 (2000): 45-70.

Narro, Augusto Ricardo Delgado. "Spatial Convergence among the Japanese Prefectures: A first approach." (2019): 33-47.

Nayyar, Gaurav. "Economic growth and regional inequality in India." Economic and Political Weekly (2008): 58-67.

Pace, R. Kelley, and James P. LeSage. "Likelihood dominance spatial inference." Geographical analysis 35, no. 2 (2003): 133-147.

Phillips, Peter CB, and Donggyu Sul. "Transition modeling and econometric convergence tests." Econometrica 75, no. 6 (2007): 1771-1855.

PM, Robinson. "Developments in the analysis of spatial data." Journal of the Japan Statistical Society 38, no. 1 (2008): 87-96.

Postiglione, Paolo, Roberto Benedetti, and Giovanni Lafratta. "A regression tree algorithm for the identification of convergence clubs." *Computational Statistics & Data Analysis* 54, no. 11 (2010): 2776-2785.

Postiglione, Paolo, M. Simona Andreano, and Roberto Benedetti. "Using constrained optimization for the identification of convergence clubs." *Computational Economics* 42 (2013): 151-174.

Purfield, Catriona. "Mind the gap-Is economic growth in India leaving some states behind?." (2006).

Rey, Sergio J., and Julie Le Gallo. "Spatial analysis of economic convergence." Palgrave handbook of econometrics (2009): 1251-1290.

Rivera, Berta; Currais, Luis (1999). Economic growth and health: direct impact or reverse causation?. Applied Economics Letters, 6(11), 761–764.

Roberts, Mark. Identifying the economic potential of Indian districts. The World Bank, 2016.

Robinson, P.M. (2009). Asymptotic Theory for Nonparametric Regression with Spatial data. Journal of Econometrics, Forthcoming.

Romer, P. M. (1986). Increasing returns and long-run growth. Journal of political economy, 94(5), 1002-1037.

Sarma, Mandira. Index of financial inclusion. No. 215. Working paper, 2008.

Solow, Robert M. "A contribution to the theory of economic growth." The quarterly journal of economics 70, no. 1 (1956): 65-94.