WP-2014-035

Spatial convergence and growth in Indian agriculture: 1967-2010

Tirtha Chaterjee

Indira Gandhi Institute of Development Research, Mumbai
September 2014
http://www.igidr.ac.in/pdf/publication/WP-2014-035.pdf

Spatial convergence and growth in Indian agriculture: 1967-2010

Tirtha Chaterjee

Indira Gandhi Institute of Development Research (IGIDR)

General Arun Kumar Vaidya Marg

Goregaon (E), Mumbai- 400065, INDIA

Email(corresponding author): tirtha@igidr.ac.in

Abstract

Inter-state diversity has been a perennial feature of Indian agriculture. The study probes if per capita income in Indian agriculture has converged across states in the last four and a half decades. It finds strong evidence in favour of beta convergence but not in favour of sigma convergence. Spatial econometric techniques used in the study aid in identifying the impact of spatial neighbours on the growth of a state. Results indicate significant spatial dependence among states. The study also identifies the drivers of growth agriculture in the last four and a half decades and results indicate that infrastructure like roads, irrigation, electricity aid in growth and so do quality of human capital. Hence, investments targeting higher quality of infrastructure, both physical and human and efficient water management will aid in agricultural growth in India.

Keywords: Agriculture, growth, regional convergence, spatial dependence

JEL Code: O13, O18, R12, R15

Acknowledgements:

Author is grateful to Prof. A. Ganesh Kumar for his valuable comments and sugestions.

Spatial convergence and growth in Indian agriculture: 1967-2010

Tirtha Chatterjee

Indira Gandhi Institute of Development Research (IGIDR)
General Arun Kumar Vaidya Marg
Goregaon (E), Mumbai- 400065, INDIA
Email (corresponding author): tirtha@igidr.ac.in

Inter-state diversity has been a perennial feature of Indian agriculture. The study probes if per capita income in Indian agriculture has converged across states in the last four and a half decades. It finds strong evidence in favour of beta convergence but not in favour of sigma convergence. Spatial econometric techniques used in the study aid in identifying the impact of spatial neighbours on the growth of a state. Results indicate significant spatial dependence among states. The study also identifies the drivers of growth agriculture in the last four and a half decades and results indicate that infrastructure like roads, irrigation, electricity aid in growth and so do quality of human capital. Hence, investments targeting higher quality of infrastructure, both physical and human and efficient water management will aid in agricultural growth in India.

Keywords:

Agriculture, growth, regional convergence, spatial dependence

JEL Codes:

O13, O18, R12, R15

Acknowledgement:

Author is grateful to Prof. A. Ganesh Kumar for his valuable comments and suggestions.

Spatial convergence and growth in Indian agriculture: 1967-2010

Tirtha Chatterjee

Indira Gandhi Institute of Development Research (IGIDR)

Inter-state diversity has been a perennial feature of Indian agriculture. The study probes if per capita income in Indian agriculture has converged across states in the last four and a half decades. It finds strong evidence in favour of beta convergence but not in favour of sigma convergence. Spatial econometric techniques used in the study aid in identifying the impact of spatial neighbours on the growth of a state. Results indicate significant spatial dependence among states. The study also identifies the drivers of growth agriculture in the last four and a half decades and results indicate that infrastructure like roads, irrigation, electricity aid in growth and so do quality of human capital. Hence, investments targeting higher quality of infrastructure, both physical and human and efficient water management will aid in agricultural growth in India.

Keywords: agriculture, growth, regional convergence, spatial dependence

JEL Codes: O13, O18, R12, R15

INTRODUCTION

There is a vast disparity in income from agriculture across Indian states potentially because of differentials in agro-ecological conditions, cropping pattern, input usage, infrastructural support, yield levels etc. It is widely accepted that performance of agriculture is hugely dependent on agro-ecological conditions of a region. A region with favourable agro-ecological will naturally have an upper hand in agriculture production and hence will have a higher chance of generating more income from the same. However, advancement in technology, investments abetting agriculture growth, irrigation and other state level policies can help a state originally un-favourably endowed with natural endowments to perform better than it would have been in their absence.

Agriculture in India has undergone profound changes since late 1960s when green revolution technology was first adopted. It was initially adopted in very few states (north-western region and deltaic region of peninsular India) where there was well assured irrigation. However, in the next decade, there was spill-over of technology to other states, in addition to improvement in irrigation possibilities which aided in reducing inter-state disparity compared to the first phase of green revolution (Bhalla and Singh*; 1997)*. Past studies[1] found that disparity across states has not remained the same in the last four decades. Bhalla and Singh (1997) found that coefficient of variation of yield[2] across 17 states was higher in 1960s and 1970s compared to mid-1990s and 2000s indicating a decline in disparity across states in the later decades. On the contrary, Chand et al (1999) found that disparity in Net state domestic product (NSDP) per hectare and per

---

[1] Bhalla and Singh(1997),Chand et al(1999), Bhalla and Singh(2009)Bhide et al (1998)

[2] Yield was computed for 43 crops whose data on area cropped and output are reported in "Government of India, Area and output of principle crops" (Bhalla and Singh, 2007).

rural person increased in the 1990s compared to 1980s. Nevertheless, both studies concluded that high inter-state disparity has been a perpetual feature of Indian agriculture and they prescribed improvement in infrastructural support especially in backward states as a cure for the same.

Various government plan documents have highlighted the need to bring down the interstate disparities in agriculture. The approach paper for the 11th plan and the National agriculture policy (NAP, 2000) emphasize on reducing regional disparity such that all the regions can grow at their optimal levels and the resources are utilized to their fullest extent. Not only policy documents but various research studies have also made recommendations on similar lines. Bhalla and Singh (2010) recommended in their study, "*The policy makers ought to devise appropriate region specific policy packages for reversing the trend of deceleration in agricultural growth registered in the post-reform period with a view to making the growth process more inclusive*"*(Bhalla and Singh; 2010, pp 210).* Chand et al (1999) also suggest that that *"Special and immediate focus is needed for eastern states namely Bihar, Orissa and Assam, hill regions and eastern Uttar Pradesh. There is no room for complacency on this score" (Chand et al; 1999, pp-5).*

This study aims to explore the nature of growth of per capita income in 17[3] major states of India from 1967-68 to 2010-11 and test if differences across states have narrowed down over the last four and half decades. It identifies the drivers of agriculture growth so that policies with maximum returns can be introduced.

Traditionally, classical sigma and beta convergence measures have been used in literature to analyse the disparity in income across regions. Sigma convergence (σ) method analyzes the cross sectional dispersion of per- capita incomes across economies and is measured by the standard deviation of the logarithm of per capita incomes. Beta convergence measures test the neo-classical growth model of Solow (1956). It tests the underlying idea that initially poorer region possibly tends to catch up with the rich ones. Econometrically, beta convergence tests are estimated through two methods, unconditional and conditional. Unconditional beta convergence (β) approach estimates the relation between average growth rates of per capita income over a time period and the level of income at the initial period, irrespective of the state specific characteristics. When the same estimation is performed after controlling the structural characteristics of the regions, it is called conditional beta convergence. An inverse relation between growth and income indicating convergence is a consequence of diminishing returns to capital accumulation.

Although there are many studies on convergence in overall income[4] for the Indian economy very few studies have explored the convergence of income specifically from agriculture sector. Bhide et al (1998) assess the trends in agricultural output growth both at the national and state level and found strong cyclical patterns and evidence of convergence at the state level in shorter intervals of time. But in longer time intervals, they are found to converge to different levels. Chand et al (1999) examined regional divergence in per rural person and per hectare NSDP from agriculture during the period 1980- 81 to 1996-97 using CV

[3] These 17 states contribute more than 96% of NDP from agriculture

[4] Majumdar and Kapoor (1980), Dholakia (1994), Cashin and Sahay (1996), Rao, Shand and Kalirajan (1999), Nagraj et al (2000), Bandopadhyay (2003), Bajpai and Sachs (1996) etc.

and found that regional divergence in agricultural income has grown. Mukherjee and Koruda (2003) explored convergence in TFP across 14 states in India covering the period 1973-1993 and found no evidence of sigma convergence. Ghosh (2006) test convergence in per capita output, land and labour productivity for 15 states from 1962 to 2002 and found no evidence in favour of sigma convergence but significant unconditional convergence only in labour productivity. However, they found statistically significant evidence in favour of conditional beta convergence for all the measures. Somasekharan et al (2011) tested the convergence hypothesis in per capita agricultural output and food-grains productivity across the fifteen major states of India during 1971-2007 and found that both sigma and beta convergence do not hold. Mukhopadhyay and Sarkar (2014) test convergence using dynamic panel estimation techniques in per capita food grain production over the period 1991 to 2011 and found lack of sigma convergence but evidence in favour of beta convergence across the states.

All these studies on convergence have assumed each state to be an independent and isolated unit. But in reality, states are not isolated "absolute" units. The performance of neighbouring states can depend on each other. For example, growth rate of income of a region surrounded by unstable/ backward region may be lower because of negative spill-over from neighbouring regions. Also, agro-ecological conditions are often spread across contiguous states and hence agricultural performances of neighbouring states depends on each other. The studies on convergence discussed above have ignored the impact of spatial dependence.

Econometrically, controlling "absolute" location in estimation implies that the impact of being located at a particular point in space is being controlled by region dummies or fixed effect estimation techniques whereas incorporating "relative"[5] 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 the spatial relations across regions and the same are used in estimation techniques.

In this study, an attempt has been made to fill this gap in literature[6] and use spatial econometric techniques to detect the presence of spatial dependence in per capita income and estimate the impact of spatial interactions in the growth and convergence process. The main sources of growth in income from agriculture have been identified. The methodology used for the study is drawn from Barro-Sala-i-Martin (92) and spatial econometrics literature (Anselin, 1988, Elhorst, 2003 etc.).

The time period from 1967 to 2010 has been divided into following three sub phases on the basis of changing policies in agriculture sector. This aids in a better understanding of agricultural growth process in India.

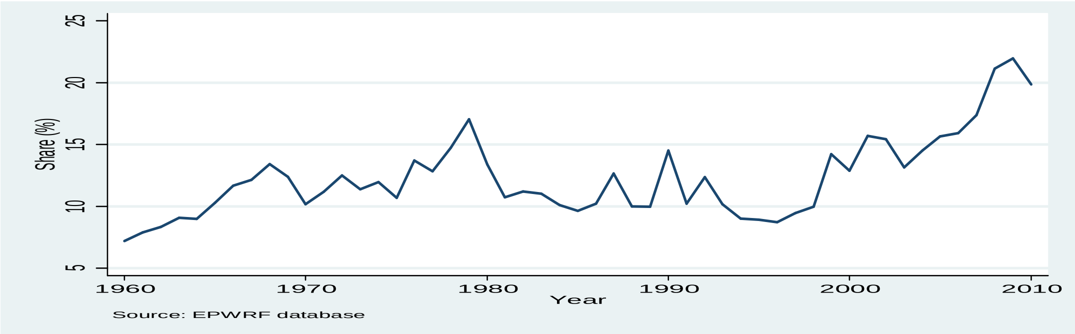
- 1st sub-phase : 1967-1977: the period of green revolution
- 2nd sub-phase: 1978-1989: period of falling public investment in agriculture
- 3rd sub-phase: 1990-2010: period of economic reforms

[5] For details on absolute and relative location, refer Abreu et al(2005)

[6] In the context of Indian agriculture, only Jones et al (2006) have used spatial econometrics to study the relation between land productivity and poverty and found statistically significant spatial dependence across states.

Fig-1 plots the share of public investments i.e. share of gross fixed capital formation (agriculture) in GDP from agriculture (both at constant 2004-05 prices). Investments had picked up in the latter half of 1960s (sub phase 1 in our study) but fell in the beginning of 1980s. The 1980s and 1990s can be majorly characterized with low levels of public investment in agriculture. One can see a rising trend in late 1990s and early 2000s[7].

Fig-1: Share of Gross fixed capital formation in agriculture to GDP from agriculture (in percentage)



In the next section, the growth performance of the states from 1967-68 to 2010-11 has been discussed. The methodology adopted in the study has been discussed in section 3. The results have been discussed in section 4 and section 5 concludes the analysis.

GROWTH PERFORMANCE ACROSS STATES

Table 1 presents a comparison across states in India over the last four and a half decades. The all India annual compound growth rate of NSDP from agriculture over the entire period is approximately 2.3 per cent. However, there is a lot of variation across the sub-phases. In the first sub-phase all India growth rate was almost close to five and a half per cent. In the second and third sub-phases, it fell down to less than one percent and one and a half per cent respectively.

On the basis of difference in growth pattern, states can be classified into three groups. First group comprised of majority of the states like Gujarat, Bihar, Jammu and Kashmir, Karnataka, Kerala, Maharashtra, Rajasthan, Tamil Nadu and Uttar Pradesh where growth rates had increased in the first phase, declined in the second phase but slightly recovered in the third phase. These states have followed the all-India growth pattern. Another group comprised of states like Haryana, Himachal Pradesh, Orissa, Punjab and West Bengal where in these states the growth rate declined both in the second and the third phases. Interestingly, most of these states have been the best performing states over the entire time period. Third group comprising of states like Andhra Pradesh, Assam and Madhya Pradesh had the least growth rates in the first phase and comparatively higher growth rates in the later sub-phases. Some of the states for e.g. Bihar, Jammu and Kashmir and Tamil Nadu had a negative growth rate in the second phase. In the third phase Madhya Pradesh recorded a negative growth rate.

[7] 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.

Difference between the growth rate of highest performing state and the lowest performing state in the first phase was approximately 13 per cent. In the second phase, difference between the highest performing state i.e. Orissa and the lowest performing state i.e. Jammu and Kashmir is almost 6 per cent. In the third phase, the difference between the highest performing state i.e. Gujarat and the lowest performing state i.e. Madhya Pradesh is 3 percent. Hence, the difference in growth rates declined in later phases. However, the average state level growth rates declined in the later sub-phases.

Interestingly, these results were in contradiction to the conclusions derived from coefficient of variation of the levels of income. The coefficient of variation of per capita NSDP from agriculture has increased from 0.41 in 1966 to 0.47 in 2010. The coefficient of variation of annual compound growth rate was highest in phase2 when the public investment in agriculture sector was the lowest and it declined (although higher than 1960s) in period post economic reforms. Hence, here one can find evidence in favour of widening inter-state disparity both in terms of level and growth of income per rural person from agriculture.

Table 1: Level & growth in per capita NSDP-agriculture in Indian states, 2004-05 constant prices (1966-2010)

STATE	NSDP per rural person from agriculture (Rupees)		Annual compound growth rate in NSDP per rural person from agriculture (%)			
	1966	2010	1966-2010	1966-77	1978-89	1990-2010
Andhra Pradesh	4936	10652	1.72	0.32	1.03	2.68
Assam	4023	5039	0.50	1.11	1.29	-0.05
Bihar &Jharkhand	755	2784	2.94	10.43	-1.14	0.56
Gujarat	2220	10953	3.61	9.00	0.12	2.97
Haryana	3188	14966	3.50	9.45	1.12	0.85
Himachal Pradesh	2714	7135	2.17	6.26	1.86	0.30
Jammu Kashmir	2502	6673	2.20	6.56	-1.15	1.12
Karnataka	2922	9159	2.57	6.36	0.70	2.14
Kerala	1875	6859	2.92	5.82	0.96	1.85
MP &Chhattisgarh	2238	6145	2.27	3.78	4.36	-0.24
Maharashtra	1507	7774	3.71	8.07	1.88	2.92
Orissa	1668	4945	2.44	6.44	4.66	1.04
Punjab	2195	17950	4.78	13.77	2.63	1.03
Rajasthan	1855	7687	3.21	8.14	0.14	1.28
Tamil Nadu	2467	6913	2.32	5.35	-0.55	2.30
UP &Uttarakhand	3091	4874	1.02	2.46	0.56	0.25
West Bengal	1374	7024	3.69	8.83	2.52	2.10
India	2449	6793	2.29	5.42	0.72	1.46
Coeff. Of Var.	0.41	0.47	0.39	0.52	1.34	0.76

Source: author's computation based on NSDP agriculture data from EPWRF database

Fig 2 plots the coefficient of variation (CV) of levels of per capita NSDP from agriculture in the total time period and also the sub-phases. One can see that it has increased over the entire time period. Additionally, it went through a lot of changes within the phases as well. In the first phase, comparing the start and end year, the CV has remained the almost the same although it showed some cyclical pattern in between. In the second phase, CV has increased. In the third phase, although CV is lower in 2010 compared to 1990, it shows a rising trend in mid 1990s and 2000s after which it declines till end of the phase.

Fig2: Coefficient of variation of per capita NSDP- agriculture

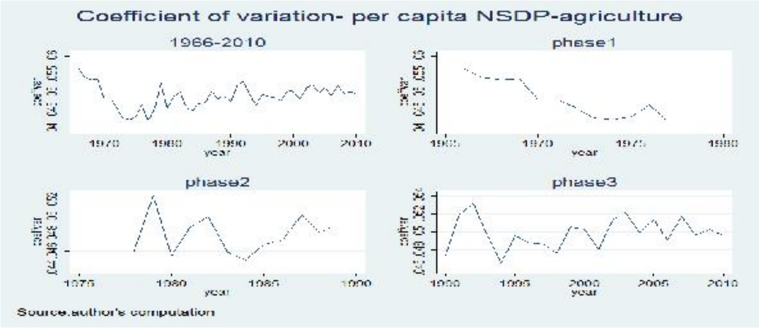
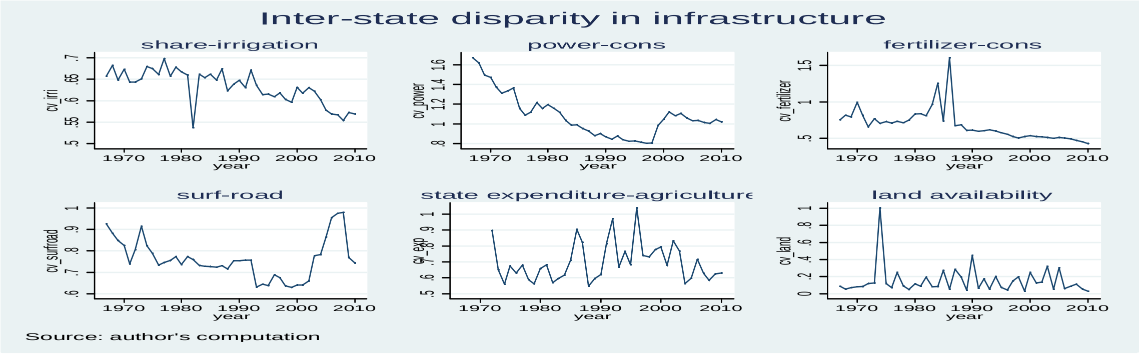


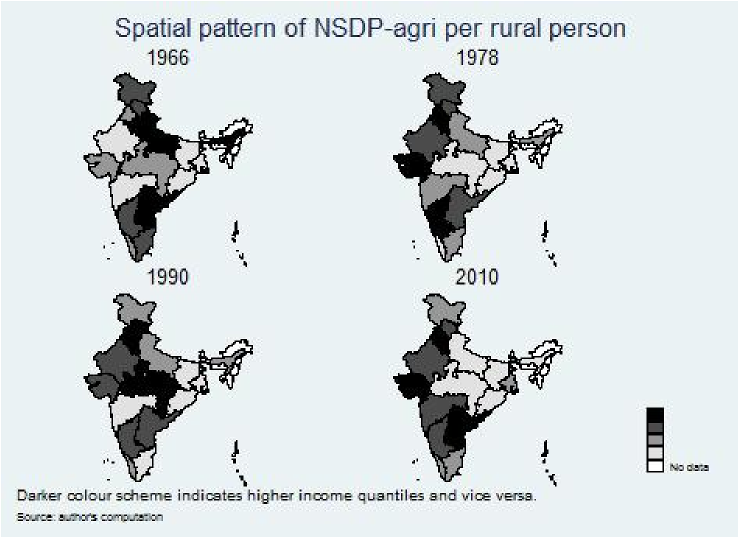
Fig3 plots the coefficient of variation of some key infrastructure like roads, electricity etc. across states from 1966 to 2010. Coefficient of variation follow a declining trend for gross area irrigated, power consumption in agriculture and fertilizer consumption but it has gone up in case of surfaced road density measured in terms of surfaced roads per unit area of the state. Although the coefficient of variation of expenditure of state on agriculture has declined if one compares 2010 with 1966, it can be seen that it has varied a lot in the years between them. Specifically, one can note the high peaks from mid-1980s and 1990s. Plot of per capita total cropped area also shows high volatility over the entire time period.

Fig 3: Inter-state disparity in infrastructure across states



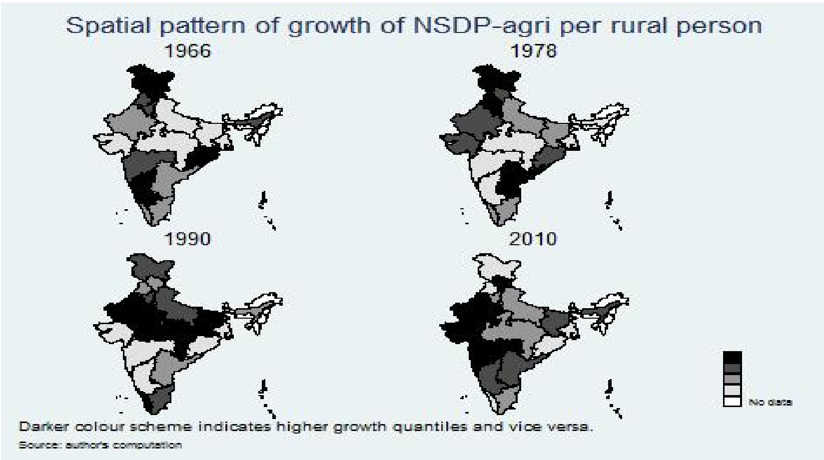
Figs 4 and 5 plot the spatial pattern of per capita income from agriculture and its growth respectively. This aids in clearer understanding of how states have performed over the years and if their respective spatial location had a role in their performances. The level of per capita income (fig 4) shows some evidence of geographic concentration. Especially in the years 1978 and 2010, the poorest quantile of states can be seen to be geographically clubbed together. States like Punjab and Haryana (geographical neighbours) post green revolution have almost always been one of the richest states in the country. M.P., Orissa, MP, Bihar and West Bengal which are again geographical neighbours have again performed similarly all through the period. However, West Bengal has performed marginally better than the other eastern states it shares border with possibly because of better state government policies.

Fig 4: Spatial maps of per-capita income from agriculture



Spatial pattern of annual growth of per capita NSDP from agriculture (fig-5) further confirms geographic clustering. One can conclude from the spatial maps, that states which are geographically closer/shared borders have generally been in the same quantile of income distribution as well.

Fig5: Spatial pattern of annual growth of NSDP-agriculture per rural person



Thus, this preliminary analysis points towards the presence of spatial dependence across states. It provides an empirical basis to analyse the convergence behaviour of per capita income from agriculture taking into account this spatial dependence across states. The next section discusses the spatial econometric techniques used in this paper. The estimation techniques used are borrowed from literature on beta and sigma convergence (Barro and Sala-I-Martin, 92 etc.) and used spatial econometric techniques (Anselin, 1988, Elhorst, 2003, 2011 etc.) for the same.

METHODOLOGY AND DATA USED

The two commonly used approaches to test convergence in literature are sigma and beta convergence. Sigma convergence refers to reduction in dispersion of the variable of interest such as the levels of income across economies. It captures the trend in regional disparities through changes in cross sectional dispersion of per capita product over time. Dispersion is typically measured by standard deviation of logarithm of NSDP per rural income. A decline in trend of dispersion over time is evidence in favour of sigma convergence while increase in dispersion over time implies sigma divergence.

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 positive association shows high growth rate for richer economies and hence a divergent growth scenario while a 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. Neoclassical growth model 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. This model predicts convergence only when there is diminishing return to capital.

Studies have acknowledged that beta convergence is not a sufficient condition for sigma convergence[8]. 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) demonstrates 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 for the present analysis on convergence across states in Indian agriculture. Additionally, in the beta convergence approach, spatial dependence has also been controlled in the estimation.

Spatial dependence is said to occur when observations of a particular spatial unit is dependent on observations of its neighbours. Spatial dependence can be either positive or negative indicating direction of relationship between value similarity and location similarity. It implies that there exists a relationship between what happens at different points in space.

[8] Quah(1993, a,b), Barro and Sala-i-Martin (1996), Young (2007)

Econometrically, spatial dependence is quantified through spatial matrix (W). "W" is a symmetric matrix and can be defined on the basis of context of the study. By convention, the diagonal elements are set to zero, $w_{ii}=0$. However, any form 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 1 if they have borders shared and 0 otherwise.

Spatial dependence typically has been detected using Global and local Moran's I tests. These test statistics use spatial weight matrices and detect spatial dependence in the data. If these tests reject the null of absence of spatial independence, then spatial modelling should be used to explain the behaviour of the data. Additionally, the value of the test statistic can be used as an indicator of the level of spatial dependence across spatial units (Rey et al, 1999 etc.).

Global Moran's I test statistics for the presence of global spatial dependence among the spatial units can be expressed as:

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

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:

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

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

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×1 vector of fixed but unknown parameters. W is a nonnegative N×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 them one from another (Lee et al, 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 spatial dependence in the disturbances, if present, will only cause a loss of efficiency. Elhorst (2011) 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 inconsistent and unbiased estimates and the estimates are unbiased and inconsistent only in cases where spatial dependence is zero. 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 ML estimator of the spatial lag and of the spatial error model with spatial fixed effects, as set out in Elhorst (2003, 2010a), will yield an 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)).

In the present analysis, spatial dynamic conditional beta convergence and sigma convergence across states in income from agriculture has been explored for 17 states in India from 1966-67 to 2010-11. The only consistent state level data available on income from agriculture for states in India from 1966 onwards is net state domestic product (NSDP) from agriculture. Data source for the same is EPWRF Income (NSDP) is measured at constant (2004-05) prices. Rural population data from CENSUS has been used to compute NSDP per rural person. Since data on rural population is available for only census years, it has been interpolated for the rest of the years (assuming constant growth rate). The 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 data set.

The factors which we have controlled in the analysis can be grouped into the following major groups namely:

1. Inputs used
    a. Per capita land availability, defined as total cropped area per rural person. The annual data has been collated from "Land use statistics, Department of economics and statistics, Ministry of Agriculture, Government of India" (various years).
    b. Mechanization in agriculture: Tractors per rural person has been used as a proxy for mechanization in the analysis. Data for number of tractors has been collated 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.
    c. Fertilizer: This is defined as total fertilizer (N+P+K) consumed in kilograms per unit total cropped area. The data for fertilizer consumed has been collated from "Fertilizer Statistics of India" (various years).
    d. Livestock, 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 has been collated from quinquennial livestock census 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. Livestock not only is an input in agriculture production process but also contributes to the income through major animal products like wool, meat, milk etc.

2. Infrastructure and other state level characteristics
    a. Road quality: It 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 has been collated from "Basic Road Statistics" and "Statistical abstracts of India" (various years).
    b. Electricity: It is defined as percentage of villages electrified. Annual state-wise data for the same was obtained from EPRWF database.
    c. 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 has been collated from "Land use statistics, Department of Economics and Statistics, Ministry of Agriculture" (various years).

d. State expenditure on agriculture: this is defined as state expenditure in agriculture per unit area of the state. Expenditure on agriculture and allied activities include on 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[9]. State-wise annual data on expenditure was collected from "Finances of state government" published by RBI.

3. Cropping pattern: It 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 different groups of crops namely cereals, pulses, fibre, oilseeds, sugar and all other crops have been clubbed together as rest. Over the years, because of changing policies and technology, profitability associated with crops underwent a major change leading to a change in cropping pattern.
4. Human capital:
   a. The quality of human capital has been estimated by controlling the rural literacy rate of the states. This is defined as percentage of literate rural persons in total rural population. Data on rural literacy rate was collected from CENSUS. The years between two consecutive surveys were interpolated using assuming constant growth rates.
   b. Share of scheduled tribes and castes in total rural population of the states. The data for rural scheduled tribes and castes have been collated from CENSUS. The years between two consecutive surveys were interpolated using assuming constant growth rates.
5. Agro-ecological conditions: Agro-ecological conditions of the states have been controlled through rainfall dummies which have been defined on the basis of absolute percentage deviation of actual average annual rainfall from normal average annual rainfall. Average annual data on rainfall was collected from various publications of Statistical Abstracts of India.
6. Spatial variables: The impacts of neighbour's characteristics have been controlled through spatially weighted dependent and independent variables. Spatially weighted variables have been constructed by weighing the variables of neighbours by the spatial weight matrices.

Hence, a conditional convergence equation using a spatial dynamic panel fixed effects model in a maximum likelihood framework has been estimated in this study. State fixed effects were used in the regression to control for all other time invariant state specific characteristics which might have driven state level growths over the entire time period.

[9] Both revenue and capital expenditure have been included.

The model used to estimate the growth convergence equation in the study is:

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

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 $\gamma_1\, to\ \gamma_5$.

The results of the spatial detection tests and sigma and beta convergence tests have been discussed in the next section.

RESULTS

Detection of spatial dependence

Presence of spatial dependence has been detected through local and global Moran's I indices. As discussed earlier, the geographical dependence is incorporated through spatial weight matrices[10]. Two spatial weight matrices have been defined on the basis of contiguity based matrix and inverse distance between two states has been used for the analysis.

In case of contiguity matrices, states which share borders are considered neighbours and are assigned value one while others (no borders shared) are not considered neighbours and are assigned zero weight in the matrix. For distance based matrix, weights are assigned on the basis of inverse distance (Euclidean distance between centroid of states) between the two states. This ensures that higher weight is given to states which are geographically closer than those which are farther away. Data for 17 states[11] have been used for the analysis and hence the dimension of the spatial weight matrix is 17 x 17. Both the matrices have been row-standardized.

The results of global Moran's I computed using the two weight matrices discussed above have been shown in table 2. Global Moran's I (Table: 2) is significant for both 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[12]. Contiguity based spatial weight matrix yields values higher than that of inverse distance based spatial weight matrices. But the number of years with significant spatial dependence is more

[10] Not much guidance is available on the choice of weight matrix in literature. Different studies have used different weight matrices for their analysis.

[11] The names of the states used for the present study can be found in table 1

[12] For e.g. Rey et al (1999).

for inverse distance based spatial weight matrices. Nevertheless, one can conclude in favour of presence of significant global spatial dependence for most years in the sample across states in India.

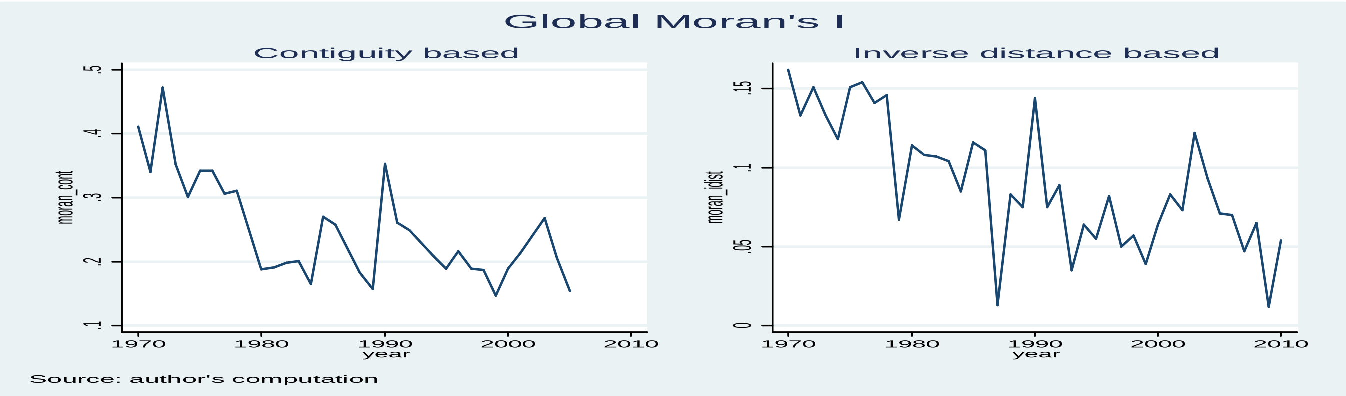
Table2: Global Moran's Test

Year	Moran's I value	p-value	Year	Moran's I value	p-value
Contiguity based spatial weight matrix			Inverse distance based spatial weight matrix		
1966	0.06	0.23	1966	-0.01	0.19
1967	0.03	0.3	1967	-0.01	0.18
1970	0.41	0.00	1970	0.16	0.00
1971	0.34	0.01	1971	0.13	0.00
1978	0.31	0.01	1978	0.15	0.00
1979	0.12	0.14	1979	0.07	0.01
1980	0.19	0.06	1980	0.11	0.00
1981	0.19	0.06	1981	0.11	0.00
1989	0.08	0.01	1989	0.16	0.08
1990	0.35	0.00	1990	0.14	0.00
1991	0.26	0.02	1991	0.08	0.01
2000	0.19	0.06	2000	0.06	0.01
2001	0.21	0.04	2001	0.08	0.00
2010	0.13	0.12	2010	0.05	0.02
2011	0.14	0.11	2011	0.05	0.02

Note-*1-tail test, Source: Author's calculations. The results for all other years can be shared on request. Moran's I gives the value of spatial dependence and p-value indicates the level of significance.

The plot of global Moran's I in Fig.: 6 shows that spatial dependence has declined over the years. But it was particularly high in 70s and 80s. One can also see that both the plots have a cyclical pattern. Hence, it can be inferred that some kind of structural changes have been taking place over the last four and half decades which might have had an impact on spatial dependence across the states.

Fig.:6 Plots of global Moran's I using different spatial weight matrices.



While global Moran's I detects the aggregate spatial growth process taking place, local Moran test (Anselin 1995) detects local dependence and helps locate areas of strong spatial linkages. It can be seen (Table-3) that states have significant local spatial dependence even for those years where there is no significant global spatial dependence.

Table 3: Local Moran's I test

Year	State	Moran's I	p-value*	Year	State	Moran's I	p-value*
Contiguity based spatial weight matrix							
1966	Orissa	0.50	0.09	1978	Punjab	1.53	0.00
1966	WB	0.74	0.05	1990	Orissa	0.63	0.05
1966	Bihar+Jharkhand	1.32	0.00	1990	Bihar+Jharkhand	1.27	0.00
1978	Orissa	0.58	0.07	1990	Haryana	1.31	0.00
1978	WB	0.74	0.06	1990	Punjab	1.53	0.00
1978	Haryana	1.09	0.00	2011	Punjab	0.66	0.04
1978	Bihar+Jharkhand	1.21	0.00	2011	Bihar+Jharkhand	1.20	0.00
Inverse distance based spatial weight matrix							
1966	Orissa	0.13	0.09	1990	WB	0.22	0.08
1966	WB	0.42	0.01	1990	Orissa	0.17	0.06
1978	HP	0.26	0.09	1990	Punjab	0.84	0.00
1978	Bihar+Jharkhand	0.24	0.05	1990	Haryana	0.77	0.00
1978	Orissa	0.18	0.04	2011	Assam	0.16	0.07
1978	WB	0.3	0.04	2011	Orissa	0.15	0.06
1978	Haryana	0.69	0.00	2011	Punjab	0.34	0.05
1978	Punjab	0.83	0.00	2011	Haryana	0.38	0.02
1990	HP	0.26	0.10				

Note-*1-tail test, Source: Author's calculations. The results for all other years can be shared on request. Moran's I gives the value of spatial dependence and p-value indicates the level of significance.

All the states with significant local spatial dependence according to Local Moran's I tests have been shown in table 4. States which had significant local spatial dependence over the years were north-western states like Punjab, Haryana, Himachal Pradesh and eastern states like Bihar, West Bengal, Orissa and Assam and Madhya Pradesh.

Table 4: States which had significant local spatial dependence

States	Years and spatial matrix criteria used
Haryana	1969-2008(contiguity based) and 1969-2010(inverse distance based)
Punjab	1969-2010(both matrices)
Himachal Pradesh	1970-80(inverse distance based) and 1970-78(contiguity based)
Bihar&Jharkhand	all years since 1966(contiguity based) and 1967-79(inverse distance based)
MP&Chhattisgarh	1972-81(contiguity based)
Orissa	1968-78 and 1998-2006(contiguity based) and 1967-79 and 1997-2010(inverse distance based)
West Bengal	1966-81(both matrices)
Assam	2007-2010(inverse distance based matrix)

Source- Author's estimations

From the above preliminary analysis one fails to reject the presence of spatial dependence among states in India. Hence analysis done without taking into consideration the spatial dependence will lead to erroneous conclusions.

CONVERGENCE ANALYSIS

Sigma convergence

An economy is said to be satisfying sigma convergence if standard deviation reduces over time otherwise it is said to be diverging. In fig: 7 plot of standard deviation of log of per capita NSDP from agriculture for the entire time shows evidence in favour of sigma convergence in phase 1 and no evidence the in later phases.

Fig7: Plots of standard deviation for the entire time period and each phase

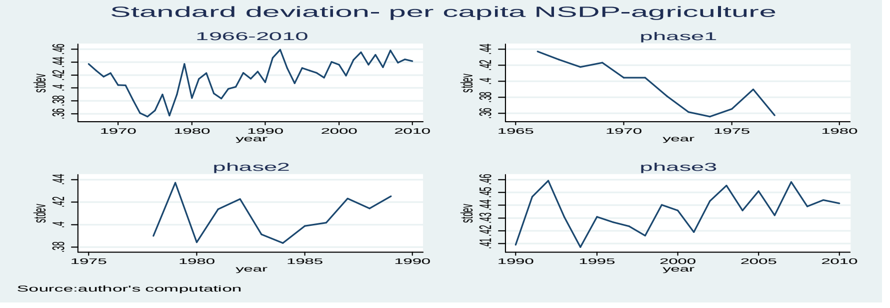
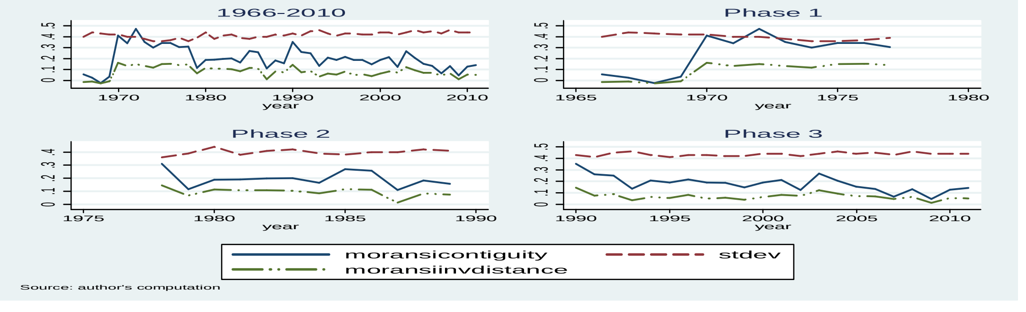


Fig 8 plots the global Moran's I statistics and standard deviation of log of per capita income over time for the full and different sub-periods. These plots point to a negative relationship between the two. Indeed, a simple correlation[13] between standard deviation of log of income and global Moran's I statistic for both the spatial weight criteria over the years confirms this. The correlation coefficient of Global Moran's I using contiguity (inverse distance) based spatial weight matrix is -0.445 (-0.449) and 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 (-0.58 for contiguity based matrix and -0.64 for inverse distance based matrix at less than 5 percent level) is seen in the first sub-phase also though in the second and third sub-phases, the correlation coefficient is not significant.

Fig 8- Plot of standard deviation and Global Moran's I statistic



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

Beta convergence

The results of the conditional beta convergence of the study can be seen in Table-5. Annual growth rate of per capita income from agriculture is the dependent variable and independent variables are per capita income and other state specific characteristics. Models 1 and 2 are respectively results for traditional non-spatial dynamic beta convergence model and spatial dynamic beta convergence models for the entire period (1967-68 to 2010-11). Models 3, 4 and 5 are respectively results for spatial model for sub-phase1, 2 and 3.

It can be seen that in the entire time period and in all the sub-phases, , the lagged per capita income (β) is significant and negative, indicating statistically significant evidence in favour of beta convergence within Indian states not only over the entire period 1967-68 to 2010-11 but also in the sub-phases .

Comparing the log-pseudo likelihood, AIC and BIC of columns 1 and 2, the spatial model is found to perform better than the non-spatial model and so spatial modelling strategy has been adopted for the study.

Spatial factors

Spatially lagged variables (through contiguity based matrix) play a significant role in explaining growth in Indian agriculture. Spatially lagged growth is significant and positive in model 2. This implies that growth of a state was positively dependent on growth of income of its neighbours in the entire time period. However, in the sub-phases, growth rate of neighbouring states did not influence in a uniform way. In the 1st phase, it was not significant. One of the reasons for this can be that in this phase, growth in agriculture was primarily because of the new technology which in turn was restricted to a few states. Therefore there was no spatial spill-over effect. In the 2nd phase, it has a negative and significant impact. This phase is associated with deceleration of growth (Table 1). It was a positive driver in the third phase. This was the phase associated with revival of growth for some of the states (Table 1) and it is possible that this turn around boosted the growth of their neighbours thereby creating a positive spatial spill-over effect.

All the explanatory variables were examined for spatial impact. Only time lagged growth, share of gross area irrigated, income and fertilizer consumed had statistically significant spatial effects. The impact of these spatially lagged factors was not uniform across phases. In model 2 (entire time), area irrigated and time lagged growth played a positive and significant role in growth of income. In the first phase, time lagged growth rate of income of neighbours had a positive impact. In the second phase, spatial income had a negative impact. However, increase in consumption of fertilizer of the neighbouring state improved the growth of the state's growth of income. In the third phase, along with spatial growth in income, spatial irrigation had positive impact. Although, there has been differential impact, one can conclude that spatial spill-over effects have significantly influenced growth of income from agriculture over the years.

Inputs

The most important inputs in agriculture production process namely, fertilizer, tractors and land availability and livestock have been controlled in the estimation models. In model 2, as expected these factors have significantly and positively explained growth However, on comparing the sub-phases, inputs can be seen to play a more determining role in the first phase and not so in the later sub-phases. Only per capita land availability, however, has been a significant driver of growth in all the models.

Interestingly, per area livestock was found to have a negative and significant impact and square of per hectare livestock was positive and significant in model 2 and 3. Livestock has a non- linear U shaped relationship with growth of agricultural output. As this result is not intuitive, the impact of share of different types of livestock namely cattle, buffaloes, sheep and goats in total livestock were further controlled in the models. Share of cattle is insignificant but square of its share is significant and negative. Share of buffaloes and sheep is negative and significant but the square of its share is significant and positive. Share of goats and its square are both insignificant. Thus, the shares of individual animal types do seem to play a role in shaping the impact of livestock on growth. 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 non-linear relation of livestock 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 cattle[14].

Infrastructure

Infrastructural support in a state has significant impact on growth. Area irrigated, electricity, road quality and state expenditure on agriculture are found to be significant and positive driver of growth of income in model 2. However, on comparing the sub-phases, only area irrigated is found to play a significant role in driving growth in Indian agriculture in all the sub-phases. Others only have impact in phase 1. Per hectare expenditure on agriculture by state is significant and positive determinant of economic growth in the entire time period but not in the sub-phases.

Cropping pattern

Cropping pattern is based on a number of factors like agro-ecological conditions, profitability of crops, availability of technology and infrastructure etc. The changing cropping pattern of the states 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 cereals, fibre, sugar and oil are all significant and positively influence the growth of income from agriculture[15]. Share of total cropped area under cereals is a significant and positive driver of growth in all the sub-phases. However share of area under other crop groups are negative in 1st sub-phase and positive later.

Human capital

Human capital has been controlled through rural literacy rate and share of scheduled castes and scheduled tribes in total rural population. Literacy has a positive role in growth while share of scheduled castes and tribes has a negative relation with economic growth in model 2. Human capital is significant in phases 2 and 3 but not in phase 1.

[14] At the all India level, from 1966 to 2007, on an average cattle account for approximately 50% of all livestock, and within cattle animals in milk constitute only approximately 30%.

[15] Share of pulses and rest of the crops was not significant and therefore have been dropped from the estimation models

Agro-ecological conditions

Higher deviation of actual rainfall from its normal level significantly reduces growth of income from agriculture in model 2. Among all the sub-phases rainfall significantly reduces growth in sub-phase 2. It remains insignificant in the other sub-phases.

Table 5- Results of conditional beta convergence models for growth of income in Indian agriculture

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.					
	Traditional (non-spatial) beta convergence models	spatial beta convergence models			
explanatory variables	all phases	all phases	phase1	phase2	phase3
	Model 1	Model 2	Model 3	Model 4	Model 5
$Income_{(t-1)}$	-0.695***	-0.648***	-0.470***	-0.942***	-0.589***
$Growth_{(t-1)}$	-0.150***	-0.188***	-0.046	-0.036	-0.214***
Fertilizer per cropped area	0.086***	0.070***	0.107**		
Per capita tractor	0.812**	0.827**			
Per capita gross cropped area	2.023***	2.235***	1.270***	3.475***	2.612***
Livestock per area	-0.156***	-0.167***	-0.797***		
Livestock per area sq.	0.010***	0.012***	0.088***		
Share of cattle in tot.live.	0.115	0.094	-1.984*		
Share of buffaloes in tot. live.	-0.353***	-0.400***	2.235		
Share of sheep in tot. live.	-0.883*	-0.817**	5.330***		
Share of goat in tot. live.	0.118	0.268	1.039		
Share of sheep sq.	2.661***	2.572***	-15.531**		
Share of buffaloes sq.	0.091***	0.095***	-7.174		
Share of cattle sq.	-0.116**	-0.091**	0.863		
Share of goat sq.	0.599	0.318	-1.661		
Share of gross area irrigated	0.166***	0.196***	0.296***	0.292**	0.236***
Villages electrified	-0.086**	-0.086***	-0.223***		
Road quality		0.112*	0.331**		
Expenditure on agriculture	0.003**	0.002**			
Share of cereals in cropped area	0.330*	0.434**	0.777*	0.619***	0.501*
Share of oil in cropped area	1.152***	1.236***		1.539**	
Share of fibre in cropped area	1.083**	1.037***	-3.089***	2.271***	0.591*
Share of sugar in cropped area	5.048***	4.278***	-7.150**		
Share of sc and st in rural pop		-0.006*		-0.018***	-0.009*
Rural literacy rate	0.007***	0.006***		0.008**	0.009***
Rain dummy_3	-0.033**	-0.031***		-0.061***	
Spatial Interactions					
$Growth_{(t-1)}$		0.146***	0.188**		
Share of gross area irrigated		0.140*			0.292***
Fertilizer per cropped area				0.133***	
$Income_{(t-1)}$				-0.218*	
$Growth_{(t)}$		0.211***	0.019	-0.138**	0.148**
Model Statistics					
N	663	646	170	187	340
log likelihood	631.893	634.731	110.409	205.878	365.586
AIC	-1231.79	-1237.46	-188.817	-379.755	-701.171
BIC	-1159.84	-1165.93	-138.644	-328.057	-643.737
r2_w	0.584	0.614	0.74	0.776	0.583

NOTE-legend: *p<.1;**p<.05;***p<.01.Col 1 presents the results of non-spatial dynamic beta convergence model, column 2 presents the results of spatial dynamic beta convergence. Columns 3,4 and 5 presents the results of spatial dynamic beta convergence model for the three sub-phases. The significant years were included in the regression models. In the first and second regression, the years which were significant were 1975, 1977, 1994, 1996 and 2010. In the first sub-phase, the significant years were 1968, 1970, 1973, 1975 and 1977. In the second sub-phase, the significant years were 1979, 1984, 1985, 1988 and 1989. In the third sub-phase, the significant years were 1994, 1996, 2007 and 2010. Source: Author's estimations

DIFFERENTIAL IMPACT ACROSS PHASES

The results (table 5) indicate that factors driving growth have not remained the same over the different sub-phases. Table 6 summarizes the differences across the sub-phases. Spatial factors, irrigation, land and rainfall have always been significant. The factors which exclusively influenced growth in 1st sub-phase were inputs, infrastructure and cropping pattern (cereal) and factors abating growth were area under fibre and sugar. These finding support studies like Bhalla and Singh (2009) that in 1960s and 1970s, production increased because of increase in irrigation potential and growth of area under cereals.

In the second phase, inputs were not significant. However, human capital was. Area not covered with cereals aided in growth here unlike phase 1. This was the phase characterized by spill-over of technology and hence other crops also gained from the same. Factors driving growth in the third phase[16] from 1990 to 2010 are similar to those of phase 2. Rainfall is not a significant explanatory factor.

Results indicate that agriculture income across states is converging to a steady state level which is dependent on the state specific characteristics. However, the determinants of growth have been changing over the phases. The most important drivers of growth over the entire phases have been input usage, irrigation and literacy. Spatial spill-over effects also have been significant drivers of growth.

TABLE 6: Changing drivers of growth in Indian agriculture

all phases	**1st sub-phase**	**2nd sub-phase**	**3rd sub-phase**
inputs(fertilizer, land, tractors, livestock)	inputs(fertilizer, land, livestock)	inputs(land)	inputs(land)
irrigation	irrigation	irrigation	irrigation
electricity	electricity		
road quality	road quality		
state expenditure on agriculture			
cropping pattern(cereals, oil seeds, fibre, sugar)	cropping pattern(cereals, fibre, sugar)	cropping pattern(cereals, oil seeds, fibre)	cropping pattern(cereals, fibre)
human capital (rural literacy, share of sc-st population)		human capital (rural literacy, share of sc-st population)	human capital (rural literacy, share of sc-st population)
rainfall		rainfall	
spatial growth		spatial growth	spatial growth
spatial irrigation			spatial irrigation
		spatial fertilizer usage	
Source: Author's estimations			

ROBUSTNESS CHECKS

The results presented so far are based on contiguity based spatial weight matrices where neighbours are defined on the basis of borders shared. It is widely accepted that results are sensitive to definition of matrices. The estimation of beta convergence was also replicated using inverse distance based spatial weight matrix and the results[17] were found to be robust. Other models of spatial dependence like lag and error models were also used to estimate the convergence equation[18]. All the models confirm convergence and Spatial Durbin model performed better. This confirms the robustness of our results and estimation strategy.

[16] Year dummy variables marking the increase in investment in agriculture post 2000s were found to be insignificant in our analysis and hence we dropped them.
[17] Results based on inverse distance based matrices can be shared on request
[18] Results on spatial lag and error models can be shared on request

CONCLUSION

A vast disparity exists across Indian states in income from agriculture because of differentials in agro-ecological conditions, cropping pattern, input usage, infrastructural support, yield levels, etc. This despite, Indian agriculture having gone through enormous changes since 1960s when green revolution technology was first introduced. It was initially restricted to certain states where there was well assured irrigation. However, in the next decade, there was diffusion of new technology across other crops and states and hence other states also gained from the new technology. The growth difference between the highest and lowest growing states has also changed over the years. The all India growth rates were high in the first sub-phase (1966-77) and declined in the second sub-phase (1978-89) with some revival in the third sub-phase (1990-2010). Majority of states followed the same pattern. Coefficient of variation in annual growth across states increased in the second phase compared to the first phase and then declined again in the third phase. Hence, inter-state disparity has not remained the same over the years.

In this paper, convergence in income in Indian agriculture was analyzed through two commonly used approaches namely, sigma and beta convergence. Sigma convergence approach measures the standard deviation of logarithm of income across states at various time points. The results of sigma test indicates that except in phase 1 when the standard deviation declined somewhat, there is no evidence of any trend in sigma convergence in any of the other sub-periods / over the entire period.

Beta convergence estimation approach was also used to test convergence in income from Indian agriculture. Existing literature on beta convergence in Indian agriculture has assumed each state to be an independent and isolated unit. But in reality the performance of neighbouring states depend on each other due to spatial spill-over. The relative location of states was incorporated econometrically using spatial weight matrices with value of 1 for neighbouring states and 0 if not. Global and local Moran's I tests 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, spatial weight matrices were used to econometrically compute the spatially lagged dependent and independent variables. A dynamic fixed effect model was used to correct the autocorrelation problem in panel data. Strong evidence was found in favour of spatial beta convergence in the entire period as well as all the three sub-phases. Spatial convergence models were found to explain the convergence model better than non-spatial models.

Factors which were found to significantly drive growth were input usage, physical infrastructure and cropping pattern. However, input usage and infrastructure were significant only in the first phase. In the second and third phases, inputs were not significant but literacy was. Land, irrigation, rainfall and spatial variables (either dependent or one of the independent variables) have however always had significant impact on growth.

The empirical evidence presented here highlights the importance of inputs and infrastructure in growth in agriculture. Therefore, economic policy measures targeting improvement and expansion of infrastructural support (for example public investments towards irrigation and electricity, roads), literacy input usage and water management can have an important impact in promoting long run agriculture growth and convergence across Indian states.

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. Moreover, spatial analysis is dependent on spatial weight matrices. Although both inverse distances based and contiguity based spatial weight matrices gave similar results, there are various other possible definition of spatial weight matrices and results might be sensitive to those.

REFERENCES

- Aroca, P., Guo, D., Hewings, G.(2006), Spatial Convergence in China: 1952-99, *Research Paper, UNU-WIDER, United Nations University (UNU), No. 2006/89*
- Abreu, M., De Groot, H. and Florax, J.G.M.(2005), Space and growth: a survey of empirical evidence and methods*, Region et development* 21-2005
- Bandopadhyay, S. (2003) Convergence Club empirics: Some dynamics and explanations of unequal growth across Indian states, *London School of Economics and Political Science*, Discussion paper No. DARP 69
- Bandopadhyay, S. (2011) Rich States, Poor States: Convergence and Polarisation across Indian States, *Scottish Journal of Political Economy*, 57(3): 414-436.
- Barro, Robert and Xavier Sala-i-Martin (1992): 'Convergence', *Journal of Political Economy*, Vol. 100
- Bhalla, G.S. and Singh, G. (1997),Recent Developments in Indian Agriculture: A State Level Analysis, *Economic and Political Weekly*, Vol. 32, No. 13 (Mar. 29 - Apr. 4, 1997), pp. A2-A18
- Bhalla, G.S. and Singh, G. (2001) Indian Agriculture–Four Decades of Development. *Sage Publications, New Delhi.*
- Bhalla, G.S. and Singh, G. (2009) Economic liberalization and Indian agriculture: A State wise Analysis, *Economic and Political Weekly*, December 2009, Vol: XLIV, NO 52.
- Bhalla, G.S. and Singh, G. (2010), Final Report on Planning Commission Project Growth of Indian agriculture: A district level study
- Bhide, S, Kalirajan, K.P., Shand, R.T., India's Agricultural Dynamics: Weak Link in Development, *Economic and Political Weekly*, Vol. 33, No. 39 (Sep. 26 - Oct. 2, 1998), pp. A118-A127
- Cashin, P. and Sahay, R. (1996). International migration, centre-state grants, and economic growth in the states of India, *IMF Staff Papers*, 43, 123-171.
- Chand, R, Raju S.S.(2008), Instability in Indian Agriculture during Different Phases of Technology and Policy, *NCAP discussion paper:* NPP 01/2008
- Chand, R., Chauhan, S. (1999) Are disparities in Indian agriculture growing? *NCAP Policy Brief No. 8*
- Dholakia, R. (1994) Spatial dimension of acceleration of economic growth in India, *Economic and Political Weekly*, 29(35): 2303-09.

– Elhorst JP (2003) Specification and estimation of spatial panel data models. *International Regional Science Review* 26(3):244-268
– Elhorst JP (2012) Dynamic spatial panels: Models, methods and inferences. *Journal of Geographical Systems, Volume 14, Issue 1, pp 5-28*
– Elhorst JP (2010) Spatial panel data models. In: Fischer MM, Getis A (eds) *Handbook of applied spatial analysis. Springer, Berlin, Heidelberg and New York,* pp 377-407
– Ezcurra, R., Iraizoz, B., Pascual, P., Rapun, M.(2008), Spatial disparities in the European agriculture: a regional analysis, *Applied Economics*, 2008, 40, 1669–1684
– *Ghosh, M. (2006). Regional convergence in Indian agriculture, Indian Journal of Agricultural Economics*, 61(4), 610–629.
– Jones, R., Sen, K., It is where you are that matters: the spatial determinants of rural poverty in India, *Agricultural Economics*, 34 (2006) 229–242
– Kar, S., Jha, D., Kateja,A. (2011) "Club-convergence and polarization of states: A nonparametric analysis of post-reform India", *Indian Growth and Development Review,* Vol. 4 Issue: 1, pp.53 – 72
– Lee LF, Yu J (2010a), Estimation of spatial autoregressive panel data models with fixed effects, *Journal of Econometrics* 154(2):165-185
– Yu, J, Lee, L.F., 2008. Quasi-maximum likelihood estimators for spatial dynamic panel data with fixed effects when both n and T are large, *Journal of Econometrics* 146, 118–134.
– Maza, A., Hierro, M. , Villaverde, Jose (2012), Income distribution dynamics across European regions: Re-examining the role of space, *Economic Modelling* 29 (2012) 2632–2640
– Majumdar, Grace and J L Kapoor, (1980). "Behavior of inter-state income inequalities in India". Paper presented at the Twelfth Conference of the Indian Association for Research on National Income and Wealth.
– Mukherjee, A. and Koruda, Y. (2003) Productivity growth in Indian agriculture: is there evidence of convergence across states? *Agricultural economics* 29 (2003) 43-53
– Mukhopadhayay, D. and Sarkar, N.(2014), Convergence of Food grains across Indian states: A study with panel data, *Discussion paper ERU*/2014-03, January, 2014
– Nagraj, R.,Varoudakis, A., VEÂ GANZONEÁ, M.A. (2000)Long run Growth trends and convergence across Indian states, *Journal of International development*, 12, 45-70(2000)
– Niebuhr, A., (2001) Convergence and the effects of spatial Interaction, *HWWA Discussion Paper*, No. 110
– Parikh, A. (1980) State-wise growth rate in agricultural output–An econometric analysis. *Arthavijnana*, 8(1):1-52.
– Pfaffermayr, M. (2012), Spatial convergence of regions revisited: a spatial maximum likelihood panel approach. *Journal of Regional Science*, 52: 857–873. doi: 10.1111/j.1467-9787.2012.00773.x
– Quah, D. T. (1993a), Empirical Cross-section Dynamics in Economic Growth, *European Economic Review*, 37 (2-3), 426-434. (a)
– Quah, D. T. (1993b), Galton's Fallacy and Tests of the Convergence Hypothesis. *Scandinavian Journal of Economics*, 95 (4), 427-443. (b)
– Rao, M., Shand, R., Kalirajan, K.P., Convergence of Incomes across Indian States: A Divergent View, *Economic and Political Weekly*, Vol. 34, No. 13 (Mar. 27 - Apr. 2, 1999), pp. 769-778

- Rey, S., Montouri, B.(1999) US Regional Income Convergence: A Spatial Econometric Perspective, *Regional Studies*, Vol. 33.2, pp. 143-156
- Bajpai, N. ,Sachs,(1996), Trends in inter-state inequalities of income in India , Development Discussion Paper No. 528, Harvard Institute of International development
- Sala-i-Martin, Xavier, 1994, Cross-sectional regressions and the empirics of economic growth, *European Economic Review*, 38, p.739-747.
- Shaban, A.(2006), Regional Structures, Growth and Convergence of Income in Maharashtra, *Economic and Political Weekly*, Vol. 41, No. 18 (May 6-12, 2006), pp. 1803-1815
- Somasekharan, J., Prasad, S., Roy, N. (2011), Convergence Hypothesis: Some Dynamics and Explanations of Agricultural Growth across Indian States, *Agricultural Economics Research Review*,Vol.24,July-December-2011,pp-211-21
- Wooldridge, Jeffrey 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