Spatial convergence and growth in Indian agriculture: 1967-2010

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ABSTRACT

Inter-state diversity has been a perennial feature of Indian agriculture. The study probes if per capita income from agriculture has converged across states and finds evidence in favour of beta convergence. Spatial econometric techniques used indicate significant spatial dependence in agricultural growth. Infrastructure like roads, irrigation, and electricity, diversification in cropping pattern and quality of human capital are found to aid in growth. However, excessive rainfall tends to decrease growth rate in India. The spill-over across states are found to be primarily driven by roads, irrigation and rural literacy and we also find significant impact of spatial income growth providing evidence in favour of agglomeration effects. Hence, investments in human capital, physical infrastructure specially water management and incentives towards growing crops which yield higher returns will aid agriculture growth in India.

Keywords: *Agriculture, growth, regional convergence, spatial econometrics*

JEL Codes: *O13, O18, R12, R15*

1. Introduction

The level and growth of agricultural income plays an undisputed role on poverty reduction, food security and employment generation (Ravallion and Datt 1996; Warr 2003; Kumar, et al, 2011). On comparing the impacts of growth in agriculture, secondary and tertiary sector on rural poverty alleviation, Ravallion and Dutt, 1996 find the highest impact is from agricultural sector. This is not surprising given that 68 % of total population in India live in rural areas and out of the total rural working population 50 % are employed in agriculture as cultivators and agricultural labour (Source: Principal Census Abstract, 2011). Kumar, et al (2011) finds evidence of a significant negative relationship between farmer's poverty and agricultural NSDP per person through a log-linear regression model. The relationship between nutrition and agriculture has been explored in many past studies. Gulati, et al (2012) finds a significant negative relationship between agricultural performance and income measures and malnutrition index. Gillespie, et al (2012) direct us towards the direct and indirect pathways through which income from agriculture can act as a way out from the curse of malnutrition. For all these reasons, from a policy perspective it is desirable to achieve some degree of convergence in the level and growth of agricultural income across regions.

However, inter-state disparity has been an enduring feature of Indian agriculture. Over the years, states in India have shown variation among themselves across various dimensions like cropping pattern, income generated from agriculture, value of output produced and land and productivity. Studies like Bhalla and Singh (1997), Bhide et al (1998), Chand and Chauhan (1999), Mukherjee and Koruda(2003), Ghosh(2006), Somashekharan, et al (2011), Birthal, et al (2011) and Mukhopadhyay and Sarkar (2014) have documented the rise in inter-state disparity. However, they also found that along with high spatial variation, there has been temporal variation in performance as well. Growth rates of better performing states in the past like Punjab and Haryana have dropped while that of states which were poorer performers earlier like Madhya Pradesh, Gujarat have gone up.

The difference across states is potentially because of differentials in agro-ecological conditions, cropping pattern, input usage, infrastructural support etc. It is widely accepted that agricultural growth is hugely dependent on agro-climatic conditions of a region. A state with favourable agro-climatic condition might have an upper hand in agriculture production and hence have higher chance of generating more income from the same. However, advancement in technology, investments aiding growth in infrastructure and input use and other state level policies can help a state initially un-favourably endowed, to perform better than it would have been in their absence. Reducing inter-state disparity has been one of the primary developmental concerns of policy makers in India.

Inter-state disparities are typically studied using beta and sigma convergence measures in the empirical literature. Sigma convergence is said to occur if the dispersion of income or any other variable of interest across a group of economies or regions declines over time. The idea of beta convergence has been derived from the Solow growth model which predicts that because of diminishing returns to capital, growth will be strong when regions first begin to accumulate capital but will slow down as the process of capital accumulation continues and that regions will converge with one another over time as initially growing regions will slow down and regions growing later will catch up with them. Beta convergence is said to be occurring when a poor economy/region tends to grow faster than the rich one. Formally, this result is obtained if a regression of income growth on initial income level has a significant negative slope coefficient. There are two forms of beta convergence viz. unconditional or absolute wherein all regions are assumed to converge to the same steady state and conditional beta convergence wherein regions are assumed to converge to different steady states depending on the region specific characteristics.

Studies like Bhide et al (1998), Chand and Chauhan (1999), Mukherjee and Koruda (2003), Ghosh (2006), Somashekharan et al (2011) and Mukhopadhyay and Sarkar (2014) have explored convergence across Indian states on various agricultural outcomes for example on per capita agriculture net state domestic product (NSDP), per capita food grain production, land and labour productivity, and total factor productivity growth. Findings from all these studies point towards increasing divergence across states when tested through sigma convergence measure and unconditional beta convergence. Bhide et al (1998) find states converging in the shorter time interval of five years but in the longer time interval of ten years, they find that state level growth rates converge to different levels. They find that changes in rainfall and irrigation to be significant in driving growth although they do not explore factors driving convergence. Ghosh (2006) on controlling other factors driving growth finds evidence in favour of conditional beta convergence and found that human capital, physical capital and rural infrastructure drive convergence in Indian agriculture.

Internationally in the broader literature on convergence for aggregate economy, studies like Rey and Montourri (1999), Egger and Pfaffermayr (2006) among many others have documented evidence in favour of significant spatial dependence in convergence across regions. The underlying idea is that a region's growth performance is dependent on where it is located either because of its own geographical features for example topography, climatic condition etc. or because of the fact that a region shares its geographical neighbourhood with another region i.e. through spatial spill-over. These two pathways linking geography and growth have been discussed in detail in Abreu et al (2005). The first pathway wherein a region's performance is believed to be because of its own geographical features is called 'absolute geography' while the second pathway wherein a region performs in a certain way because of the fact that it is geographically located near another region is known as 'relative geography'.

The significance of role of relative spatial dependence in agriculture i.e. impact of geographical location of regions with respect to each other on land use, deforestation patterns, farming decisions and land price volatility is gaining popularity in recent years (Irwin and Bockstael, 2002, Nelson and Hellerstein, 1997 and Binkley, 1994, Florax et al, 2002 and Schmidtner, 2012).The underlying idea is that forces driving regional agricultural performance could exhibit significant geographical dependence because of agro-climatic zones being spread over multiple regions, spill-over of information and technology and trade and transportation infrastructure into neighbouring regions, institution of market, common river basins across regions etc. Because of the inter-play of these and other possible factors, regions act like interacting agents and not as isolated 'absolute' units..

Econometrically, controlling 'absolute' location in estimation implies that the impact of being located at a particular point in space is controlled by explicit region specific geographic factors and/or region dummies or through fixed effect estimation techniques. Incorporating 'relative' location in estimation technique implies that the effect of being located closer or farther away from specific regions is being controlled. This is done through spatial weight matrices which help in quantifying spatial dependence across regions by giving it a structure and the same are used in estimation techniques.[1] As will be seen later, the spatial econometric models and estimation techniques to assess the role of relative geography requires the use of panel data. Consequently, they do not permit incorporating multiple time-invariant absolute

[1] For details on absolute and relative location, refer Abreu, De Groot and Florax(2005).

geographic factors in the empirical model. Nevertheless, absolute geography is incorporated into the model as state fixed effects.

The impact of geographic factors, in particular relative geography, on convergence, to our best possible knowledge, has not been studied in the empirical literature on Indian agriculture. This study aims to fill this gap in the literature on Indian agriculture. It examines spatial convergence across states in per capita income from agriculture, through sigma and beta convergence measures, controlling for relative geography in our empirical models for beta convergence. We identify the drivers of convergence of per capita income and test if differences in the same across 17[2] major states of India have narrowed down over the period from 1967-68 to 2010-11. The methodology used for the study is drawn from Barro and Sala-I-Martin, 1992 and spatial econometrics literature (Anselin, 1988, Elhorst, 2003).The analysis has been done at the state level because of paucity of a rich data set for such a long time span at a lower level of geographical aggregation for example districts although spatial dependence is expected to be stronger at a lower level of geographical aggregation.

One of the contributions of this study is use of alternative spatial weight matrices. We try out four different spatial weight matrices viz. state-contiguity based, inverse distance based, common border based and district contiguity based in this study beyond the conventional matrices used in the literature. This helps us to compare and identify the spatial weight matrix which explains spatial dependence across states in the best possible manner. Further the use of alternative matrices adds robustness to our results.

Findings from the study give evidence in favour of significant spatial dependence across regions and highlight the importance of inputs and infrastructure in growth in agriculture. In particular, we are also able to identify the channels of spatial spill over on income convergence. Further, we find that spatial dependence is robust across different spatial weight matrix and that district based spatial weight matrix explains spatial dependence in the best possible manner among all other matrices.

The rest of the paper is organized as follows: The next section briefly describes the methodology adopted and data used in the study. The growth performance of the states from 1967-68 to 2010-11 have been compared and spatial patterns discussed in section 3. Section 4 reports the results of the analysis while section 5 provides some concluding remarks.

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[2]These 17 states contribute more than 96% of the national Net Domestic Product (NDP) from agriculture. The states are Andhra Pradesh (AP), Assam, Bihar+Jharkhand, Gujarat, Haryana, Himachal Pradesh (HP), Jammu & Kashmir (JK), Karnataka, Kerala, Maharashtra, Madhya Pradesh +Chhattisgarh (MP), Orissa, Punjab, Rajasthan, Tamil Nadu (TN), Uttar Pradesh+ Uttarakhand (UP) and West Bengal (WB)

Methodology and data used

As discussed, the two commonly used approaches to test income convergence in literature are sigma and beta convergence. Sigma convergence refers to reduction in dispersion in the levels of income across regions over time. Beta convergence estimation is based on a log-linear approximation around the steady state of a Solow type growth model. In this approach, an empirical relationship between the initial income level in a region and the subsequent growth rate is estimated. A significant positive association shows high growth rate for richer economies and hence a divergent growth scenario while a significant negative relationship indicates convergence i.e. that poorer regions are growing faster than the richer ones and hence is evidence in favour of "catching up" by the poorer states. It is based on the Neoclassical growth model which predicts that regional incomes will overtime converge to their respective steady states, which depends on savings rate, population growth rate and rate of technological progress in a region, which are assumed exogenous in the model. Therefore, the exogenous rates at which all the factors of production in an economy grow, determine the long run steady rate of growth of the economy.

Studies like Quah, 1993, a, b; Barro and Sala-I-Martin, 1992Young, 2008 have acknowledged that beta convergence is not a sufficient condition for sigma convergence. Sala-I-Martin (1994) suggests that beta convergence measure is more interesting concept since it responds to questions, such as, whether poor economies (countries or regions) are predicted to grow faster than rich ones, how fast the convergence process is, whether the convergence process is conditional or unconditional and whether there is a different convergence process between groups of economies with different structures. However, Quah, 1993a suggests that sigma convergence is of greater interest since it speaks directly as to whether the distribution of income across economies is becoming more equitable. Additionally, Quah, 1993b shows that a negative relationship between growth rates and initial values do not indicate a reduction in cross-sectional variance and it is also possible to observe a diverging distribution (sigma dispersion) in presence of such negative relationship. Given that there is no general consensus on this issue, in this study, both approaches have been used to analyze convergence across states in Indian agriculture. Additionally, spatial dependence among states has also been controlled in the estimation of beta convergence.

Spatial dependence is said to occur when observations of a particular spatial unit is dependent on observations of its neighbours. It implies that there exists a relationship between what happens at different points in space. Econometrically, one of the first and most important steps towards quantifying relative spatial dependence is specifying the structure of spatial relationship among regions. Empirically, spatial dependence is quantified through spatial matrix (*W*)(Anselin, 1988, Elhorst, 2003, 2010a). '*W*' is a symmetric 'nxn' matrix where 'n' is the number of regions and the numerical values of the elements of the matrix are driven by the criteria of neighbourhood definition. *W* can be defined on the basis of context of the study. By convention, the diagonal elements are set to zero,$w_{ii}=0$. However, *W* must satisfy two basic rules of being finite and non-negative (Anselin, 1988). In the simplest case, the weights are defined on the basis of contiguity i.e. regions are assigned 'one' in the matrix if they share borders and 'zero' otherwise.

It is necessary that the relative spatial location is specified correctly in *W* so that the relation among states is appropriately controlled for in the estimation strategy. Eventually *W* will determine the extent and possibility of spatial spill over across regions which are later controlled through the spatial models. Stetzer (1982) shows that the specification of weight is important for parameter estimation, especially when sample sizes are small and the data is auto correlated. Griffith and Lagona (1998) show that incorrectly specified weight matrix can lead to a loss of efficiency of the estimators. Monte-Carlo study by Stakhovych and Bijmolt (2009) conclude that a weights matrix selection procedure that is based on 'goodness-of-fit' criteria increases the probability of finding the true specification. In case the spatial interaction model is estimated based on different spatial weights matrices and the log-likelihood function value of every model is estimated, one may select the spatial weights matrix with the highest log-likelihood function value (Elhorst, 2010b). This method of selecting spatial weight matrices has been criticized by Harris & Kravtsova (2009). They claim that it would only find the best among the competing spatial weight matrices and will not be able to identify the true spatial relationship unless one of the competing matrices is actually the true spatial relationship. However, Elhorst (2010B) argues that, 'the Monte Carlo results found by Stakhovych and Bijmolt (2009) partly refute this critique. Although there is a serious probability of selecting the wrong spatial weights matrix if spatial dependence is weak, the consequences of this poor choice are limited because the coefficient estimates are quite close to the true ones. Conversely, although the wrong choice of a spatial weights matrix can distort the coefficient estimates severely, the probability that this really happens is small if spatial dependence is strong.'(Pp: 17, Elhorst; 2010 b). Elhorst (2010b) additionally stress on the importance of correct specification of spatial weight matrices and suggests that researcher must correctly specify it and check for robustness.

In this study, we have used and compared four spatial weight matrices namely, state-contiguity based, inverse-distance based, shared border based and district-contiguity based matrices. In case of state-contiguity based matrices, weight 'one' implies that states are contiguous to one another and 'zero' implies that they are not. In case of inverse-distance based matrix, inverse of the Euclidean distance between the geographical centroid of two states is used as the weight. This weighing scheme ensures that higher weight is given to states which are closer to each other and vice-versa. In case of length of border based spatial weight scheme, weights are assigned according to the length of the border shared between two states. The idea behind using length of shared borders between states is that spatial spill-over is expected to be proportional to the possibility of connectivity between two states which is more for states with higher length of shared borders. For example if a state shares its borders with two other states, then through this spatial weight matrix, higher weight is given to the state with which it shares longer border compared to the second state with which it shares a smaller border length.

In case of contiguous-district based spatial scheme, weight is assigned according to the total number of contiguous districts between two states. The idea behind using districts based spatial weight matrix is again to control spatial effects in a manner that they are proportional to the possibility of spatial spill-over. States in India are spread across diverse agro-ecological zones and hence controlling state level contiguity does not guarantee that spatial dependence is completely incorporated. Quite often districts within a state are more homogeneous to contiguous districts in the neighbouring states than non-contiguous districts of the same state. For example eastern and western parts of the state of Uttar Pradesh fall under different agro-ecological zone, while eastern part is similar to eastern state of Bihar, western part is similar to northern state of Himachal Pradesh. Hence, giving a uniform weight of 'one' to both Bihar and Himachal Pradesh will not correctly quantify the spatial dependence. This district based matrix will give a higher weight to states with which Uttar Pradesh has more number of contiguous districts. Although this does not ensure that spatial dependence is completely controlled, it is expected to be an improvement over basic state level contiguity. All the matrices have been row standardized.[3]

[3]Lesage and Pace (2009)

Spatial dependence is typically detected using Global and local Moran's I-tests. If these tests reject the null of absence of spatial dependence, then spatial modelling should be used to explain the behaviour of the data. Global Moran's I-test statistics for the presence of global spatial dependence among the spatial units is given by:

$$I = \frac{n}{\sum_i \sum_j w_{ij}} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n} (x_i - \bar{x})^2} \quad (1)$$

Where n is the number of regions, w_{ij} is the element of the weight matrix W, x_i is the value of the variable at region i and $\bar{x}$ is the cross-sectional mean of x. A significant correlation statistic indicates presence of spatial dependence. However, these global tests overlook the local spatial dependence. It is possible that for a given year global spatial detection tests indicate no spatial relation while local spatial tests indicate strong dependence across some regions in the total set of regions. Hence, to have a better idea on local spatial dependence, local Moran's I-tests are used. For each location, these values compute its similarity with its neighbours and test whether the similarity is statistically significant.

For each location, local Moran's I-test statistic can be computed and this is given by

$$I_i = \frac{(x_i - \bar{x}) \sum_j w_{ij}(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2 / n} \quad (2)$$

Under the null hypothesis of no spatial dependence, both the global and Local Moran's I-test statistic asymptotically follow a standard normal distribution.

Once, spatial dependence is detected, relationships across spatial units are incorporated in the estimation strategy. There can be three types of spatial relation: (1) spatial dependence in dependent variable i.e. spatial lag model, (2) spatial dependence in error i.e. spatial error model and (3) spatial dependence in explanatory variables i.e. spatial Durbin model. A full model in a panel framework, once all types of spatial interactions are incorporated will be as follows:

$$Y_{i,t} = \eta_i + \rho Y^*{}_{i,t} + \alpha + X_{i,t}\beta + X^*{}_{i,t}\theta + u_{i,t}, \qquad (3)$$

$$u_{i,t} = \lambda u^*{}_{i,t} + \varepsilon_{i,t}$$

where the variable $Y^* = WY$ captures the spatial dependence among the dependent variables, $X^* = WX$ the spatial effects among the independent variables, and $u^* = Wu$ the spatial effects among the disturbance terms of the different units, $\boldsymbol{\rho}$ is called the spatial autoregressive coefficient, $\boldsymbol{\lambda}$, the spatial autocorrelation coefficient, while $\boldsymbol{\theta}$, just as $\boldsymbol{\beta}$, represents a $K \times 1$

vector of fixed but unknown parameters. W is a nonnegative $N \times N$ spatial weights matrix of known constants representing the spatial arrangement of the units in the sample.

However, if all three forms of spatial interaction effects are estimated simultaneously, then it is not possible to distinguish and identify one from another (Lee and Yu, 2010). According to Lesage and Pace (2009), the cost of ignoring spatial dependence in the dependent variable and/or in the independent variables is relatively high because of omitted variable bias and the estimator of the coefficients for the remaining variables is biased and inconsistent. In contrast, ignoring significant spatial dependence in the disturbances will only cause a loss of efficiency. Elhorst (2012) suggests that the best option to estimate a spatial model is to exclude the spatially auto correlated error term and to consider a model with spatial interaction effects in dependent and explanatory variables (Spatial Durbin model). Both Anselin (1988) and Lesage (2009) show that least squares estimators, if used in case of models with spatially lagged dependent variables lead to biased and inconsistent estimates. They recommend the use of maximum likelihood estimation techniques to estimate the coefficients of the model. In panel data framework, Lee and Yu (2010) show that the maximum likelihood estimator of the spatial lag and of the spatial error model with spatial fixed effects, as set out in Elhorst (2003, 2010), will yield inconsistent estimates of all parameters of the spatial lag and of the spatial error model with spatial and time-period fixed effects. To correct this, they propose a simple bias correction procedure based on the parameter estimates of the uncorrected approach. Panel data suffers from initial values problem and this is controlled through dynamic panel models where the lagged value of the dependent variable is also used as an additional explanatory variable. This corrects the autocorrelation problem in panel data models (Wooldridge (2005), Pfaffermayr (2012)).

Hence, in this study, spatial dynamic conditional beta convergence and sigma convergence across states in income from agriculture has been explored for 17[4] states in India from 1967-68 to 2010-11. The only consistent state level data available on income from agriculture for states in India from 1967 onwards is net state domestic product (NSDP) from agriculture. Our primary variable of interest is annual growth in NSDP per rural population. Data on NSDP was collected from EPW Research Foundation and rural population from CENSUS. The

[4]The 17 states are Andhra Pradesh (AP), Assam, Bihar+Jharkhand, Gujarat, Haryana, Himachal Pradesh (HP), Jammu & Kashmir (JK), Karnataka, Kerala, Maharashtra, Madhya Pradesh +Chhattisgarh (MP), Orissa, Punjab, Rajasthan, Tamil Nadu (TN), Uttar Pradesh+ Uttarakhand (UP) and West Bengal (WB)

newly formed states of Jharkhand, Chhattisgarh and Uttaranchal have been clubbed together with their parent states of Bihar, Madhya Pradesh and Uttar Pradesh respectively to maintain uniformity in the panel data set.

For purpose of analysis, the time period from 1967-68 to 2010-11 has been divided into following three sub phases on the basis of changing policies in agriculture sector. This aids in better understanding of the changing pattern of growth of agricultural income in India.

- 1st sub-phase : 1967-1977: the period of green revolution
- 2nd sub-phase: 1978-1989: period of falling public investment in agriculture
- 3rd sub-phase: 1990-2010: period of economic reforms

Figure 1plots the shares of public investments i.e. share of gross fixed capital formation (agriculture) in GDP from agriculture (both at constant 2004-05 prices). Investments were higher in the latter half of 1960s (sub phase 1 in our study) compared to the beginning of 1980s. The 1980s and 1990s are characterized with low levels of public investment in agriculture. One can however see a rising trend in late 1990s and early 2000s[5].

[Figure 1]

Following other studies on Indian agriculture (like Fan et al, 2000, Binswanger, 1993), we have controlled for state level inputs, infrastructure, human capital, and rainfall, besides spatial variables while testing for conditional beta convergence .The conditional convergence equation using a spatial dynamic panel fixed effects model in a maximum likelihood framework used for the analysis can be written as:

$$\begin{aligned} growth_{it} &= ln(y_{i,t}) - ln(y_{i,t-1}) \\ &= \alpha_i + \beta\, ln(y_{i,t-1}) \\ &+ \delta growth_{i,t-1} + \gamma_1 inputs_{it} \\ &+ \gamma_2 infrastructure\ and\ other\ state\ level\ characteristics_{it} \\ &+ \gamma_3 human\ capital_{i,t} + \gamma_4 rainfall_{i,t} + \gamma_5 spatial\ variables_{i,t} + \in_{i,t} \qquad (4) \end{aligned}$$

Here, coefficient of β gives evidence in favour or against convergence across states α_i is the state specific effects and the impact of the other factors on growth can be obtained from coefficients$\gamma_1\, to\ \gamma_5$.

[5]The rise in share of gross fixed capital in the 3rd phase has been controlled in the study through year dummies as number of years post rise in investment was very low to accommodate a separate phase and perform a robust statistical analysis.

Among inputs we control for land, tractors, fertilizer and livestock as inputs in agriculture. The annual data on land use is available in "Land use statistics, Department of economics and statistics, ministry of agriculture". Data for number of tractors was obtained from quinquennial livestock Census which is conducted by Department of animal husbandry, dairying and fishing, Government of India. The data has been interpolated using compound growth rate to get a panel data set on tractors used from these quinquennial surveys. Fertilizer use has been defined as total fertilizer (Nitrogen+Phophate+Potassium) consumed in kilograms per unit total cropped area. The data for fertilizer consumed is available state-wise and annually from "Fertilizer Statistics". Livestock has been defined as number of livestock per unit total area of the state. Data for number of livestock in total and also number of cattle, buffaloes, goats and sheep was collected from quinquennial livestock census conducted by conducted by Department of animal husbandry, dairying and fishing, Government of India. The data from these quinquennial surveys has been interpolated using compound growth rate to get a panel data set on total livestock and its types.

Infrastructure and other state level characteristics have been controlled through road quality, irrigation, electricity, state expenditure on agriculture and cropping patterns. Road quality is defined as a ratio of total surfaced road length to total road length (both in kms.) in the state. The state-wise annual data on total road length and surfaced road length was collected from "Basic Road Statistics" and "Statistical abstracts of India". Electricity is defined as percentage of villages electrified. Annual state-wise data for the same was obtained from EPRWF database. A dummy variable with value equal to 'one' when less than 100 per cent villages have been electrified and 'zero' if 100 per cent villages are electrified. Irrigation is defined as share of gross area irrigated in total cropped area. State-wise annual data on gross area irrigated and total cropped area from "Land use statistics, Department of Economics and Statistics, Ministry of Agriculture". State expenditure on agriculture is defined as state expenditure in agriculture per unit sq. km. area.[6]. State-wise annual data on expenditure was collected from "Finances of state government" published by RBI. Cropping pattern is defined as share of area under different crops. State-wise annual data was collected from "Area, Yield, Production of Principle Crops" by Ministry of Agriculture. Share of area under

[6]Expenditure on agriculture and allied activities include expenditure on crop husbandry, soil and water conservation, animal husbandry, dairy development, fisheries, forestry and wild life, plantations, food storage and warehousing, agriculture research and development, food and nutrition, community development and other agricultural programmes. Both revenue and capital expenditure have been included. This data is available from 1972.

different groups of crops namely cereals, pulses, fibre, oilseeds, sugar and all other crops have been clubbed together as rest.

As in other studies on Indian agriculture (Fan et al, 2000), rural literacy rate has been used as a proxy for quality of human capital. This is defined as percentage of literate rural persons in total rural population. Data on rural literacy rate was collected from CENSUS (various years). The years between two consecutive censuses were interpolated using assuming constant growth rates.

Rainfall has been controlled in such a manner that the impact of different levels of deviation of actual rainfall from the normal levels can be differentiated. Three rain dummies have been defined on the basis of absolute percentage deviation of actual average annual rainfall from normal average annual rainfall. The dummies are based on rain dummy_1 =‘one’ if percentage absolute deviation of rainfall from normal is between 5 and 10 per cent otherwise zero. Rain dummy_2 =‘one’ if percentage absolute deviation of rainfall from normal is between 10 and 20 per cent otherwise zero and rain dummy_3 =‘one’ if percentage deviation of actual average annual rainfall is between 20 and 100 otherwise zero. Average annual data on rainfall was collected from various publications of Statistical abstract of India.

Spatially weighted variables have been constructed by weighing the neighbouring states using the different spatial weight matrices described earlier; i.e. these newly created variables are the weighted means of observations of neighbouring states where the weights are used according to the spatial weight criteria in the models.

Growth performance across states

As a prelude to examining convergence in agricultural income across states, we first look at the growth performance across states. Figure 2 and Table 1, which give the levels and growth of per capita NSDP at 2004-05 constant prices, brings out some interesting features on the regional pattern of agricultural growth in India. Taking the entire period, the all India annual compound growth rate of NSDP from agriculture at 2004-05 constant prices was 2.29 per cent. During this entire period, the highest growth rate was recorded by northern state of Punjab (4.78 per cent) while the lowest growing state was eastern state of Assam (0.50 per cent).The other states with high growth in the entire time period were Haryana in the north, Maharashtra and Gujarat in the west and West Bengal in the east. Apart for Assam, the states with low growth were Andhra Pradesh in the south and Uttar Pradesh in central India, JK and

HP in the north. The coefficient of variation of growth rates across states in the entire time period was 39.26 per cent.

There were important changes in the regional growth pattern in the sub-phases. In sub-phase 1 (green revolution phase), growth rate of income from agriculture in India was 5.42 per cent. This period recorded the highest growth rate among all the sub-phases. However, this phase also recorded a high coefficient of variation across states (51.75 per cent). Growth rate was highest for Punjab (13.77 per cent) in north while it was lowest for Andhra Pradesh (0.32 per cent) in south. The other states with a high growth rate in this phase were Haryana in the north-west, Gujarat in the west and Bihar and West Bengal in the east. And the states with low growth rates were Andhra Pradesh and Tamil Nadu in the south, Assam in the east, Uttar Pradesh and Madhya Pradesh in central India.

In the 2nd sub-phase, growth rate of agricultural income at the national level fell to 0.69 per cent. This was the phase with the lowest growth rates and highest disparity measured in terms of coefficient of variation (78 per cent). States like Bihar (-1.34 per cent), Jammu and Kashmir (-0.85 per cent) and Tamil Nadu (-0.83 per cent) recorded a negative growth rate in this sub-phase. Growth rate of Orissa (4.62 per cent) was the highest while Bihar grew at the lowest rate. The states which performed better compared to the rest of the states were Orissa and West Bengal in east, Madhya Pradesh in central India, Punjab and Himachal Pradesh in the north while the states which performed the worst during the 1980s were Bihar in the east, Jammu and Kashmir in north, Tamil Nadu in south, Rajasthan and Gujarat in west.

The all India growth rate in the third sub-phase was 1.46 per cent and the coefficient of variation fell to 49.87 per cent. Maharashtra, Gujarat, Kerala, Andhra and TN grew at the highest rates while the states like Madhya Pradesh, Uttar Pradesh, Himachal Pradesh, Assam and Orissa grew at the lowest rate. Clearly, western and southern states were the best performers in this phase and eastern states performed the worst and had negative growth rates.

Hence, there is both evidence of rising spatial disparity across states and also of catching up in the sense that some of the states like Gujarat and Maharashtra in the west, which were comparatively poorly performing in earlier phases were recovering in the later sub-phases. This catching up process will be empirically tested using beta convergence estimation in the next section.

Table 1- growth performance across Indian states

Figure 2: Levels and growth of NSDP agriculture per rural person

Figure 3 plots the coefficient of variation (CV) of levels of per capita NSDP from agriculture and key infrastructure like roads, electricity, irrigation and state expenditure on agriculture across states from 1967 to 2010 to have a better idea of pattern of inter-state disparity. All the key infrastructure and per capita income show a decline in CV in the 1970s (sub-phase 1). In sub-phase 2, the decline continues except for income and power. In sub-phase 3 however, CV increases for all except expenditure on agriculture and power consumption.

[Figure 3]

Results

Spatial dependence across states

The empirical analysis begins with testing for spatial dependence through local and global Moran's I-tests described earlier. These tests are carried out for all the four alternative spatial weight matrices defined on the basis of state-contiguity based matrix, inverse-distance between two states, district-contiguous based matrix and length of borders shared between two states.

The results of global Moran's I computed have been given in Table 2 which shows that it is significant for all the weight structures from 1970. Moran's I result for significant years shows positive autocorrelation i.e. regions with similar levels of per-capita income were also geographically closer. The value of the Moran's I statistic can be interpreted as the level of spatial dependence[7]. Moran's I values for inverse distance based spatial weight matrices are the lowest compared to all other spatial weight matrices.

Table 2: Results of global Moran's test

The plot of global Moran's I in Figure 4 shows that spatial dependence has declined from 1970 to 1990 but there is a turn-around since late 1990s after which there seems to be a positive trend in spatial dependence. But it was particularly high in early 70s and 90s.

[Figure 4]

While global Moran's I detects the aggregate spatial pattern, local Moran test (Anselin, 1995) detects local dependence and helps locate areas of strong spatial linkages. Local Moran's I

[7] Rey and Montouri (1999).

for 1966 and 2010 are given in Table 3[8]. States have significant local spatial dependence in 1966 when there was no significant global spatial dependence.

Table 3-Results of Local Moran's test

States which had significant local spatial dependence for almost all the years were Northern states like Punjab, Haryana, Himachal Pradesh and Uttar Pradesh and eastern states like Bihar, West Bengal, Orissa, Assam , western states like Madhya Pradesh, Maharashtra, Rajasthan and Gujarat and Andhra Pradesh in south.

Sigma convergence

Figure 5 which plots the standard deviation of log of NSDP per rural person from agriculture for the entire time shows evidence in favour of sigma convergence in phase 1 as it can be seen that standard deviation of income across states follows a declining trend only in phase 1. However, we find evidence against sigma convergence in the later phases.

[Figure 5]

Figure 6 plots the global Moran's I statistics and standard deviation of log of per capita income over time for the full and different sub-periods. These plots point to a negative relationship between the two. Indeed, a simple correlation[9] between standard deviation of log of income and global Moran's I statistic for all the spatial weight criteria over the years confirms this. The correlation coefficient of Global Moran's I using contiguity, inverse distance, border and district based spatial weight matrix are -0.65, -0.61,-0.61 and -0.67 respectively and they are statistically significant at less than 1 percent level. This implies that a greater spatial dependence across states can help in reducing the inter-state disparity in per capita income. A similar significant correlation of -0.80, -0.79, -0.86 and -0.85 is seen for contiguity, inverse distance, border and district based spatial weight matrix respectively at less than 1 percent level in the first sub-phase also though in the second and third sub-phases, the correlation coefficient is not significant. This inverse relation between sigma convergence measure and spatial dependence possibly points towards the conceivable role of spatial dependence as a channel in reducing inter-state disparity. The results of beta convergence discussed below bring out this relationship more explicitly.

[Figure 6]

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[8]Results of local Moran's I for other years have not been shown in the table owing to paucity of space. They can be shared on request

[9]Rey and Montouri (1999) also find a statistically significant positive correlation between standard deviation and Moran's I statistic of per capita income of US.

Beta convergence

Table 4 gives the results of conditional beta convergence models. Annual growth rate of per capita income (NSDP) from agriculture is the dependent variable and explanatory variables are per capita income and other state specific characteristics discussed earlier. We estimate non-spatial model in Model 1 of Table 4. Hausman test confirms that fixed effects model performs better than random effects model. Therefore, we find that absolute geography which has been controlled through state fixed effects significantly drives agricultural growth convergence. In models 2-5, we estimate spatial models controlling for state fixed effects. Lagged per capita income (β) is significant and negative in all the models, indicating statistically significant evidence in favour of beta convergence within Indian states over the entire period 1967-68 to 2010-11.

Like other studies on convergence in Indian agriculture, our results show evidence in favour of conditional beta convergence but no such evidence in favour of sigma convergence. Ambivalence in results from beta and sigma convergence is not new in this literature. The concerns in empirical literature regarding these measures of convergence are discussed in Azariadis and Drazen (1990), Quah (1993 b), Durlauf and Quah (1999), and Islam (2003), Young et al, 2008. A negative beta coefficient, implying convergence, is consistent with a rising variance which indicates a lack of sigma convergence. Additionally, in presence of multiple equilibriums this approach tends to reject the null hypothesis of no convergence too often (Bernard and Durlauf, 1996). Further studies like Quah, 1993, a, b; Barro and Sala-I-Martin, 1992 Young, 2008 have acknowledged that beta convergence is not a sufficient condition for sigma convergence. Even existing studies on convergence in Indian agriculture like Ghosh (2006), Birthal, et al (2011) find no evidence of convergence when measured through sigma convergence but do find evidence in favour of robust conditional beta convergence.

One plausible reason driving this lack of unanimity can be that these two measures explore different aspects. While sigma convergence measures whether the distribution of the levels of variable of interest is becoming more equitable, beta convergence measures ask a very different question. Conditional beta convergence explores whether after controlling for region specific characteristics, growth rates are inversely correlated to levels in variable of interest. Young, et al (2008) show in their analysis that it is possible that regions are beta converging towards one another yet random shocks are pushing them away from each other leading to unambiguous results from beta and sigma measures. Another plausible explanation can be possibility of club convergence among regions. That is if states are not all converging to unique steady states after controlling for state specific characteristics, are they converging to multiple equilibriums.

Turning to the role of spatial dependence, if any, on the basis of log-likelihood, AIC and BIC, we find that spatial models (models 2 – 5) perform better than the non-spatial model (model 1) for the entire period (1967-68 to 2010-11) which confirms the presence of significant spatial dependence in income growth in Indian agriculture. As literature does not provide much guidance on the spatial weight criteria, the spatial models have been compared on the basis of log-likelihood, AIC and BIC and the contiguous districts based spatial matrix (model 5) performs the best among all other models. This confirms that spatial dependence across states in India is controlled better through contiguous district based spatial weight matrices where higher weight is given to states with more number of contiguous districts. There is a lot of diversity within the states in India and hence often one can find more homogeneity between contiguous districts of neighbouring states compared to non-contiguous districts on the same state. The contiguous-district based spatial weight matrix controls for this spatial homogeneity among neighbouring states. The results from the other spatial weight matrices (models 2-4) give evidence of significant spatial dependence thereby adding robustness to our results.

Results show that channels of spatial spill-over in income from Indian agriculture has been income growth, rural literacy, gross area irrigated and road quality. Spatial income growth is positive and significant for all the models implying that higher growth of a state has positive spill-over effect over its neighbours. In case of contiguity based matrix (model 2), additionally spatial literacy has a positive coefficient implying that states with higher literacy rate have a positive impact over income growth of their neighbours. In case of inverse distance based spatial matrix (model 3), it can be seen that spatial impact is through road quality i.e. higher road quality accelerates growth in neighbouring regions through better connectivity/networking possibilities. Using length of shared borders between states (model 4) and number of contiguous districts (model 5) as weighing criteria, rural literacy, gross area irrigated and road quality have a positive and significant spatial on growth in income among states. Infrastructure therefore has significant spatial dependence across states and aids in growth in neighbouring states.

The findings are in line with studies on other countries like Tong (2012) found significant spatial spill-over through road infrastructure. Similarly there are a number of studies like Patton and McErlean, 2005 on land market, Schmidtner et al (2011) for farming decisions in Germany, which give evidence of significant spatial lag dependence which has often been interpreted as an agglomeration effect. Studies like Alston (2002) discuss knowledge based channels in detail and conclude that it as a primary source of spatial spill-over in agriculture. We believe that rural literacy acts as a channel of spatial spill over through diffusion of knowledge externalities from neighbouring states. With evidence in favour of increasing inter-state migration (Lusome and Bhagat, 2006) it is conceivable that diffusion of knowledge gets accentuated through migration. Further, demonstration effects can also be a possible channel through which literacy acts as significant channel of spatial spill over. It is widely accepted that literacy increases the prospect of adoption of newer technology, farming techniques thereby further accentuating agriculture growth and income at the state level. With higher inter-state mobility and plausible demonstration effects we believe that literacy acts as an important channel of spatial spill over.

With regard to spatial irrigation, to the best of our knowledge we could not find evidence in existing literature on the plausible reasons for its significant. One possible reason for spatial irrigation to have spill-over effect could be that when neighbouring states receive irrigation investments, especially large surface irrigation projects, its impact does not suddenly stop at the state boundaries. In fact quite often such projects tend to cover several states across multiple agro ecological zones thereby potentially leading to a spatial spill-over across states.

Among inputs, tractors, land and livestock play a statistically significant impact in all the models[10]. Both tractor and land ownership have a positive impact on growth indicating the importance of asset ownership in growth of income. Among livestock, only buffaloes and sheep play a significant role in growth while other forms of livestock remained insignificant and hence were dropped from the analysis. Interestingly, buffaloes have a negative impact on growth in spatial models (insignificant in non-spatial model) while sheep have a positive impact. Livestock not only acts as an input in agriculture production process but also acts as a source of income in the form of wool, meat, milk etc. Although the reason driving the negative relation between buffaloes and growth and insignificant relation between cattle and

[10]Fertilizer consumed per unit of cropped area is not significant in any of the models and hence has been dropped from the analysis.

goats and growth is not very clear, it is possible that these results point towards a non-optimal mix of different types of livestock dominated by bovines[11].

Results show that infrastructural support in a state has statistically significant impact on its income growth. Key infrastructure like gross area irrigated, villages electrified, road quality and state expenditure on agriculture are significant and positive drivers of growth of income in all the models. Results suggest that higher the infrastructural support in the state more is the growth in income from agriculture.

Cropping pattern has been controlled through share of total cropped area under different groups of crops like cereals, pulses, sugar, oil seeds, fibre etc. Share of area under fibre, sugar and oil-seeds are all significant and positively influence the growth of income from agriculture[12]. In India, cropping pattern has shown structural rigidity till 1980s when food grains were the dominant crop in India. However, post 1980s, there has been an increase in area under other crop like oil-seeds at the cost of area under pulses and coarse cereals (Bhalla and Singh, 1997). A change in cropping pattern is based on a number of factors like agro-ecological conditions, profitability of crops, availability of technology and infrastructure etc. These results in favour of significant impact of fibre, sugar and oil-seeds support findings from studies like Joshi, Birthal and Minot (2006) which concludes that diversification has been a dominant source of growth since the 1980s in Indian agriculture. The impact of diversification becomes clearer in the next sub-section where we identify the differential impact across the sub-phases.

Human capital has been controlled through rural literacy rate and as expected it has a positive impact on growth of income from agriculture. Deviation of actual rainfall from its normal level greater than 10 per cent significantly reduces growth of income from agriculture in all the models and the impact on income growth is proportional to the level of deviation of actual rainfall from normal.

Table 4- Results of beta convergence

Beta convergence: sub-phases

Comparison of growth process across sub-phases has been done using district based spatial weight matrices in Table 5 since district based spatial weight matrix performed the best

[11] At the all India level, from 1966 to 2007, on an average bovines account for approximately 65% of all livestock, and within bovines, animals in milk constitute only approximately 35%.

[12]

across all other spatial weight criteria (Table 4). The results (Table 5) on spatial beta convergence for the sub-phases indicate significant conditional convergence in all the sub-phases.

In the first sub-phase i.e. models 1 and 2, land ownership is the most important income generating input. Fertilizer is significant only if year effects are not controlled (model 1). Among infrastructure, density of surfaced roads is the key growth driving factor in first sub-phase. This phase of green revolution witnessed enormous expansion of area under food-grains especially wheat at the cost of area under other crops and results indicate that share of irrigated area under cereals had a positive impact on income growth. However, area covered under fibre and sugar had negative impact on growth. Spatial rural literacy was a significant driver of growth in this phase. Income growth also had significant spatial dependence as growth in this phase owing to the selective introduction of the new technology was concentrated in certain geographically contiguous states. This phase also witnessed severe to moderate droughts which get reflected in the negative year effects (1968, 1969, 1976).

In the second sub-phase (model 3), growth was dominated by inputs namely land, tractors and livestock. Among infrastructure, density of surfaced roads again had a significant impact on growth like sub-phase one. Area under cereals like sub-phase one, again led to positive growth. Additionally, area under fibre and oil-seeds also contributed positively to growth. This again validates the findings from studies like Bhalla and Singh (1997) that unprecedented changes took place in the 1980s in cropping pattern and area under other crops expanded at the cost of area under pulses and coarse cereals. Although area under wheat and rice continued to increase in this phase and hence share of area under cereals continue to be a significant driver of growth but one case see that area under other crops were slowly gaining importance in explaining growth of income from agriculture. Excessive rainfall had a negative impact on growth. Spatial growth and irrigation were significant drivers of growth in this phase.

In the third sub-phase (model 4), again land ownership significantly affected income growth. Irrigation contributed in this sub-phase. However, here cereals no longer were a significant driver of growth. Rather in this phase, growth was because of fibre crops. Again this validates the pattern which emerged in studies like Bhalla and Singh (1997) and Joshi, Birthal and Minot (2006) that impact of diversification was highest in the 1990s compared to earlier sub-phases. Literacy was a significant driver of growth in this phase. Spatial spill-over in this phase was because of irrigation and income growth of neighbouring states.

Interesting pattern which comes up from the comparison across sub-phases is the consistent spatial dependence of growth of income and significance of key infrastructure like roads, rural literacy and irrigation across all the sub-phases. Reduction in impact of cropped area under cereals over phases and gaining significance of area under other crops provide evidence in favour of higher returns from diversification. Primary driver of growth in the first phase was growth in area under cereals and land ownership while the second phase saw the emergence of impact of mechanization of agriculture and diversification and third phase continued to witness the impact of diversification. Among the spatial factors, rural literacy and irrigation have almost consistently had a significant impact on growth of per capita income in agriculture.

Table 5–Results of beta convergence for sub-phases

Conclusion

Inter-state disparity has been an enduring feature of Indian agriculture possibly due to differences across states in agro-ecological conditions, cropping pattern, input usage, infrastructural support etc. States like Punjab and Haryana in the north have always had a higher level of per capita income while states like Bihar and Uttar Pradesh have been always been poor performers. This persistent inter-state disparity provides an empirical basis to analyse the convergence behaviour of per capita income from agriculture. Studies like Bhide et al (1998) and Ghosh (2006) have explored convergence across states in India using sigma and beta convergence measures and find that state specific factors like human capital, physical capital and rural infrastructure play an important role in driving convergence across states.

The broader literature on convergence for aggregate economy has documented the role of geography in the growth convergence process. Two broad pathways through which geography plays a role on growth of a region are absolute geography, i.e., through geographic factors specific to a region and relative geography, i.e., the impact of a region on its neighbour through spatial spill-over.The role of relative geography in particular, has not attracted much attention in the empirical literature on convergence in Indian agriculture, though absolute geography has been controlled in many of the past studies .

This paper tries to fill this gap in literature and explores the role of relative geography on convergence in terms of income per rural person across states in India between 1967 and 2010. We follow the literature on convergence and use sigma and beta convergence measures which are the two most commonly used approaches for analysing convergence and further incorporate spatial dependence in our estimation strategy. The relative location of states was incorporated econometrically using spatial weight matrices. One of the contributions of the study is comparing different spatial weight matrices and identifying the one which explains spatial dependence across states in the best possible manner. Stetzer (1982), Stakhovych and Bijmolt (2009) Elhorst (2010 b) document that it is of extreme importance that spatial weight matrices are correctly specified as this matrix will eventually define and quantify the spatial dependence across regions. For that, in addition to the conventional state-contiguous, inverse-distance based matrices, district-contiguous and length of state borders shared have also been used in the analysis. These matrices help to differentiate the impact of two contiguous neighbours as the one with higher number of contiguous districts or length of border shared gets a higher weight in the matrix. This weighing scheme ensures that the incorporated spatial effects are proportional to the possibility of spatial spill-over.

Global and local Moran's I-tests using these weights found statistically significant spatial dependence across states. Therefore, ignoring relative spatial location in convergence analysis would lead to model misspecification and hence erroneous conclusions.

For spatial convergence analysis, spatially lagged dependent and independent variables were computed using spatial weight matrices. A dynamic fixed effect model was used to correct the autocorrelation problem in panel data. We find that among all spatial weight matrices district based spatial weight matrix explains spatial dependence across states in the best manner. This is potentially because states are large geographical units and therefore spatial structure at the state level masks the heterogeneity existing within the states. For example districts in the eastern Uttar Pradesh are similar to one another in terms of both agro-climatic conditions and performance to its neighbouring districts in Bihar rather than districts in west Uttar Pradesh which are in turn more similar to those of Himachal Pradesh. The district based spatial weight matrix we use incorporates this heterogeneity within states and homogeneity across states.

Like past studies on Indian agriculture which have used sigma convergence measures, we do not find any evidence in favour of sigma convergence, rather we find that disparity across states have increased over the years. However, on the same lines as findings from Ghosh (2006) we too find evidence in favour of conditional beta convergence both in the entire time period and the sub-phases. We find that irrespective of the criteria used for spatial weight matrices, there is consistent significant spatial dependence across states for all the three sub-phases and entire time period. Further, we find that the significant channels of spatial spill over across states are rural literacy and infrastructure like roads and irrigation. Other state specific factors which significantly drove growth in the entire time period were input usage, physical infrastructure and cropping pattern. We find that there has been a reduction in impact of cropped area under cereals over the three sub-phases and increasing significance of area under other crops provide evidence in favour of higher returns from diversification. Primary drivers of growth in the first phase were growth in area under cereals and land ownership while the second phase saw the emergence of impact of mechanization of agriculture and diversification and third phase continued to witness the impact of diversification. Among the spatial factors, rural literacy and irrigation have almost consistently had a significant impact on growth of per capita income in agriculture.

The empirical evidence presented here highlights the importance of inputs and infrastructure in convergence in agriculture. Therefore, economic policy measures targeting improvement and expansion of infrastructural support and literacy for example public investments towards irrigation and electricity, roads and rural literacy and input usage can have an important impact in promoting long run agriculture growth and convergence across Indian states. In particular, our findings point towards the significant role of infrastructure and literacy in reducing regional disparity through their spatial spill-over effects.

Some of the limitations of the present study have to be kept in mind while drawing conclusions. A major limitation here is the quality of data availability. It is widely accepted that there is discrepancy in data from government sources on agricultural production, land use etc. because of irregularity of publications and updating the records. Moreover, data on livestock and machinery etc. are not annually available and they had to be interpolated to obtain an annual series. Interpolation potentially might have introduced some errors in the data. Spatial analysis is dependent on spatial weight matrices. Nevertheless, the results confirm spatial dependence in Indian agriculture and point towards channels of intervention which can potentially reduce inter-state disparity.

Tables

TABLE 1- growth performance across Indian states

	Income levels				Compound growth rate			
State	1966	1977	1989	2010	1966-2010	1966-77	1978-89	1990-2010
Andhra	4936	5126	6421	10652	1.72	0.32	1.89	2.44
Assam	4023	4592	5086	5039	0.50	1.11	0.85	-0.04
Bihar+Jharkhand	755	2483	2113	2784	2.94	10.43	-1.34	1.32
Gujarat	2220	6241	6491	10953	3.61	9.00	0.33	2.52
Haryana	3188	9420	11487	14966	3.50	9.45	1.67	1.27
Himachal Pradesh	2714	5627	7068	7135	2.17	6.26	1.92	0.04
Jammu & Kashmir	2502	5362	4840	6673	2.20	6.56	-0.85	1.54
Karnataka	2922	6122	6389	9159	2.57	6.36	0.36	1.73
Kerala	1875	3696	4109	6859	2.92	5.82	0.89	2.47
Maharashtra	1507	3825	4605	7774	3.71	8.07	1.56	2.52
MP+Chhattisgarh	2238	3491	5229	6145	2.27	3.78	3.42	0.77
Orissa	1668	3527	6066	4945	2.44	6.44	4.62	-0.97
Punjab	2195	10322	14871	17950	4.78	13.77	3.09	0.90
Rajasthan	1855	4742	4889	7687	3.21	8.14	0.25	2.18
Tamil Nadu	2467	4613	4173	6913	2.32	5.35	-0.83	2.43
UP+Uttarakhand	3091	4138	4390	4874	1.02	2.46	0.49	0.50
West Bengal	1374	3794	4820	7024	3.69	8.83	2.02	1.81
India	2449	4615	5009	6793	2.29	5.42	0.69	1.46
CV	41.30	40.04	49.22	46.77	39.26	51.75	78.37	49.87

Source: author's computation

TABLE 2: Results of global Moran's test

year	contiguous states	inverse distance	shared-border	contiguous districts
1966	-0.036	-0.030	0.090	0.062
1970	0.355***	0.153***	0.418***	0.412***
1978	0.351***	0.152***	0.492***	0.468***
1990	0.269**	0.136***	0.412***	0.384***
2010	0.192**	0.066**	0.317**	0.283**

Note: *: p<0.10;**: p<0.05;***: p<0.01 Source: author's estimations.Note: results of other years can be shared on request

TABLE 3-Results of Local Moran's test

Year	State	Moran's I	Year	State	Moran's I
Contiguity			District		
1966	West Bengal	0.735**	1966	Bihar+Jharkhand	0.925**
1966	Bihar+Jharkhand	0.72**	1966	West Bengal	2.198***
2010	Punjab	0.747**	2010	Haryana	0.606*
2010	Bihar+Jharkhand	1.389***	2010	Bihar+Jharkhand	1.202**
			2010	Punjab	1.667***
Inverse Distance			Border		
1966	West Bengal	0.393**	1966	Bihar+Jharkhand	1.087**
2010	Assam	0.164**	1966	West Bengal	2.446***
2010	Orissa	0.152**	2010	Haryana	0.855**
2010	Punjab	0.367**	2010	Bihar+Jharkhand	1.211***
2010	Haryana	0.399**	2010	Punjab	1.885***

Note: *: P<0.10;**: P<0.05;***: P<0.01 Source: Author's Estimations.Note: Results Of Other Years Can Be Shared On Request

TABLE 4- Results of beta convergence

Dependent variable is growth rate defined as annual growth rate i.e. ln(y_t)-ln($y_{(t-1)}$) where y_{it} is the income per rural person in i-th state and t-th year.					
Variable	non-spatial	contiguity	inverse-distance	shared border	contiguous districts
	[1]	[2]	[3]	[4]	[5]
lagged income	-0.623***(0.094)	-0.627***(0.074)	-0.625***(0.083)	-0.625***(0.071)	-0.624***(0.069)
lagged growth	-0.197***(0.032)	-0.162***(0.028)	-0.167***(0.027)	-0.163***(0.028)	-0.160***(0.028)
per capita tractor	0.959** (0.340)	1.304***(0.398)	1.241***(0.296)	1.378***(0.361)	1.359***(0.377)
per capita land	2.060*** (0.380)	2.034***(0.343)	1.991***(0.358)	2.052***(0.370)	2.046***(0.362)
buffaloes per sq. km.		-0.167**(0.076)	-0.123*(0.063)	-0.183**(0.085)	-0.178**(0.085)
sheep per sq. km.	0.153*** (0.038)	0.122***(0.041)	0.106***(0.036)	0.139***(0.039)	0.134***(0.032)
irrigation	0.121*** (0.030)	0.113***(0.023)	0.119***(0.029)	0.126***(0.023)	0.127***(0.023)
village electricity dummy	-0.053** (0.020)	-0.058***(0.021)	-0.034*(0.021)	-0.054***(0.020)	-0.055***(0.019)
road quality	0.154* (0.084)	0.110*(0.064)	0.135**(0.065)	0.126**(0.052)	0.122**(0.052)
agriexp per area	0.003** (0.001)	0.003***(0.001)	0.002**(0.001)	0.003***(0.001)	0.003***(0.001)
share of oil	1.105***(0.168)	1.107***(0.186)	0.999***(0.188)	1.041***(0.172)	1.033***(0.173)
share of fibre		0.915***(0.322)	0.846**(0.383)	0.923***(0.335)	0.906***(0.328)
share of sugar	2.948* (1.469)	3.139**(1.274)	2.989**(1.262)	2.835**(1.255)	2.926**(1.221)
rural literacy	0.009*** (0.002)	0.004*(0.002)	0.006***(0.002)	0.004*(0.002)	0.004*(0.002)
rain dummy 2	-0.014** (0.006)	-0.014**(0.007)	-0.014**(0.006)	-0.012*(0.007)	-0.012*(0.007)
rain dummy 3	-0.042***(0.013)	-0.040***(0.012)	-0.040***(0.012)	-0.039***(0.012)	-0.039***(0.012)
spatial rural literacy		0.006***(0.001)		0.003**(0.002)	0.003**(0.002)
spatial irrigation				0.101***(0.037)	0.094***(0.036)
spatial road quality			0.685***(0.215)	0.164**(0.071)	0.160**(0.072)
spatial growth		0.267***(0.044)	0.319***(0.062)	0.258***(0.044)	0.273***(0.047)
STATISTICS					
No. of observation	663	646	646	646	646
log-likelihood	587.857	607.532	602.566	612.487	615.42
AIC	-1147.713	-1183.065	-1173.131	-1192.973	-1198.84
BIC	-1084.758	-1111.532	-1101.599	-1121.44	-1127.307
R-square	0.525	0.567	0.565	0.571	0.573

Note: *:p<0.10;**:p<0.05;***:p<0.01 Source: author's estimations, se within parenthesis

TABLE 5 –Results of beta convergence for sub-phases

Dependent variable is annual growth rate i.e. $\ln(y_t)-\ln(y_{(t-1)})$ where y_{it} is the income per rural person in i-th state and t-th year.				
Variable	phase1	phase 1	phase2	phase3
	[1]	[2]	[3]	[4]
Time lagged income	-0.402***(0.045)	-0.409***(0.030)	-0.940***(0.110)	-0.582***(0.059)
Time lagged growth				-0.211***(0.046)
Fertilizer per sq. km.	0.125**(0.056)			
per capita land	1.369***(0.316)	1.658***(0.246)	2.813***(0.413)	1.759***(0.322)
per capita tractor			2.268**(1.025)	
livestock per sq. km			0.130***(0.047)	
surf. Road per sq. km	0.060**(0.028)	0.074**(0.029)	0.102***(0.024)	
gross irri per sq. km.				0.176***(0.044)
share of cereals	0.617**(0.274)	1.120***(0.385)	0.579**(0.252)	
share of pulses		1.959**(0.913)		
share of fibre	-3.212**(1.403)	-3.012**(1.348)	1.303**(0.646)	0.903***(0.344)
share of sugar	-6.979***(2.676)			
share of oil			1.707**(0.750)	
rural literacy	0.006***(0.002)	0.006**(0.002)		0.007***(0.002)
rain dummy_3			-0.074***(0.020)	
spatial rural literacy	0.011***(0.004)	0.016***(0.004)		
spatial irrigation			0.465*** (0.148)	0.201***(0.065)
spatial growth	0.547***(0.070)	0.176**(0.087)	0.150***(0.048)	0.218***(0.076)
year effects	NO	YES	YES	YES
		STATISTICS		
No of observations	170	170	187	340
Pseudo-log likelihood	77.449	98.944	197.183	356.437
AIC	-132.899	-169.888	-364.367	-688.874
BIC	-98.405	-125.987	-315.9	-642.926
R-sq.	0.453	0.696	0.753	0.55

Note: *:p<0.10;**:p<0.05;***:p<0.01 Source: author's estimations, se within parenthesis. Significant years were 1968, 1969, 1970, 1976 in first sub-phase, 1979, 1983 and 1984 in second sub-phase and 1994, 2007 and 2010 in third sub-phase

Figures

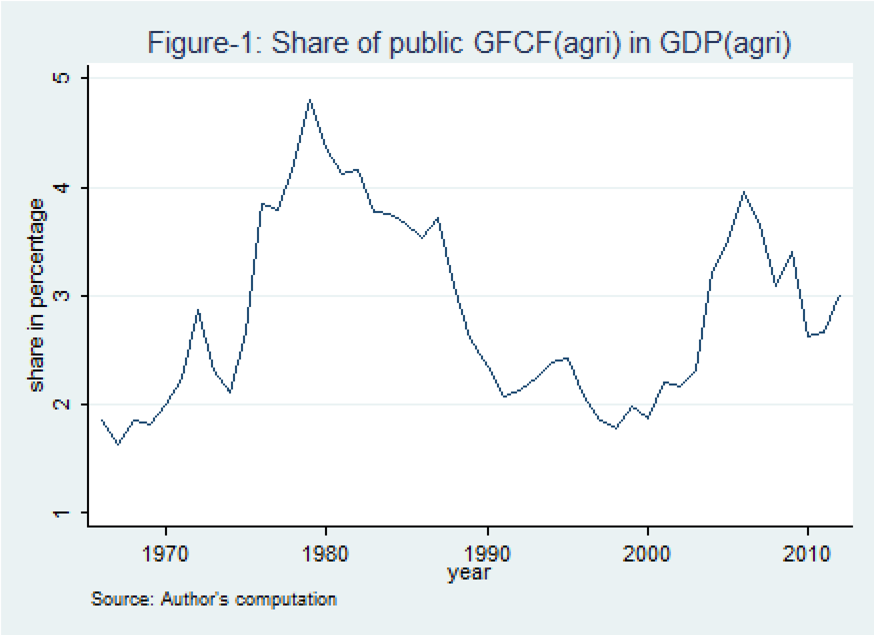

Figure 1: Share of public GFCF (agri) in GDP (Agri)

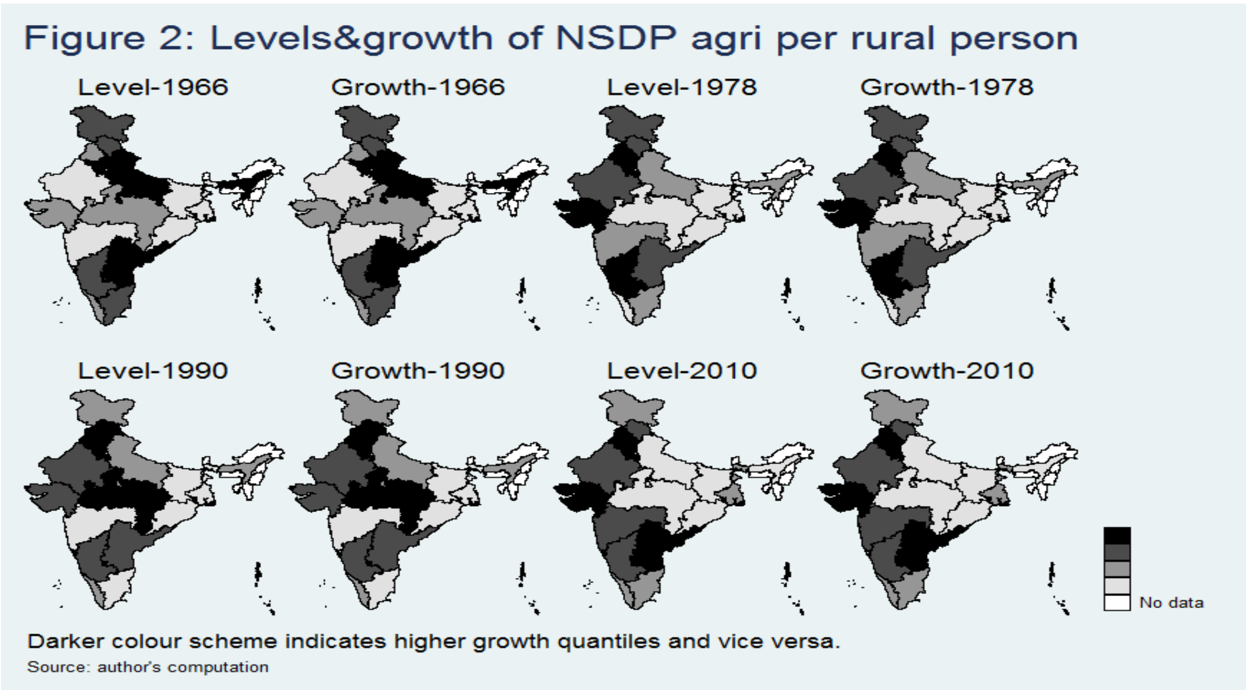

Figure 2: Levels & growth of NSDP agri per rural person

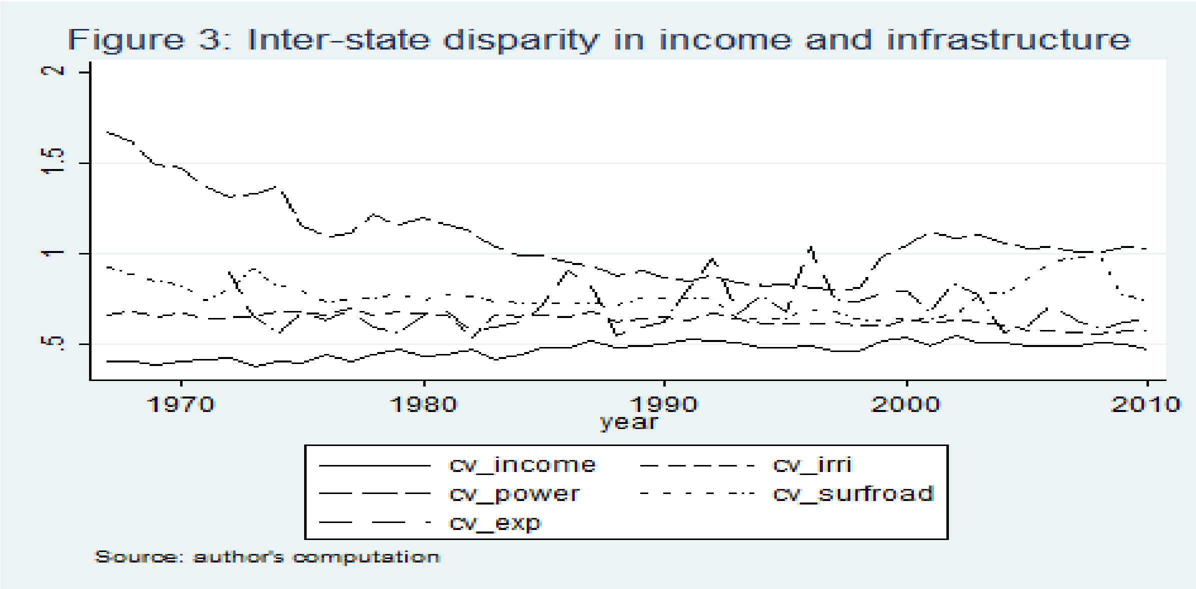

Figure 3: Inter-state disparity in income & infrastructure

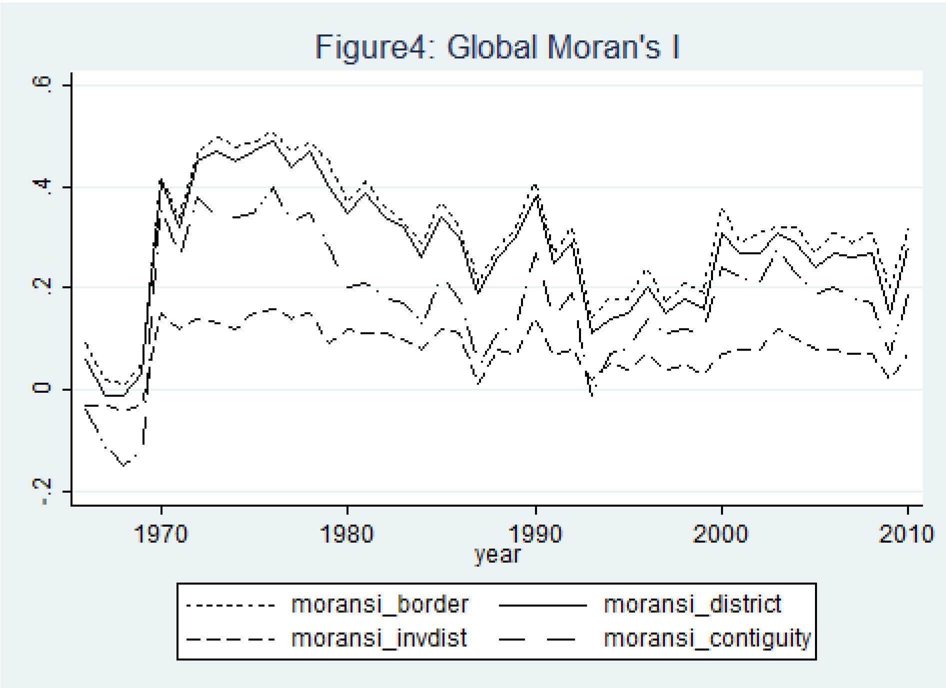

Figure 4: Global Moran's I

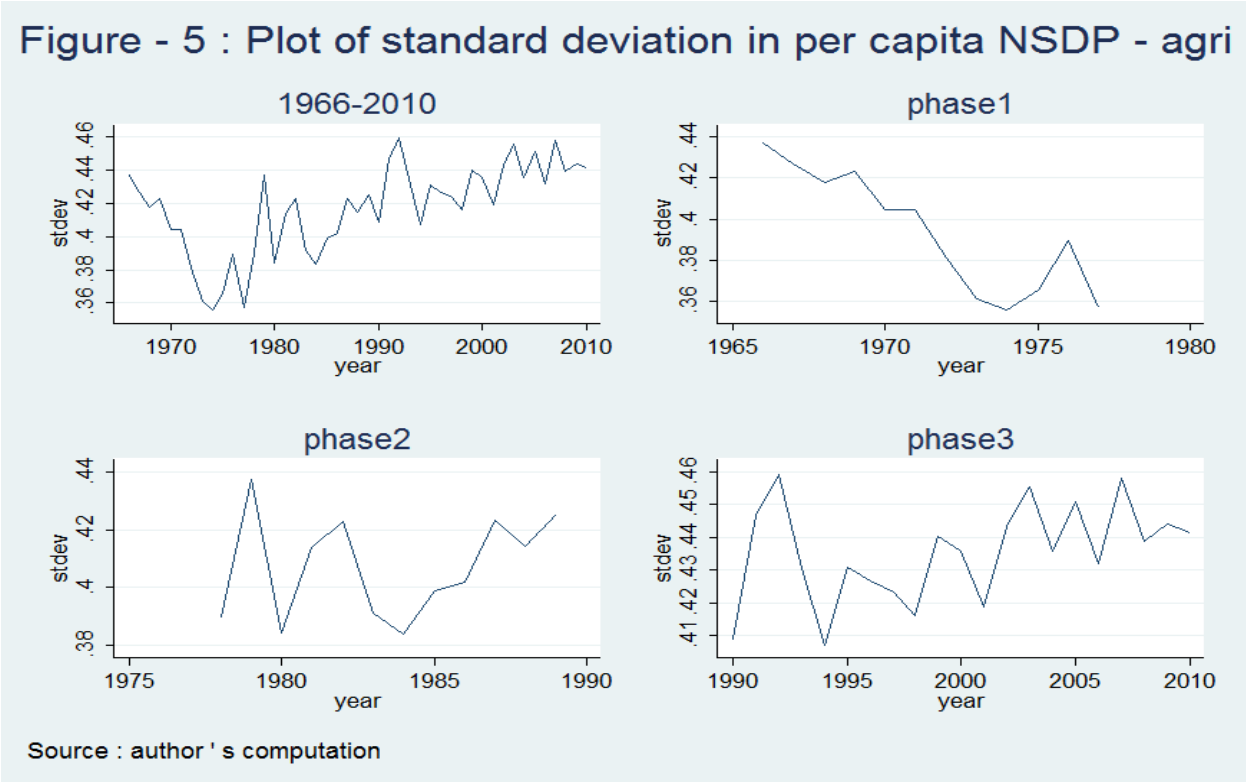

Figure 5: Plot of standard deviation

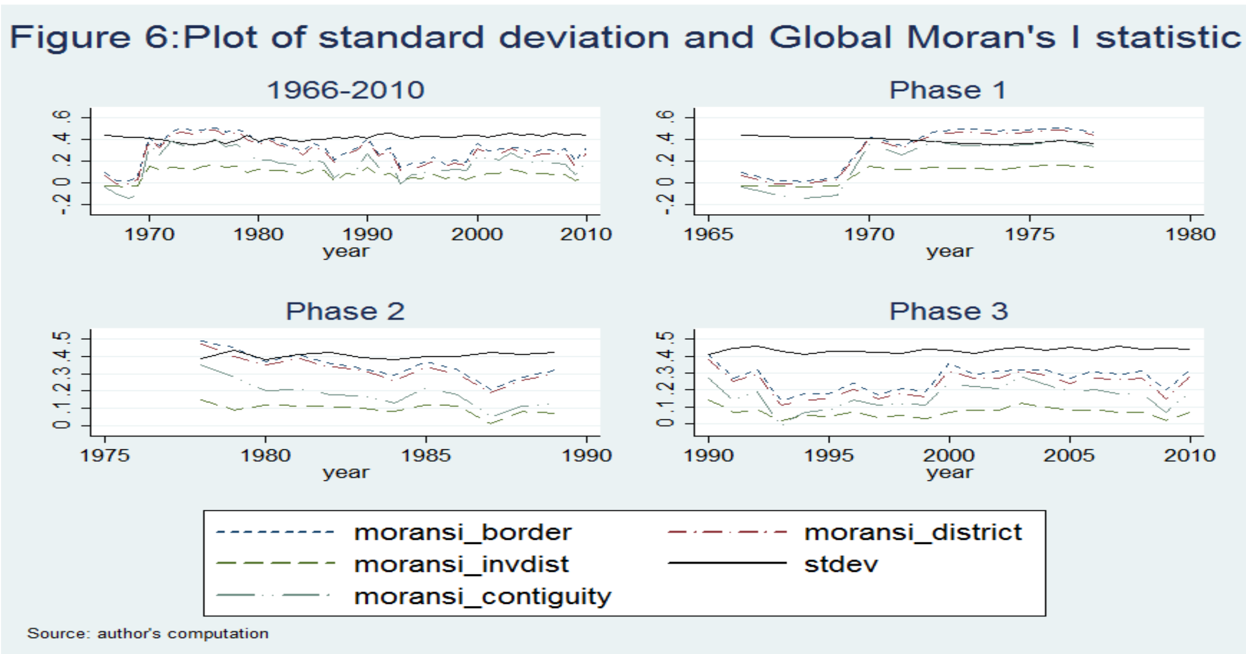

Figure 6: Plot of standard deviation & Global Moran's I statistic

References

Abreu, M., De Groot, H. and Florax, J.G.M., 2005.Space and growth: a survey of empirical evidence and methods. *Region et development,*21

Alston, J. M., 2002. Spillovers. *Australian Journal of Agricultural and Resource Economics*. 46, 315–346.

Anselin, L., 1988. Spatial Econometrics: Methods and Models. Kluwer Academic, Dordrecht.

Anselin, L., 1995. Local Indicators of Spatial Association—LISA. *Geographical Analysis*.27, 93–115.

Barro, Robert and Xavier Sala-I-Martin, 1992. Convergence, *Journal of Political Economy* 100

Bhalla, G.S. and Singh, G., 1997. Recent Developments in Indian Agriculture: A State Level Analysis. *Economic and Political Weekly,* 32(13), A2-A18

Binswanger, H.P., Khandker, S., 1993. How infrastructure and financial institutions affect agricultural output and investment in India. *Journal of Development Economics*, 41(2), 337-366.

Birthal, P. S., Singh, H., & Kumar, S. (2011). Agriculture, economic growth and regional disparities in India. *Journal of International Development*, *23*(1), 119-131.

Bhalla, G.S. and Singh, G., 1997. Recent Developments in Indian Agriculture: A State Level Analysis. *Economic and Political Weekly,* 32(13), A2-A18

Bhide, S, Kalirajan, K.P. and Shand, R.T., 1998. India's Agricultural Dynamics: Weak Link in Development, *Economic and Political Weekly,*33(39), A118-A127

Chand, R. and Chauhan, S., 1999. Are disparities in Indian agriculture growing? *NCAP Policy Brief No. 8*

Elhorst, J.P., 2003.Specification and estimation of spatial panel data models. *International Regional Science Review,* 26(3), 244-268

Elhorst J.P., 2010. Spatial panel data models, in Fischer M.M. and Getis A (Eds) *Handbook of applied spatial analysis.* pp. 377-407,*Berlin, Heidelberg and New York*

Elhorst J.P., 2012. Dynamic spatial panels: Models, methods and inferences. *Journal of Geographical Systems 14(1), 5-28*

Fan, S., Hazell, P. and Haque, T., 2000. Targeting public investments by agro-ecological zone to achieve growth and poverty alleviation goals in rural India.*Food Policy*, 25(4), 411-428

Gillespie, S., Harris, J. and Kadiyala, S., (2012), The Agriculture-Nutrition Disconnect in India: What Do We Know, No 1187, IFPRI discussion papers, International Food Policy Research Institute (IFPRI). Accessed from: http://econpapers.repec.org/paper/fprifprid/1187.htm

Ghosh, M., 2006.Regional convergence in Indian agriculture*, Indian Journal of Agricultural Economics*61(4), 610–629.

Gulati, A., Kumar, A. G., Shreedhar, G., & Nandakumar, T. (2012). Agriculture and malnutrition in India. *Food and nutrition bulletin*, *33*(1), 74-86.

Jones, R. and Sen, K., 2006. It is where you are that matters: the spatial determinants of rural poverty in India, *Agricultural Economics,*34, 229–242

Joshi, P.K., Birthal, P.S. and Minot, N., 2006. Sources of agricultural growth in India: Role of diversification towards high-value crops, IFPRI, MTID Discussion paper No. 98

Kumar, A., Kumar, P., and Sharma, A. N. (2011). Rural poverty and agricultural growth in India: Implications for the Twelfth five year plan. *Indian Journal of Agricultural Economics*, *66*(3), 269-278.

Lee L.F. and Yu J., 2010. Estimation of spatial autoregressive panel data models with fixed effects*, Journal of Econometrics* 154(2), 165-185

Lesage*, J.P.,* and Pace, R.K., 2009.*Introduction to Spatial Econometrics. New York: Taylor & Francis/CRC Press, 2009.*

Lusome, R., &Bhagat, R. B. (2006, June).Trends and patterns of internal migration in India, 1971-2001.In Annual conference of Indian Association for the Study of Population (IASP) during (Vol. 7, p. 9).

Mukherjee, A. and Koruda, Y., 2003. Productivity growth in Indian agriculture: is there evidence of convergence across states? *Agricultural economics*29, 43-53

Mukhopadhayay, D. and Sarkar, N.,2014. Convergence of Food grains across Indian states: A study with panel data, *Discussion paper Number*-03

Patton, M. and McErlean, S., 2003.Spatial Effects within the Agricultural Land Market in Northern Ireland. Journal of Agricultural Economics, 54, 35–54.

Pfaffermayr, M., 2012.Spatial convergence of regions revisited: a spatial maximum likelihood panel approach. *Journal of Regional Science,* 52, 857–873

Quah, D. T., 1993a. Empirical Cross-section Dynamics in Economic Growth, *European Economic Review,*37, 426-434

Quah, D. T., 1993b.Galton's Fallacy and Tests of the Convergence Hypothesis. *Scandinavian Journal of Economics,* 95 (4), 427-443

Ravallion, M., &Datt, G. (1996). How important to India's poor is the sectoral composition of economic growth?. *The World Bank Economic Review*, *10*(1), 1-25.

Rey, S. and Montouri, B., 1999. US Regional Income Convergence: A Spatial Econometric Perspective, *Regional Studies,*33(2), 143-156

Sala-I-Martin, Xavier, (1994) Cross-sectional regressions and the empirics of economic growth*, European Economic Review,*38(3-4), 739-747.

Schmidtner, E., Lippert, C., Engler, B., Ha¨ring, A., Aurbacher, J. and Dabbert, S., 2012. Spatial distribution of organic farming in Germany: does neighbourhood matter? *European Review of Agricultural Economics,*39(4), 661–683.

Somasekharan, J., Prasad, S. and Roy, N., 2011. Convergence Hypothesis: Some Dynamics and Explanations of Agricultural Growth across Indian States, *Agricultural Economics Research Review*24,211-216

Tong, Tingting, 2012."Evaluating the Contribution of Infrastructure to U.S. Agri–Food Sector Output."Master's Thesis, University of Tennessee.

Warr, P. 2003. "Poverty and Economic Growth in India." In *Economic Reform and the Liberalization of the Indian Economy*, edited by K. Kalirajan and U. Shankar, 185–209. Cheltenham, UK, and Northampton, MA, US: Edward Elgar.

Wooldridge, J. M., 2005. Simple Solutions to the Initial Conditions Problem in Dynamic, Nonlinear Panel Data Models with Unobserved Heterogeneity. *Journal of Applied Econometrics,* 20(1), 39–54.

Young A., Higgins, M. and Levy D., 2008. Sigma convergence versus beta convergence: evidence from US county level data, *Journal of Money, Credit and Banking*40, 1083-1093