Regional Income Convergence in India and Spatial Dependence

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Abstract:

This paper examines the convergence of India's economic growth in per capita incomes of 28 states for the period 1981-2010 and provides the first estimates from spatial panel data model. Our analysis reveals significant local and global spatial dependence in the growth of PCI of Indian states. This implies that all the earlier estimates of convergence rates and the impact of initial income on growth may be inaccurate and biased. Our findings suggest that in addition to a state's own initial income, what matters is how rich or poor their neighbours are. This implies that an initially poor state may grow faster if its neighbours are richer or growing fast. This has implications for growth policy-making in India.

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1. Introduction

One of the key questions in empirical growth economics is whether rich regions will remain rich and the poor remain poor for long periods of time or whether the initially poor ones will grow faster and catch up with the rich (Barro, 1991; Baumol, 1986; Sala-i-Martin, 1996). The theory of economic growth postulates that in the long run there would be a convergence of growth rates due to a transfer of technology and factors of production (Solow, 1956). Wide regional variations in growth performance of the states in India has kept alive the research interest in this area (Bajpai, & Sachs, 1996; Cherodian & Thirlwall, 2013; Dholakia, 1994; Ghosh, et al., 1998; Kurian, 2000).

The post independence era was characterised as a closed economic set up (Basu & Maertens, 2007). India became a liberalised open economy from the mid 1980s and more rapidly from early 1990s (Cashin & Sahay, 1996; Ghosh et al., 1998; Kalra & Thakur, 2015). It was expected that all the states and regions would benefit from the market-oriented reforms (Ahluwalia, 2000; Ghosh et al., 1998). Contrarily, dispersion in per capita incomes and social development has increased over time (Kar,et al, 2011; Lolayekar & Mukhopadhyay, 2016)

Empirical studies traditionally have typically highlighted that economic growth is influenced by certain factors like initial level of income, human capital, investment, physical infrastructure and institutions (Barro, Sala-I-Martin, Jean Blanchard, & Hall, 1991; Karnik & Lalvani, 2012; Mankiw, Romer, & Weil, 1992; Nayyar, 2008). It is now increasingly recognised that geographic space and physical distances between regions play an important role in determining growth outcomes. Therefore a region's growth may not be generated independently (Anselin, 1988). Spatial dependence occurs when there is a dependence among the observations at different points in space. Spatial data may show dependence in the variables and error terms. In this paper we 1) test whether growth of Indian states exhibits spatial dependence and then 2) estimate the convergence rate after controlling for spatial impacts.

The rest of this paper is organised as follows: In section 2 the empirical evidence on convergence and spatial dependence is discussed. Section 3 and 4 describes the Data and Method of spatial data analysis. We present the results of our analysis in Section 5 and in Section 6 the paper concludes.

2. Convergence and Spatial Dependence

Growth theory suggests that if regions have historically had unequal incomes then they will experience unequal growth rates in the short run till they converge towards a common steady state rate of growth in the long run(Solow 1956). Two measures of convergence that are commonly discussed in the literature are: " β " and " σ " convergence

a) **β convergence** occurs when poor regions grow faster than the richer regions, thus catching up with the rich ones. Growth in any period (t) is dependent on the initial income, such as

(1) $$Y_i = \beta_0 + \beta_1 \ln(y_{i,o})$$

Where $Y_i = \ln(y_{i,t}) - \ln(y_{i,o})$is the growth rate of per capita income (PCI) in a region "i", $\ln(y_{i,t})$ is the natural log of PCI at "t" the current time period and $\ln\left(y_{i,o}\right)$is the natural log of initial PCI (when t=0). If $\beta < 0$ there is convergence in income over time.The higher the absolute value of "β" the quicker the convergence process. However if $\beta > 0$, then we have divergence.

b) **σ convergence** occurs when there is a decline in regional dispersion of PCI over time. It is measured by examining the variance in PCI among regions over time.

(2) $$\sigma_t < \sigma_0$$

where "σ_t" is the standard deviation of PCI across regions at time period "t" and $\sigma_0$the standard deviation in the initial period.

The concepts of β- and σ-convergence are co-related. β-convergence is a necessary but not a sufficient condition for the reduction in the disparity of per-capita income over time. Thus β -convergence will lead to σ -convergence. It is also possible theoretically that the initially poor countries may grow faster than rich ones, without a decline in the cross-sectional dispersion over time. This happens if the initially poor economy grows faster than the rich (β-convergence) but, the growth rate of poor economy is so much larger than that of the rich that by time period $t+T$, the initially poor economy becomes richer than the rich economy. As the dispersion between these two economies may not have fallen, there may be no σ-convergence (Barro & Sala-i-Martin, 1992; Sala-i-Martin, 1996; Rey & Montouri, 1999).

Solow's (1956) theory of convergence had to wait till Baumol's (1986) empirical examination of the convergence hypothesis for a small group of nations. This was followed by (Barro 1991;Barro & Sala-i-Martin 1992); Barro, et al, 1991;Sala-i-Martin 1996) among others. A large literature has emerged on the idea of unconditional convergence (where the economies converge to a common steady state rate of growth) and conditional convergence (where economies reach different steady states). Different empirical strategies have been employed in the literature. Some have studied a small number of countries over large number of years (Maddison, 1983), while others have used large number of countries over shorter periods of time (Barro & Sala-i-Martin, 1992; Barro, 1991; Islam, 1995). Some have also undertaken intra- country (state level) analysis (Evans & Karras, 1996; Kanbur & Zhang, 2005). There is evidence of regional convergence over long sample periods of 100 years for US states and over 60 years for Japanese prefectures and also over much shorter sub-periods within the same sample (see Barro, et al., 1991, Barro & Sala-i-Martin, 1992, Sala-i-Martin, 1996). Developing countries however have not exhibited growth convergence (Kanbur & Zhang, 2005).

In keeping with the international interest in convergence, regional convergence in India has also attracted due attention. Income convergence across the states has been explored previously in a number of studies. While some found evidence of convergence in per capita state domestic product (SDP) growth rates (Bajpai, & Sachs, 1996; Cashin & Sahay, 1996; Dholakia, 1994), others found evidence of regional divergence in the pre and the post reforms periods (Ahluwalia, 2000; Dasgupta, et al, 2000; Ghosh, et al., 1998; Kurian, 2000; Mitra & Marjit, 1996; Rao & Singh, 2001). The empirical methods adopted have included time series analysis, panel regressions as well as non - parametric techniques like transition matrix and kernel densities.

Oddly in all the studies mentioned above, the states in India have been viewed as independent entities and the possibility of dependence among them has been ignored. The role of spatial effects in convergence processes has now been demonstrated in the literature. The use of OLS, time series or panel techniques without controlling for neighbourhood effects could lead to serious bias and inefficiency in the estimation of the convergence rate (Arbia, et al 2005; Getis, 2008).

Spatial effects could be of two types:

1) Spatial Dependence (Spatial Autocorrelation)

When variables of one region depend on (or are correlated) to values observed in neighbouring regions it caused spatial autocorrelation. If a variable tends to cluster in area then spatial autocorrelation is high and when neighbouring geographical areas have uncorrelated values then spatial autocorrelation is low.

2) Spatial Heterogeneity

It is the variation in relationships across the space. There could be a cluster of forward states (rich regions or the core) and a cluster of backward States (poor regions or the periphery). The regions therefore cannot be considered as independent of their neighbours.

Thus while analysing regional convergence all these issues need to be considered (Anselin, 1988).

Spatial techniques are now available to control for space in econometric analysis. A number of studies have shown how the unconditional regression model is misspecified if spatial dependence is ignored. Ramirez & Loboguerrero (2002) found strong evidence of spatial interdependence across 98 countries over the period 1965-95. Using different specifications as well as different measures of proximity for 93 countries over 1965 - 1989, Moreno and Trehan (1997) found that demand and technology spillovers from neighbouring countries strongly influence a country's growth. In addition to the country level analysis many contributions have examined spatial dependence at the regional level or the sub national levels too (see Patacchini& Rice, 2005; Rey and Montouri 1999; Elias and Rey 2011; Baumont, et al, 2002; Fischer and Stumpner 2008; Ertur, et al, 2007; Magalhães, et al , 2005; Khomiakova, 2008).

A more recent development has been the use of spatial panel data models made possible by increasing access to larger data sets for different spatial units over time (see Arbia, et al 2005; Chaterjee 2014 ; Piras and Arbia 2007).

It is well understood that simple cross section methods do not take into account the heterogeneity or the spatial effects. The panel data models with greater degrees of freedom, more variation and less amount of collinearity among the variables have more efficiency in the estimation (Elhorst, 2014). The classical panel fixed effects models are able to overcome the problems of individual heterogeneity and omitted variables. However, they do not control for spatial dependence. This paper provides the first estimates of regional income convergence in India controlling for spatial dependence.

We use the Exploratory Spatial Data Analysis (ESDA) to test for spatial effects in the data. Our analysis has relied on QGIS (v 2.0.1), Stata (v12) and Geoda (1.4.6) software packages for the analysis.

3. Methodology

As discussed earlier, ordinary least square estimation is not a suitable method when we anticipate spatial dependence between the observations (Anselin, 1988). This dependence could be present in the explanatory variables as well as the error terms. The consequence of ignoring this varies with the type of spatial dependence in the data. The different types of spatial problems are given below;

a) Spatial Lag - spatial lag occurs (when the dependent variable y in state *'i'* is affected by the dependent variables in both place *'i'* and *'j'*) and we ignore it. We may encounter an omitted variable problem, akin to excluding an important explanatory variable. The OLS would then produce biased and inconsistent estimates.

b) Spatial Error- in this case the error terms across different spatial units are correlated. If there is spatial error, ignoring it would result in an efficiency problem and the OLS estimates would be unbiased but inefficient. These estimates would violate the BLUE assumptions.

Spatial econometrics provides a mechanism to overcome the problem of spatial dependence in the OLS and panel regression approach. The standard approach in most empirical work is to start with a non-spatial regression model and then to test whether or not the model needs to be extended with spatial interaction effects (Anselin, 1988; Elhorst, 2014). In a spatial econometric model there are three kinds of interaction effects

a) Endogenous interaction effects: These are the effects among the dependent variables(Y). Here the dependent variable of a particular unit say, 'A' depends on the dependent variable of other units, say, 'B', and vice versa.

b) Exogenous interaction effects: here the dependent variable of a particular unit A, depends on independent explanatory variables of other units ay 'B'. These are the effects among the independent variables(X). For example, the per capita income of an economy may depend on the other explanatory variables in the neighbouring states. In the empirical convergence literature, the economic growth of a particular country thus can depend not only on the initial income level, saving rates, population growth, technological change and depreciation of its one's own economy, but also on these variables in neighbouring countries.

c) Interaction effects among the error terms (e): here the omitted variable from the model are spatially auto correlated, or there could be situations where there is a spatial pattern in the unobserved shocks.

In terms of data requirement, spatial models require geo coding of observational units. Every single observation needs to have coordinates, borders, distance or some other geo coded information. The advantage of the spatial models is that they can deal with a variety of spatial impacts to see the influence of neighbours.

Spatial dependence is quantified through the Spatial Weight Matrix (SWM) W =[W_{ij}](where *i* and *j*=1,...,n, which incorporates the spatial relationship among the 'n' observations that are considered as neighbours).

The expectation is that if two observations are close to each other they will influence each other a lot more than observations which are located further away. The spatial weight W_{ij} reflects the "spatial influence" of unit *j* on unit *i*. Each unit's value is the weighted average of its neighbours. The SWM is row standardized, thus weights add up to 1 in each row. This is done to create proportional weights when regions do not have equal number of neighbours. Each cell's row standardized weight is the fraction of all spatial influence on unit *i* attributable to unit *j*. The diagonal elements of the matrix are equal to zero. The non - diagonal elements are non - zero for observations that are close spatially and zero for those that are far away. The SWM have different values and based on:

1) Contiguity: Value of W_{ij} is dependent on whether the observation units touch, share a border, a line or vertex. W_{ij} is equal to one if i is contiguous to j and zero otherwise, or
2) Distance: Value of W_{ij} is based on the distance between observations *'i'* and *'j'*, and spatial effects would exist within a particular distance band. Thus the *Wij* takes value one if the distance between i and j is within the distance band and it is zero otherwise.

3.1 Exploratory Spatial Data Analysis

The Exploratory Spatial Data Analysis (ESDA) checks for the presence of spatial heterogeneity and autocorrelation. The test commonly used for detecting spatial autocorrelation is the Global Moran's I and Local Moran's I (also called the LISA – Local Indicators of Spatial Autocorrelation) tests.

3.1.1 Global Moran's I

The Global Moran's I test statistics to check for the presence of global spatial dependence among observation units is calculated as follows;

$$I = \frac{\mathrm{N}}{\Sigma_{\mathrm{i}}\Sigma_{\mathrm{j}} W_{ij}} \frac{\sum_{i=1}^{\mathrm{n}} \sum_{\mathrm{j}=1}^{\mathrm{n}} W_{ij}\,(\mathrm{X_i}-\bar{X})(X_{\mathrm{j}}-\bar{X})}{\sum_{i=1}^{n} (\mathrm{X_i}-\bar{X})^2} \tag{3}$$

where N is the number of regions(points or polygons), W_{ij} is the relevant element (cell value) of the weight matrix W, X_i is the value of the variable in region i , X_j is the variable value in another region j, and $\bar{X}$ is the cross-sectional mean of X.

Moran's I involves only one variable - the correlation between variable, X, and its "spatial lag" calculated by averaging all the values of X for the neighboring polygons. The global measure uses a single value of Moran's I for the entire data set and the entire geographic area. The spatial models become relevant if these tests reject the null hypothesis of absence of spatial dependence.

Presence of spatial dependence is confirmed if the correlation statistic is significant, suggesting that the distributional evolution of a variable is clustered in nature. High values of a variable will be located close to other high values and vice versa.

3.1.2 Local Moran's I

The Local Moran’s I test statistic on the other hand is computed for each location as follows:

$$I_{\mathrm{i}} = \frac{(X_{\mathrm{i}} - \bar{X}) \sum_{j=1}^{n} W_{ij} (X_j - \bar{X})}{\sum_{i=1}^{n} (\mathrm{X}_{\mathrm{i}} - \bar{X})^2 / \mathrm{n}} \tag{4}$$

Local Moran's I indicates the location of local clusters and spatial outliers. We can also map the polygons having a statistically significant relationship with its neighbors, and show the type of relationship.Local Moran's I statistics identify the locations contributing most to the overall pattern of spatial clustering. It detects significant spatial clustering (referred as hotspots) around an individual location (Pisati, 2001).

In the presence of Global Spatial Autocorrelation (GSA), the p-values of Local Moran's I statistics should be regarded as an approximate indicator of statistical significance. Like GSA, the Local Moran's I detects the presence of both the positive and negative spatial autocorrelation. The sum of local values of all observations is proportional to Global Moran's I (Anselin, 1995). With the Moran scatter plot we can visualize the type and strength of spatial autocorrelation.

The Moran's I test and LISA statistics detect if there is spatial dependence and thus justify the use of spatial econometric models. However, even if spatial autocorrelation statistics indicate a significant pattern of spatial clustering, it is only the first step in the analysis. The next step would be to model the relationship across the spatial units or the different interaction effects. This is what we discuss in the next section.

4. Spatial Dependence Models in Cross-Section Data

In order to test for β-convergence across regions in India, we begin with cross-sectional OLS approach followed by a diagnostics test for the presence of spatial effects. A linear regression model without any spatial effects is stated as follows;

(5) $$Y_i = \alpha_i + \beta X_i + u_i$$

In the equation above, per capita income (PCI) growth "Y_i"is the dependent variable and the initial income level " X_i" is the explanatory variable in region "i".α and β are parameters to be estimated, and u_i is the error term.

4.1 Cross Section Models

We discuss four kinds of spatial models which are commonly used for cross section as well for panel data analysis.

a) The Spatial Lag Model or the Spatial Autoregressive (SAR) model contains endogenous interaction effects, b) Spatial Error Model (SEM) considers the interaction effects among the error terms, c) When endogenous interaction effects and the error interaction effects is considered together we have the Spatial Autocorrelation (SAC) model (Le Sage & Pace, 2009) and d) the Spatial Durbin Model which includes both endogenous and exogenous interaction effects.

When all types of spatial interactions are considered in a cross section model it is referred to as the *General Nesting Spatial (GNS) Model*, as stated below;

(6) $Y_i = \alpha_i + \beta X_i + \rho W Y_i + \theta W X_i + u_i$, where

(7) $u_i = \lambda W u + e_i$, implying

(8) $Y_i = \alpha_i + \beta X_i + \rho W Y_i + \theta W X_i + \lambda W u + e_i$

In equation (6) and (8) *"WY"*, captures the spatial dependence in the dependent variables (endogenous interaction effects),"*WX*", denotes the exogenous interaction effects among the independent variables and "Wu" denotes the spatial dependence in the error term. The estimated parameter " ρ " is known as the spatial autoregressive coefficient (coefficient estimated for the spatial lag), " λ " is the spatial autocorrelation coefficient, while θ and β represent the fixed but unknown parameters and W is a non-negative spatial matrix, that describes the spatial arrangement of the units in the sample.

These cross section spatial models with interactions effects can be replicated for panel data models described in the section below.

4.2 Panel Data Models

Panel data models examine the cross-sectional (group) and the time-series (time) effects. Panel data models also offer different effects that may be fixed and/or random. Fixed effects assume that individual group/time have different intercept in the regression equation, while random effects assume that individual group/time have different disturbance but a common intercept. The cross section of "n" observations in the equations (6-8) can be extended for a panel of "n" observations over numerous time periods "T" , by adding a subscript "t" to all the variables and the error term in the model.

A simple growth equation using panel data without including any form of spatial effects is expressed in the following way;

(9) $$Y_{it} = \alpha_{it} + \beta X_{it} + \mu_i + \eta_t + u_{it}$$

With "i=1 ...n" denotes regions and "t=1 ...T", denotes time periods. The dependent variable Y_{it} is the annual growth rate of PCI and X_{it} is the initial value of PCI in region "i" and time "t". In the above equations, the intercept "μ_i" considers the omitted variables which are specific to each spatial unit, and "η_t" represents time specific effects. The spatial and the time effects can be divided into the fixed and random effects. In fixed effects models, a dummy variable is introduced for each of the spatial units and time periods, while in random effects model, both μ_i and η_t are considered as random variablesthat are independently and identically distributed (i.i.d) with zero mean and variance. Further, μ_i, η_t and u_{it} are assumed to be independent of each other.

Equation (9) represents a fixed effect panel data model, in which β is the fixed parameter estimated by a Least Square Dummy Variable process. It is time invariant and represents the region specific effects.

We can account for spatial dependence in the GNS model by extending equation 6 and 9 in the following way:

(10) $$Y_{it} = \alpha_{it} + \beta X_{it} + \rho WY_{it} + \mu_i + \eta_t + \theta WX_{it} + u_{it}\text{, where}$$

(11) $$u_{it} = \lambda Wu + e_{it}, \quad \text{implying}$$

(12) $$Y_{it} = \alpha_{it} + \beta X_{it} + \rho WY_{it} + \mu_i + \eta_t + \theta WX_{it} + \lambda Wu + e_{it}$$

We can thus create different linear spatial econometric models by imposing restrictions on one or more of its parameters (Elhorst 2014). The random effects model was tested against the fixed effects model using Hausman's specification test. Since the hypothesis of random effects models was rejected in favour of the fixed effects model, we have used the fixed effects spatial models. We next describe the different models popularly used briefly below.

4.2.1 Spatial Lag Model or Spatial Autoregressive Model (SAR):

The fixed effect SAR model considers the spatial dependence in the dependent variable. The spatial impact of error term and the independent variable is dropped here, so $\lambda = 0$ and $\theta=0$. Equation (12) reduces to

(13) $$Y_{it} = \alpha_{it} + \beta X_{it} + \rho W Y_{it} + \mu_i + \eta_t + u_{it}$$

In this model, spatial dependence is explained by interactions among the dependent variables across regions.Here, ρ is the spatial autoregressive coefficient.

In the context of convergence and economic growth of the states, it would imply that the growth rate of one state is related not only to its own initial level of per capita income but also on the current income levels in the other states.

4.2.2 Spatial Error Model (SEM):

The SEM considers only the spatial dependence in the error term, thus $\rho = 0$ and $\theta=0$. Equation (10) reduces to

(14) $$Y_{it} = \alpha_{it} + \beta X_{it} + \mu_i + \eta_t + u_{it}, \text{ where}$$

(15) $$u_{it} = \lambda W u + e_{it}$$

The error term here is not IID. Therefore like the GNS, the error term is adjusted to accommodate spatial dependence and a random error "e_{it}" that confirms to I.I.D requirements.

This type of spatial dependence could be because of some missing variables as a result of an underspecified model. The parameter λ shows the intensity of the spatial relationship through the error term (Rabassa & Zoloa, 2016).

4.2.3 The Spatial Autocorrelation (SAC) model:

The fixed effects SAC model includes interaction effects among endogenous variables and interaction effects among the error terms and thus $\theta=0$. The spatial impact of the other explanatory variable is dropped here and only the spatial impact of the dependent variable is used as an explanator. This specification is also known as the spatial autoregressive model with autoregressive disturbance (SARAR) model,

(16) $$Y_{it} = \alpha_{it} + \beta X_{it} + \rho W Y_{it} + \mu_i + \eta_t + u_{it}, \text{ where}$$

(17) $$u_{it} = \lambda W u + e_{it}$$

This model implies that the growth rate of an individual region is affected by the growth of the neighbouring regions. Unlike the SDM model which we discuss the impact and the spatial dependence of the other factors is represented by the error term.

4.2.4 Spatial Durbin model (SDM):

The fixed-effects SDM includes both the endogenous and the exogenous interaction effects. It includes the spatial lags of the explanatory variables as well as the dependent variable,but assumes $\lambda = 0$ in equation 12.

The spatial impact of error term is dropped here and only the spatial impact of the dependent and independent variable is employed. Equation (10) reduces to

(18) $$Y_{it} = \alpha_{it} + \beta X_{it} + \rho W Y_{it} + \mu_i + \eta_t + \theta W X_{it} + u_{it}$$

This model implies that the growth rate of one state depends on the growth rate of the neighbouring states.

This completes our discussion on the different spatial models. In the next sub section we discuss the data used in our empirical analysis

4.3 Data

Macroeconomic data in India is provided by a number of organisations. The data is released officially both by the Central Statistical Office, Government of India and the Reserve Bank of India. However they do not provide long term constant series. Our study therefore uses the data from Economic and Political Weekly Research Foundation (EPWRF). The variable of interest to us is the per capita Net State Domestic Product (PCNSDP). State level income data prior to 1981 is available only for the major states but not for all the states and union territories (U.T). The PCNSDP current price series is used in the paper after controlling for price variability over time by using a price deflator (Dornbusch, et al, 2002).The deflator was obtained by dividing NDP for India at current prices by NDP at constant prices (base 2004-5 prices). We use data up to 2010 as it allows us to take 5-year averages, since PCNSDP up to 2015 is not available yet.

This period (1981-2010) saw reorganisation of states. Three states were created in the year 2000, namely Chhattisgarh Jharkhand and Uttaranchal; and were carved out of the existing states of Madhya Pradesh, Bihar and Uttar Pradesh, respectively. In our analysis these newer states were combined with their parent states to facilitate the analysis. A panel is formed by splitting the time-period of 30years into six, five-year sub periods namely, 1981- 85, 1986–90, 1991-95, 1996-00, 2001-05 and 2006-10.In each period initial value of NSDP per capita is measured at the beginning of each five-year period in the panel. So, for example, the growth equation for 1981-1985, would use the PCNSDP of 1981 as an explanatory variable.

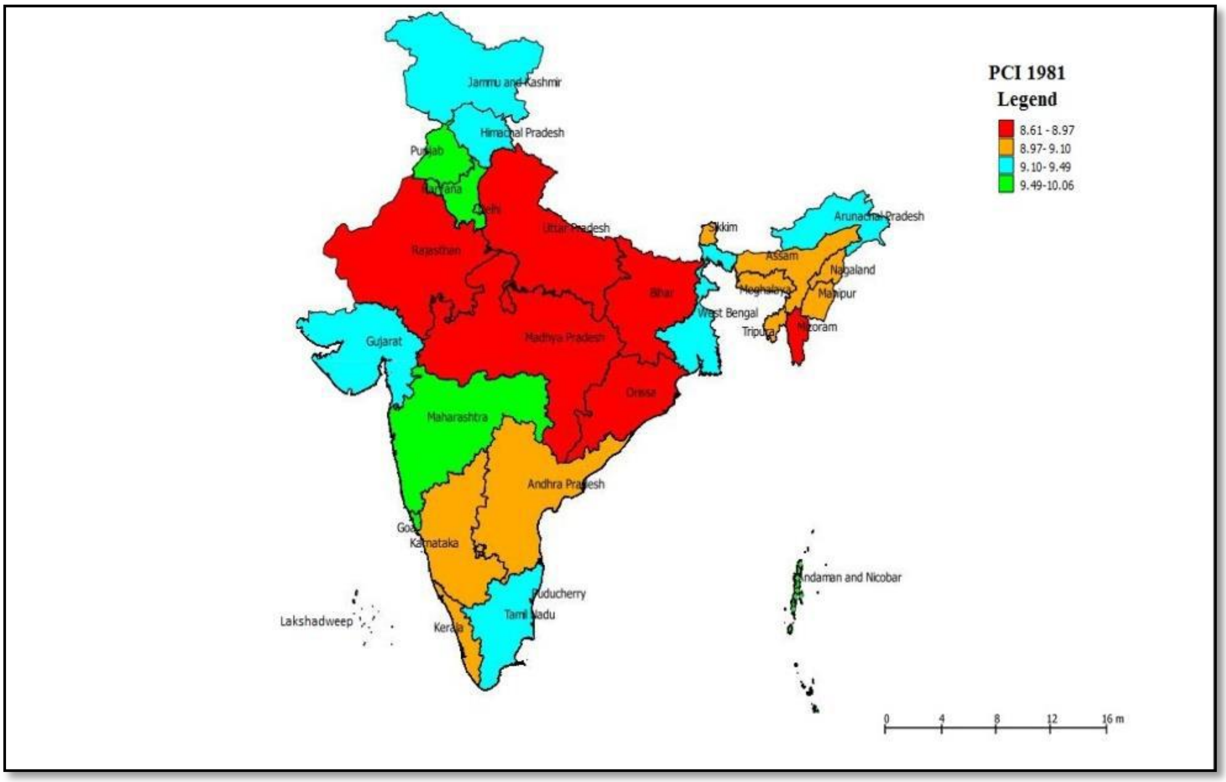
The spatial component is introduced by using a shape file in QGIS that includes geographic attribute data such as names and identity codes for each state. The QGIS software allows the PCNSDP data to be combined with the spatial data given in the shape file. The distribution of states based on their growth rate is taken for 2 time slots 1981 and 2010.

We now proceed to present the results of our empirical analysis.

5. Results

If we look at a time span of three decades 1981 to 2010 and examine the distribution of the per capita incomes geographically (state-wise), we find visual evidence of this divergence (Figure 1and Figure 2). We divided the states and UTs into four groups depending on their PCI -- green coloured states are the ones with highest per capita income and red states have the lowest PCI. States with income levels below the highest PCI group are coloured in blue followed by the orange coloured states which are a little above the lowest PCI group.

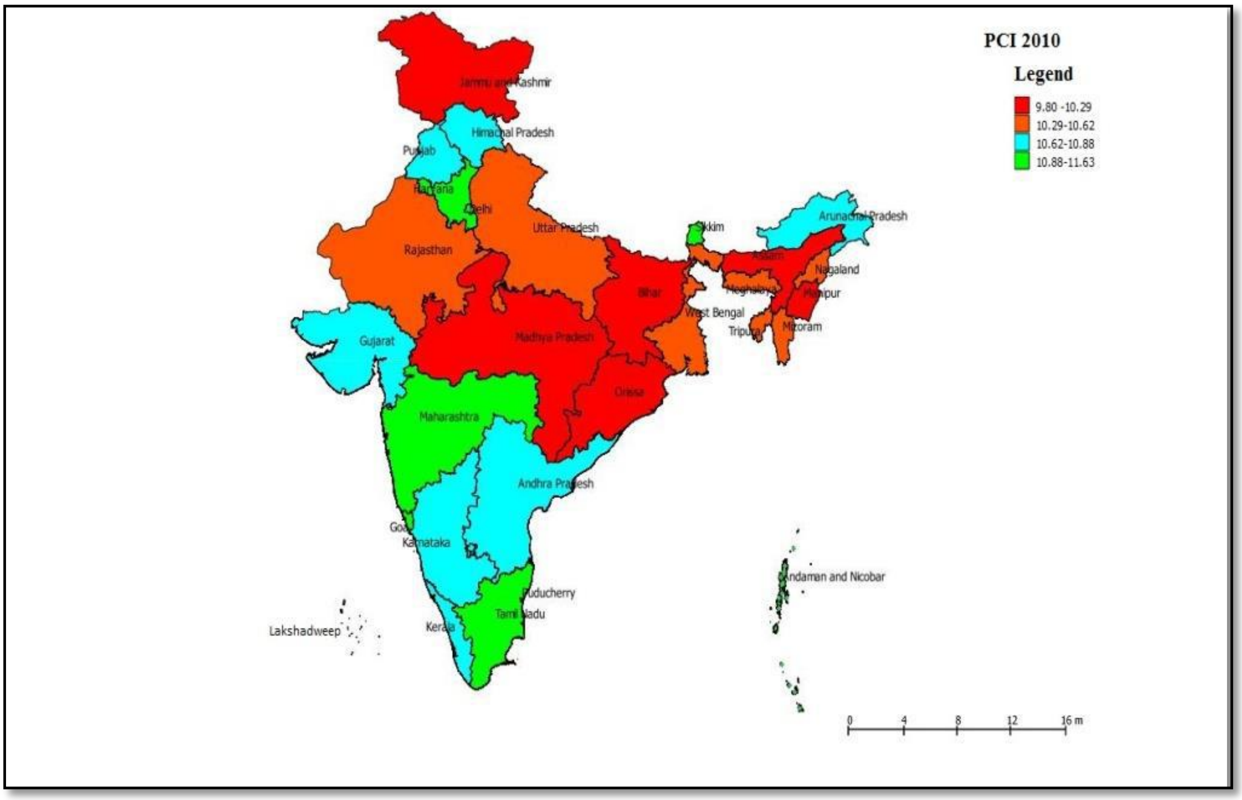
Figure 1: PCNSDP among Indian states - 1981



Source: Author's calculations based on EPWRF data using QGIS

If we compare these groups in 1981 and 2010, we find that central India was in red in 1981 and continues to be in red in 2010 (with the exception of Rajasthan). Many of the north eastern states which were in orange in 1981 have sled to the red group with the exception of Sikkim. J&K too has joined the lowest PCI group in 2010. The beneficial effects of growth have been reaped by states along the western border of the country including Rajasthan. The clustering of states by PCI is suggestive of spatial effects in the growth process in India.

Figure 2: PCNSDP among Indian states - 2010



Source: Author's calculations based on EPWRF data using QGIS

After having looked at the distribution of the per capita incomes geographically, we present the results on a common statistic that is examined in the spatial models that is the Moran's I.

5.1 Moran's I statistics

The results of the Moran's *I* statistic for global spatial autocorrelation for the PCNSDP for 1981 and 2010, as well as for real per capita growth (from 1981 to 2010) are reported in the Table 1 below. Both the contiguity and distance based matrices are presented. The values of Moran's I show the degree of spatial dependence and its significance implies that geographically proximate regions exhibit spatial dependence in India.

Table 1:Moran’s I Global Spatial Autocorrelation Statistic for Indian States

	Contiguity Matrix	Distance Weight Matrix
PCNSDP 1981	0.151*	0.070**
PCNSDP2010	0.219**	0.073***
Growth Rate 8110	0.226**	0.105***

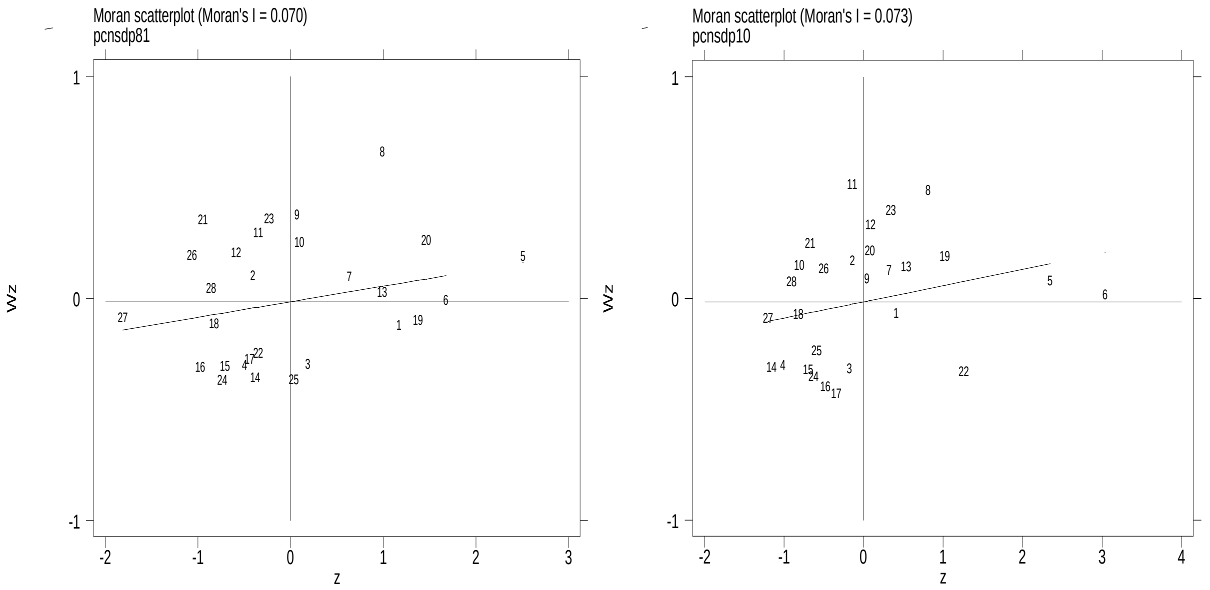
Source: Author's calculations based on EPWRF data using QGIS and Stata
Significance at ***1%, **5%, and *10% level

These results suggests that there is a strong positive and statistically significant spatial dependence in the PCI for both the years (1981 and 2010) and growth (1981-10) whether we use the contiguity measure or the distance measure.

Moran's scatter plot shows the correlation between variable X, and the “spatial lag” of X. This lag is formed by averaging all the values of X used to identify the type of spatial association. for the neighboring states (Anselin, 1996).

The standardized income of a state (y-axis) is plotted against the weighted average of the incomes of its neighbouring states (x-axis). The weights are obtained based on the inverse distance and the contiguity matrices (discussed earlier).In Figure 3 below, on the vertical axis we represent "W_z" which is the lag of variable X and on the horizontal axis is "z" which is variable X. The slope of the regression line obtained by regressing "W_z" (lag of variable X) and "z" (variable X) gives us the Moran’s I (I = 0.070 in 1981 and I=0.073 in 2010) based on the inverse distance matrix (Anselin, 1996, p. 116).

Figure 3: Moran's scatter plot of PCI 1981and 2010 (2004-5 constant prices) based on inverse distance matrix



Source: Author's calculations

Note: 1-A&N Islands, 2-Andhra Pradesh, 3-Arunachal Pradesh, 4-Assam, 5-Delhi, 6-Goa, 7-Gujarat, 8-Haryana, 9-Himachal Pradesh,10-J&K, 11-Karnataka, 12-Kerala, 13-Maharashtra,14-Manipur,15-Meghalaya, 16-Mizoram, 17-Nagaland, 18-Orissa, 19-Puducherry, 20-Punjab, 21-Rajasthan,22-Sikkim,23-Tamil Nadu,24-Tripura,25-West Bengal,26-Uttar Pradesh,27-Bihar,28-Madhya Pradesh

The Moran's scatter plot is divided into four quadrants, each representing different kinds of spatial association or dependence.

a) The first quadrant (upper right quadrant (HH)) shows the spatial clustering of regions with high income and surrounded with similar regions with high income neighbours. Thus, the locations are associated with positive values of I_i.

b) The third quadrant (lower left quadrant (LL)) shows the spatial clustering of low income states which have low income states as neighbours. These locations are also associated with positive values of I_i

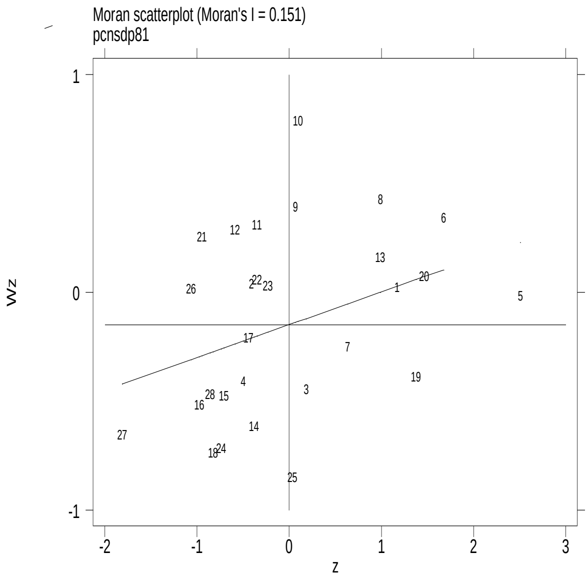
c) The second quadrant (upper left quadrant (LH)) shows clustering of low incomes states surrounded by regions with high incomes. These locations have negative values of I.

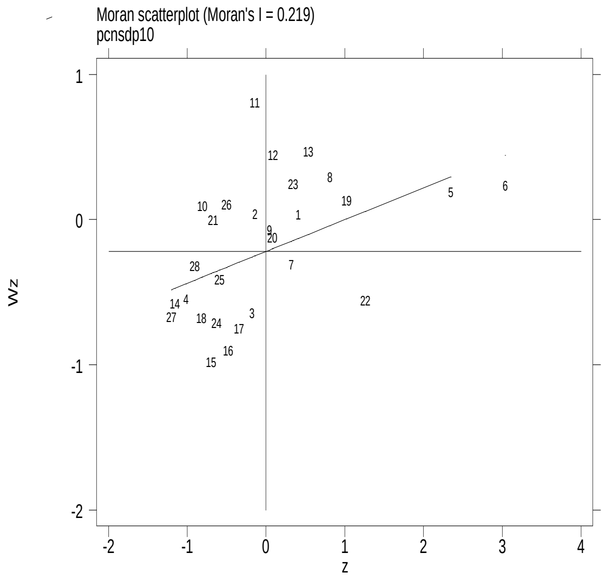
d) The fourth quadrant (lower right quadrant (HL)) shows spatial clustering of high income states surrounded by regions with low incomes. These locations are also associated with negative values of I.

If we examine the per capita incomes in the two periods 1981-82 and 2010-11, we find evidence of spatial concentration of the states. In 1981, Delhi, Goa and Punjab were the richest states surrounded by high income neighbours. Contrarily , Puducherry was a high income state surrounded by regions with low incomes. In quadrant 2, U.P, M.P, Rajasthan, Kerala and Andhra Pradesh were the low income states surrounded by richer neighbours. In the third quadrant Assam, Manipur, Meghalaya, Mizoram, Nagaland, Sikkim, Tripura (North eastern states) along with Bihar and Odisha were the poorest and also had poor neighbours.

In 2010, Delhi, Goa were the richest states and there has been an increase in the number of high income neighbours surrounding them. Kerala and Tamil Nadu, which earlier belonged to a lower income category, joined the cluster in quadrant 1 in 2010. Similarly, Puducherry which was surrounded by low income neighbours in quadrant 4, joined the cluster in quadrant 1 in 2010. Unfortunately Assam, Manipur, Meghalaya, Mizoram, Nagaland, Tripura (North eastern states) have continued to be in the third quadrant. Arunachal Pradesh and West Bengal have now joined this cluster. Sikkim has been a remarkable outlier and moved from being a low income state to a high income state. It is however surrounded by low income neighbours and therefore is placed in quadrant 4. Our results confirm a strong regional concentration of per capita income in India, with most of the richer states located in the Southern and the Western parts of India, along with Delhi, Haryana, Punjab in the North (Lolayekar & Mukhopadhyay, 2016).

Figure 4:Moran scatter plot of PCNSDP in 1981 and 2010 (2004-5 constant prices) based on contiguity matrix





Source: Author's calculations using EPWRF data.

Note: 1-A&N Islands, 2-Andhra Pradesh, 3-Arunachal Pradesh, 4-Assam, 5-Delhi, 6-Goa, 7-Gujarat, 8-Haryana, 9-Himachal Pradesh,10-J&K, 11-Karnataka, 12-Kerala, 13-Maharashtra,14-Manipur,15-Meghalaya, 16-Mizoram, 17-Nagaland, 18-Orissa, 19-Puducherry, 20-Punjab, 21-Rajasthan,22-Sikkim,23-Tamil Nadu,24-Tripura,25-West Bengal,26-Uttar Pradesh,27-Bihar,28-Madhya Pradesh

The scatter plots created from contiguity matrix reveal similar results (from inverse distance) with respect to the pattern of spatial concentration in India, with a few exceptions (see Figure 4). We find that Delhi, Goa, Haryana, Punjab and Maharashtra were the richer states surrounded by high income neighbours in 1981. In contrast (to the findings of the distance matrix), Gujarat is located in quadrant 4 surrounded by states with low income (in contrast to Figure 1).

Since spatial dependence is confirmed by Moran's I and LISA statistics, we now proceed to set up the spatial econometric models to examine the growth relationship across the states.

5.2 OLS estimation and spatial cross section model

For the OLS estimation we use different period combinations in contrast to the panel estimation (time-period of 30 years split into six, five-year sub periods namely, 1981- 85, 1986–90, 1991-95, 1996-00, 2001-05 and 2006-10). We start by estimating the standard OLS regression model (equation 5) for four period combinations namely 1981-10, 1991-10, 1981-90 and 2001-10. Growth is regressed against initial income of the periods. The reason for choosing this time slots is

a) 1981-10, covers the beginning and the end of our period of study

b) 1981-90 and 1991-10 allows us to compare the pre and the post liberalisation period

c) 2001-10, this is the most accelerated period of liberalisation

After estimating the OLS regression we examine if there is spatial dependence using a number of diagnostic tests. We have earlier used the Moran's I to test for spatial dependence. In addition we use two Lagrange Multiplier (LM) tests to check for spatial dependence in "Error" and "Lag" terms using their robust versions to control for heteroskedasticity. The tests help us to decide which specification - spatial error or the spatial lag is the most appropriate (Anselin and Florax 1995). LM tests are asymptotic and follow a $\chi 2$ distribution with one degree of freedom and they test the null hypothesis of no spatial dependence against the alternative hypothesis of spatial dependence. To choose between the two models the values of Akaike Information Criteria (AIC) and Schwartz criteria (BIC) are considered. The model with the smaller value of the information criterion (either AIC or BIC) is considered to be better. The " speed " of convergence or divergence (calculated by dividing the β estimate by number of years in the period combinations namely 1981-10, 1991-10, 1981-90 and 2001-10) measures how fast states converge or diverge towards the steady state per annum (see Table 2). The result of these regression and diagnostic tests is presented below.

Table 2: OLS estimation: Unconditional Convergence Model

Equation	Dependent Variable	constant	β Lnpcnsdp	Divergence speed	AIC	BIC	R2	R squared		Moran's I (error)	Robust LM (error)	Robust LM(lag)
1	Gr81-10	-0.038 (0.053)	0.009 (0.005)	0.0002	-175.45	-172.79	0.09	0.05		1.45 (0.14)	0.615 (0.43)	0.000 (0.98)
2	Gr81-90	0.12 (0.078)	-0.010 (0.008)	0.0007	-154.3	-151.72	0.05	0.01		-1.32 (1.81)	**4.93 (0.02)**	**3.14 (0.07)**
3	Gr91-10	.004 (0.069)	0.005 (0.007)	0.0003	-161.21	-158.55	0.05	0.02		1.49 (0.13)	0.66 (0.41)	0.002

												(0.96)
4	Gr01-10	.005 (0.107)	.0065 (0.01)	-0.0003	-131.56	-128.8	0.005	-0.03		**1.61 (0.10)**	0.40 (0.52)	0.006 (0.94)
Robust standard errors in parentheses , significance *** p<0.01, ** p<0.05, * p<0.1 No of observations 28										p-values are in the parentheses		

In the pre reform period (1981-90) both the robust LM tests, (for the lag and error) are significant. The significance of Moran's I provide evidence of spatial dependence during the post reform period 1991-10. The above findings indicates the presence of spatial error as well as spatial lag. The results confirm that the OLS estimates suffer from a misspecification because of the omitted spatial dependence. In the case of spatial error autocorrelation, the OLS estimator of the response parameters remains unbiased, but it is inefficient. While in case of a spatially lagged dependent variable, the OLS estimator of the response parameters loses its property of being unbiased and also becomes inconsistent. This has implications for all the earlier studies on convergence in India which have used OLS estimates for testing convergence (Ahluwalia, 2000; Cashin & Sahay, 1996; Kurian, 2000; Mitra & Marjit, 1996).

The next step in our analysis involves controlling for spatial dependence in the cross model. Since the OLS estimation method however is inappropriate for models with spatial effects. Thus weuse the maximum likelihood (ML) technique for spatial regression models namely SAR, SDM, SEM and SAC. This is applicable for both, the cross section and the panel data estimation (to be discussed later in section 5.3). We first present the test for spatial dependence using the inverse distance matrix (Table 3) followed by the contiguity matrix in (Table 4).The results of the spatial dependence model for unconditional β convergence over the 4 periods of interest are presented in Table 3.

Table 3:Maximum Likelihood Estimation of spatial cross section models based on inverse distance matrix

Model specification	β (Initial lnPCNSDP)	λ	ρ	θ	Divergence speed	Moran's I(error)	Robust LM(error)	Robust LM(lag)

1	2	3	4	5	6	7	9	11
	1981-10							
SAR	0.008 (0.005)		-4.52 (6.19)		0.00018	24.83***	0.24	0.02
SAC	0.009 (0.007)	0.92*** (0.13)	-3.77 (6.96)		0.00018	644.3***	621.2***	462.4***
SEM	**0.009*** **(0.005)**	0.92*** (0.23)			0.00021	651.6***	757.42***	593.0***
SDM	0.008 (0.005)		5.53 (14.7)	-0.07 (0.68)	0.00018	21.9***	0.53	0.42
	1981-90							
SAR	-0.006 (0.007)		-5.14 (9.25)		-0.00067	-56.1***	0.008	1.52
SAC	-0.007 (0.007)	.92*** (0.06)	-8.06 (9.67)		-0.0007	634.7***	519.3***	362.4***
SEM	-0.006 (0.007)	.88*** (0.14)			-0.0006	650.3***	758.6***	593.9***
SDM	-0.007 (0.005)		-53.8*** (14.35)	.25*** (0.063)	-0.0007	-94.0***	0.17	0.91
	1991-10							
SAR	0.006 (0.006)		-6.3 (6.26)		0.00036	4.28***	0.006	0.0017
SAC	0.006 (0.007)	0.81 (7.29)	-6.34 (6.48)		0.00036	576.4***	400.7***	360.6***
SEM	0.006 (0.007)	0.88			0.00066	217.0***	83.62***	180.9***
SDM	0.005 (0.006)		3.46 (15.23)	-0.063 (0.091)	0.00031	0.63	0.22	0.22
	2001-10							
SAR	.007 (0.010)		-23.1*** (8.70)		-0.0003	-23.5***	0.23	0.002
SAC	-0.004 (0.008)	-15.5 (15.89)	-10.24 (15.80)		-0.0004	458.4***	51.9***	191.8***
SEM	**0.01**** **(0.006)**	7.42			-0.0005	602.7***	628.4***	569.2***
SDM	.005 (0.009)		-7.82 (18.31)	-.10 (.11)	-0.0004	-30.5***	3.77	3.49*
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1								

The estimated coefficients of the spatial variable are reported in column 3, 4 and 5 for different models. We find that of all the models tested here, only the SEM model (in 1981-2010 and 2001-2010), has a significant β coefficients. In the SEM model, the coefficients on the error term are significant over two periods (1981-2010 and 1981-90). The SAC model reports a "λ" significant for the sub periods 1981-90 and 1981-2010, while the coefficient on the lag term "ρ" is not significant in any of the periods. In the SDM model, the coefficient on the spatial lag of initial level of income "ρ" and the spatial lag of growth rate "θ " is significant only in the pre reform period 1981-90.

Table 4:Maximum Likelihood Estimation of spatial cross section models based on Contiguity Matrix

Model specification	β (Initial lnPCNSDP)	λ	ρ	θ	DIvergence speed	Moran's I(error)	Robust LM(error)	Robust LM(lag)
1	2	3	4	5	6	7	9	11
	1981-2010							
SAR	0.009* (0.005)		0.09 (0.14)		0.0012	1.50	2.43	1.41
SAC	0.008 (0.006)	0.142 (0.28)	0.052 (0.24)		0.001	1.62*	3.20**	2.02
SEM	0.006* (0.004)	0.198 (0.21)			0.00021	1.70*	3.08*	1.71**
SDM	0.008 (0.005)		-0.20 (0.20)	-0.001 (0.001)	0.00018	1.60*	823.80***	822.96***
	1981-90							
SAR	-0.004 (0.006)		-0.64 (0.23)		-0.00067	-0.98	0.003	0.68
SAC	-.004 (0.006)	-.03 (0.06)	-.61 (0.74)		-0.0007	-1.0	0.004	0.70
SEM	-0.002 (0.005)	-.642 (.24)			-0.0006	-1.33	0.59	2.21
SDM	-0.005 (0.006)		-0.66*** (0.24)	.004*** (0.001)	-0.0004	-1.67*	0.34	0.14
	1991-2010							
SAR	0.006 (0.005)		0.151 (0.14)		0.00036	1.85**	4.30***	2.65
SAC	.005* (0.002)	0.43*** (.18)	-0.22		0.00036	1.68*	4.48**	3.90**
SEM	.005* (0.002)	.22 (0.22)			0.00066	1.69*	5.32**	4.65**
SDM	.005 (0.006)		.228 (0.22)	-.001 (.001)	0.00031	1.66*	4.69e+04***	4.69e+04 ***
	2001-2010							
SAR	0.005 (0.01)		.17 (0 .18)		-0.00033	1.74*	5.21**	3.79**
SAC	.004* (0.002)	0.71*** (0.19)	-0.71* (0.39)		-0.0004	1.56	3.00*	2.12
SEM	0.005 (0.006)	0.24 (0.21)			-0.0005	1.77*	4.65**	3.17*
SDM	.004 (0.010)		.25 (0.224)	-0.001 (0.002)	-0.0004	1.79*	4313.6***	4312.1***

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

We performed the same tests for the four models using the contiguity matrix. The results are presented in Table 4. We find that the "β" is significant only for the period 1991-2010 in the SEM model. A note of caution needs to be placed here. The cross section analysis has its limitations (Elhorst, 2014). This sets the analytical need to use panel models, which we present next.

5.3 Spatial Dependence Models for Panel Data

We generate the panel here by splitting the time-period of 30 years into six, five-year sub periods namely, 1981- 85, 1986–90, 1991-95, 1996-00, 2001-05 and 2006-10.The fixed effect model is used since the units of observations remain the same during the period. We start by presenting results of the simple panel fixed effect model (Table 5).

Table 5: Panel Data Fixed Effect Model Results

Variable	Coefficient
Initial Lnpcnsdp (β)	0.03*** (0.008)
constant	-0.24*** (0.077)
Observations (N)	168
R-sq:	
within	0.094
between	0.059
overall	0.072
Convergence speed	0.006
Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$	

The β - coefficient of initial income is significant at 1% level. The positive sign of the coefficient confirms that there is divergence in the rate of growth among the states in India. Over the period 1981-2010, the estimated coefficient of the initial per-capita income level is 0.03 which implies a rate of divergence is 0.006.

We will now extend the simple panel model to test for the presence of spatial dependence. This not only allows us to solve the problems associated with unobserved factors that influence growth, but also removes the bias introduced by spatial dependence in the error terms. For reasons discussed earlier, we use the maximum likelihood technique for the SAR, SDM, SEM and SAC for panel data estimation.

Results of the four types of spatial models are presented in Table 6 using Contiguity Matrix.

Table 6: MLE using different model specifications (Spatial Panel Data fixed effects) using Contiguity Matrix.

Dependent Variable- Growth Rate (Contiguity Matrix)								
	1	2	3	4				
	Lnpcnsdp (β)	ρ	θ	λ	Log-likelihood	AIC	BIC	Divergence speed
SAR	.021 *** (0.008)	.27*** (0.06)			310.59	-615.1	-605.8	0.004
SDM	-0.017 (0.02)	.21*** (0.07)	0.05*** (0.02)		317.52	-627.0	-614.5	-0.003
SEM	.022** (0.01)			0.23*** (0.10)	308.98	-611.9	-602.6	0.004
SAC	.020*** (0.006)	.37*** (0.1)		-0.14 (0.16)	310.84	-613.6	-601.1	0.004
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.								

Source: Author's calculations based on QGIS and EPWRF data.

Interestingly now the β coefficient is positive in all models (except for the SDM) confirming that once we control for spatial dependence and missing variables there is strong evidence of income divergence. The significance of ρ, θ, λ values confirms that there is spatial dependence of growth rates and state '*j*' will influence the state 'i', independent of the impact of initial per capita income. This confirms our claims that estimates from previous studies are biased, inconsistent and inefficient. Expectedly therefore the values of β in all the spatial models (about 0.02) is less than the non-spatial panel model (0.03) confirming that the earlier econometric results overestimate the value of β if we do not control for spatial dependence.

The SDM model confirms the spatial dependence among the independent variables as well. The growth rate in a state '*i*' depends on the per capita income levels of the neighbouring states *'j'*. The SEM model finds divergence in growth rates among the states as well as strong spatial dependence among the error term of the states. In contrast the SAC model finds that there is significant spatial dependence in growth among the states but no significant relationship is seen among the error terms.

Table 7: MLE using different model specifications (Spatial Panel Data fixed effects) using Inverse Distance Matrix

Dependent Variable- Growth Rate (Inverse Distance Matrix)								
	Initial Lnpcnsdp (β)	ρ	θ	λ	Log-likelihood	AIC	BIC	Divergence speed
SAR	0.014 (0.01)	13.6 *** (2.99)			310.59	-615.1	-605.8	0.002
SDM	-0.017 (0.02)	1.58*** (0.07)	1.58*** (0.79)		315.3	-622.6	-610.1	-0.003
SEM	0.005 (0.28)			16.49*** (6.9)	309.2	-612.5	-603.1	0.001
SAC	.014 * (0.011)	14.94*** (2.92)		-3.91 (7.7)	310.6	-613.3	-600.8	0.002
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.								

If we use the inverse distance matrix with same models (Table 7) the β is significant and positive only in the SAC model as is the 'ρ' coefficient. It also reaffirms that the 'β' value is much lower than what earlier results have found. This implies that the speed of divergence for the spatial models is much lower than that obtained in non-spatial fixed-effect panel model.

6. Conclusion

The literature on convergence in India by a large majority has established that there is divergence in the growth rates. We find confirmation of these findings. However, our results above suggest that the OLS and panel data estimates on convergence in these studies suffer from bias, inconsistency and inefficiency due to misspecification caused by the omitted spatial component in their analysis. Our estimates from the fixed effect spatial panel confirm that the process of growth in India is spatially dependent. Further, the impact of initial income on growth is much smaller than earlier anticipated once we control for spatial dependence. Our analysis suggests that neighbourhood effects play a significant role in determining growth outcomes of Indian states. We believe that this is the first attempt to demonstrate this in the Indian context and has important implications for policy making. Areas of low incomes could benefit from growth spill over effects from richer neighbours and be able to break the vicious circle of poverty and the drop of a low initial income. This raises hope that a virtuous circle of growth could emerge in India.

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