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Abstract

In this study we trace how number and members of income clusters have changed in Indian agriculture over the last four and a half decades. Two features which stand out in our results are that not all geographical neighbors belong to the same cluster and clusters include both geographical neighbors and non-neighbors. To identify the factors driving a pair of states to common cluster we then use a logit model and find that smaller is the relative difference between them in terms of mechanization, infrastructural support, deviations from normal rainfall and price differences, higher are the chances that they will be in the same income cluster. Between contiguous and non-contiguous state pairs we find that apart from the common factors, smaller relative differences in irrigation support, rainfall and price differences additionally brings non-contiguous states together.

Keywords: agriculture, rural development, club convergence, income cluster determinants, geography

JEL Code: O13, O18, O47, Q18, R11, R12

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1. Introduction

Huge disparity across states has been a perennial feature of Indian agriculture, and the subject matter of several studies, government reports and policy documents (Bhalla and Singh (1997, 2009), Bhide et al (1998), Chand and Chauhan (1999), NAP (1999), Ghosh (2006), Chand and Raju (2008)). Most of these studies have focused on sigma convergence (income disparity), and a few on beta convergence (Bhide et al (1998), Ghosh (2006)).

Sigma convergence method analyzes the cross sectional dispersion of per-capita incomes across economies/regions 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) and tests the underlying idea that regions tend to catch up with their steady-state growth rate. Both these tests measure different aspects of convergence.

The problems in the empirical literature on convergence are discussed in Azariadis and Drazen (1990), Quah (1993), Durlauf and Quah (1999), and Islam (2003). The main issue is the inconsistency in the results on beta and sigma convergence. Often beta convergence is seen along with sigma divergence. Besides, there is also the issue of multiple steady states, which gives inconsistent results. In this context, the question then arises “do regions over time tend to converge into clubs/clusters”.

Studies like Hobijn and Franses (2000), Busetti et al (2006) among many others have suggested tests to identify club convergence. However, these studies only test for certain aspects of convergence and the underlying time series testing procedures more often than not depend on stationarity properties (Bartkowska and Reidl (2012), Kim and Rous (2012)). These shortcomings are corrected in the methodology suggested by Philips and Sul, 2007 (PS) where panel data is modeled as ‘non-linear, time varying coefficients factor model’. They show that the asymptotic properties of convergence are well-defined and their approach also does not depend on stationarity assumptions. The advantage of their method is that it takes care of a wide variety of possible transition paths towards convergence including sub-group convergence and divergence.

In Indian agriculture as well, conclusions on sigma and beta convergence from the above mentioned studies have often not matched. Results from Chatterjee (2014), after controlling for relative geographical location of states suggest that although income per rural person from agriculture across states in India converges according to the beta convergence measures but there is no evidence in favor of sigma convergence.

Hence, here we look into club convergence in Indian agriculture for Net State Domestic Product (NSDP) per rural person using PS from 1966 -67 to 2010-11 and trace if over time states have converged to form multiple clusters. The analysis has been done for three sub-phases to understand the temporal and spatial dynamics of cluster formation in Indian agriculture. As will be seen later both the number and members of clusters have changed in these sub-phases. We found that there were four, one and three clusters respectively in the three sub-phases.[1]

Two features of these clusters stand out in our results: (i) Not all geographically neighboring states belong to the same income cluster; and (ii) most of the clusters include both geographical neighbors as well as non-neighbors. What explains these phenomena?

Internationally there are very few studies that have explored the factors that drive cluster formation. Bartkowska and Reidl (2012) and Kim and Rous (2012) use ordered probit and multimomial logit models, respectively, to relate clusters to certain determining factors. Corrado et al (2005) computed cluster correlations between clusters generated on the basis of Hobijn and Franses (2000) and hypothetically created clusters on the basis of various criteria like core-periphery, spatial proximity etc. to identify the reasons driving cluster formation. However, to the best of our knowledge, none of the studies address the issues of why all geographical neighbors are not members of the same cluster and why are non-neighbors members of the same cluster.

This paper tries to address these issues by first identifying the clusters through PS methodology and then tries to identify the factors which drive states to common income clusters. For that we consider a setting that differs from others as here we try to understand why a pair of states are in the same cluster and estimate how relative similarity between them pushes them towards the same cluster. Further, we also try to understand if factors driving state pairs which are not geographical neighbors are different from those pairs which are geographical neighbors.[2]

The rest of the paper is organized as follows: The next section briefly describes the data used for the analysis. The methodology adopted for identifying clusters and the results have been discussed in section 3. Section 4discusses the methodology used to identify the factors

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[1]In Indian context, Ghosh et al (2013) is the only other study that used PS methodology on per capita NSDP for the aggregate economy and for agriculture, industry and services sub-sectors from 1968 to 2008 and they found two clusters in agriculture sector.

[2] Here, geographical neighborhood has been defined on the basis of state contiguity i.e. if the state shares a common border with another state it has been considered as a neighbor otherwise not.

determining the clusters and reports the results of the analysis while section 5 provides some concluding remarks.

2. Data

The main variable of interest here is the NSDP per rural person, which is constructed out of the data on NSDP taken from the EPWRF database and rural population data from Census. The analysis is carried out for 17 states[3], which on an average account for over 95% of Net Domestic Product from agriculture. Data on the newly formed states of Jharkhand, Chhattisgarh and Uttaranchal have been merged with their parent states of Bihar, Madhya Pradesh and Uttar Pradesh, respectively, to maintain uniformity in the panel data set.

To understand the changing patterns of growth of agricultural income, the time period in this study, viz., 1966-67 to 2010-11, has been divided into three sub-phases on the basis of changing policies in agriculture sector: 1st sub-phase (1966-1977) the period of Green Revolution; 2nd sub-phase (1978-1989) period of falling public investment in agriculture; and 3rd sub-phase (1990-2010) period of economic reforms. As seen in Figure-1, public investment in agriculture as a percentage of agricultural GDP was high in the latter half of 1960s and 1970s (1st sub-phase), fell sharply in the 1980s (2nd sub-phase) and continue to fall for most of the period of economic reforms (3rd sub-phase). Only since the late-2000s, is there a pickup in public investments in agriculture.

Table 1 reports the levels and growth of NSDP over the various phases and brings out some interesting aspects of the inter-state variation over the years. In terms of levels of per capita income, compared to other states Uttar Pradesh and eastern states like Assam and Bihar have always been poorly performing states while Punjab and Haryana in north-west have always been better performers. However, as documented in results from studies like Bhalla and Singh (1997) and also from Table 1 we can see that growth rates of states like Punjab and Haryana have come down in the later sub-phases. Growth rates for almost all the states were highest in the first sub-phase (1966-2010) which was the initial green revolution period while they were lowest and had the highest coefficient of variation in the second sub-phase (1978-89). Third sub-phase (1990-2010) saw some revival but growth rates were still lower than the first sub-phase. Yet, one can also see some instances of catching up in states like Gujarat and

[3] 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)

Maharashtra in the west and Andhra Pradesh and Tamil Nadu in the south as they experience a higher growth rate in last sub-phase.

[Figure-1]

[Table 1]

Data sources for the explanatory variables were quinquennial livestock Census which is conducted by Department of animal husbandry, dairying and fishing, Government of India for tractors, “Basic Road Statistics” and “Statistical abstracts of India” for road density which is defined as of total road length per square kms geographical area in the state, EPWRF database for power consumed for agricultural purposes, “Land use statistics, Department of Economics and Statistics, Ministry of Agriculture” for data on share of gross area irrigated in total cropped area, “Finances of state government” published by RBI for state expenditure in agriculture[4]. Data of share of area under each crop-groups like cereals, fiber, pulses, sugar, oilseeds and rest was obtained from “Area, Yield, Production of Principle Crops” by Ministry of Agriculture. Average annual data on rainfall (both actual and normal) was collected from various publications of Statistical abstract of India. Data on markets was compiled from ‘Bulletin on Food statistics’ published by Ministry of Agriculture for various years. Aggregate price index (ratio of NSDP from agriculture in current prices to constant prices) is used as a proxy for market integration and both the data was collected from EPWRF database.

3. Identifying clusters

In order to analyze the transitional behavior of per capita income among the states in India, we apply the test developed by PS (the method has been described in detail in the appendix).Briefly, this method first tests whether all the states converge with each other at the end of the time period and then if not, it proposes a cluster identification algorithm. The states are first sorted in descending order. Then starting from the 1st state, the first convergence cluster is identified by testing each state sequentially for membership of the group. The states that are not members of this group are then tested again sequentially to see if they form a second cluster, and so on till all the clusters are identified.

[4]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 programs(Both revenue and capital expenditure have been included)

Accordingly, we tested for convergence for the three sub-phases and the t-values turned out to be -121.45, -35.75 and -92.17 for the three sub-phases, respectively, all of which are significant at <5%. That is, the null hypothesis that all the states converge with each other is rejected for all the three sub-phases. Hence, we proceed with the cluster identification algorithm.

Results of the clusters so identified for the three sub-phases are given in Table 2. The results show that in the first sub-phase there were four converging clusters with different number of members and no divergent states. In the 2^{nd} sub-phase, there is only one cluster with 11 states and 6 diverging states, while in the 3^{rd} sub-phase there are 3 clusters with different number of members and 2 divergent states.

We can see a clear pattern from Table 2 that some states have been in the same cluster always. For example, Andhra Pradesh and Gujarat have been together always, though the rank of the income cluster (representing the level of income) that they were in has been changing over the sub-phases. Similarly, Karnataka and HP have been together, as also Assam and Orissa, Madhya Pradesh and Uttar Pradesh, and Punjab and Haryana. Besides these pairs of states, the five states of Jammu and Kashmir, Kerala, Tamil Nadu, Rajasthan and West Bengal as a group also show a similar pattern. Bihar is the only state that has always been the member of the last club with the lowest income levels and growth rates.

[Table 2]

To see if these clusters themselves are converging or diverging relative transition parameters are estimated using h_{it} from Equation 3 in Appendix. Plots of these transition parameters for the three sub-phases are given in Figure 2. It can be seen that the clubs and divergent states indeed follow a different pattern from one another and none of them tend to converge with one another.

Two interesting features of these clusters come out from a geographical perspective. From Figure 3 it can be seen that in each sub-phase several clusters include both contiguous and non-contiguous states. For example, in 1^{st} sub-phase cluster-2 includes Gujarat, Karnataka, HP and AP, of which only Karnataka and AP are neighboring states. A second feature of these clusters is that not all neighboring states belong to the same cluster. For instance, Punjab-Haryana are neighbors and form the first income cluster in 1^{st} sub-phase, their neighbors Jammu & Kashmir, HP, Rajasthan and UP are not members of this cluster. These two features are seen in several clusters in the three sub-phases. The next section explores the factors that determine cluster formation, and in particular examines the reasons behind this spatial pattern in the income clusters.

4. Factors driving states to common clusters

To identify the factors which drive the states to common income clusters we estimate a logistic model where the dependent and explanatory variables have been constructed in such a way that each cross-sectional observation refers to a particular pair of states. That is, first the 17 states were arranged in alphabetical order and every possible state-pair combination was taken to constitute one cross-sectional observation for a particular sub-phase.

The dependent variable is a binary variable which takes the value one if both states in a state pair are members of the same income cluster in a particular sub-phase as reported in Table 2 above; and zero otherwise. Thus, out of the time series data for a particular sub-phase we come out with a cross-sectional data that tells whether a pair of state has been in the same cluster over that period. Therefore, there are 136 ($^{17}C_2$) observations for each sub-phase and total number of observations over the three sub-phases is 408.It is worth stressing here that the dependent variable does not differentiate among high, low or middle level of clusters. For example in 1stsub-phase, both the state pairs Punjab-Haryana (highest income cluster 1) and Bihar-Uttar Pradesh (lowest income cluster 4) are given a value of one.

On the same line as the dependent variable, explanatory variables were constructed in such a manner that they concurrently represent the state-pairs and the sub-phases. For each explanatory variable, the absolute difference between the two states in a state pair was constructed to capture the relative gap between the two states. Absolute differences were used because the order of the states in a state pair is alphabetic, and hence the sign of the difference has no particular interpretation. Absolute differences were computed for the initial and final time period of each sub-phase, which can be written mathematically as: $|x_{i0} - x_{j0}|$ and $|x_{iT} - x_{jT}|$respectively where 'i' and 'j' are the states and 0 and T are the initial and last years of each sub-phase. Additionally, ratio of the difference in the final values to difference in the initial values of the explanatory variable was also constructed as a proxy for the relative growth of the two states in a state pair. This can be written as:$|x_{iT} - x_{jT}|/|x_{i0} - x_{j0}|$. When this ratio takes a value greater (lesser) than one then it implies that the two states are moving away from (closer to) each other in the explanatory variables.

[Figure-2]

[Figure-3]

Binary logistic regressions with state fixed effects are then estimated to identify the determinants of cluster formation. To study the factors that drive neighbors (non-neighbors) into different (same) income cluster, we divide the state-pairs into two sub-groups on the basis of state-level contiguity and estimate separate logistic models. Out of the total 408 observations, 96 are contiguous state-pairs and 312 non-contiguous state-pairs observations. The sub-group regressions help us understand how factors driving contiguous states to a common income cluster are different from those of non-contiguous ones.

Combined sample results: Columns 1-3 in Table 3 gives the results of the logistic regression with state fixed effects. It was found that power consumption and irrigation are highly correlated and hence they could not be used together in the same regression model. So in columns 1 and 2 we have controlled for irrigation only while in column 3 only power consumption has been controlled.

Per capita tractor ownership, which is a proxy for both mechanization and asset ownership, is a significant driver. Lower the difference between the states in per capita tractor ownership, higher is the probability of the states to form a part of the same cluster. It is worth stressing here that the model only captures the probability of the two states being in the same income cluster be it high/medium /low-income cluster. This probability is influenced by the relative gap in the explanatory variable (for example per capita tractor ownership), and not so much the level of tractor ownership per se, which could be high /medium / low in the two states. The model by no means implies any relationship between the level of the explanatory variables and the levels of income across the states. This aspect needs to be borne in mind while interpreting the results vis-à-vis the other explanatory variables.

Among variables indicating status of key infrastructure in the states, we find that relative differences in growth in total road density, irrigation measured in terms of share of gross area irrigated and power consumed for agricultural purposes per total cropped area in the state are significant drivers in the sense that smaller is the difference between any two states in these infrastructural status, higher are the chances that the two states are in the same income clusters. Impact of state support has been controlled in terms of expenditure of state on agriculture and it is also a significant driver. Share of area under all the crops grown in the states was used as a substitute of cropping pattern and among all the crop-groups, share of area under fiber was a significant factor. Again smaller is the difference in the absolute deviation of actual rainfall from normal levels, higher is the probability that states will be in the same cluster.

Recent literature stresses on the importance of market integration in growth of income and following that line, we created an aggregate price index (deflator[5]) for agriculture for the states and it was found to be again a significant driver i.e. smaller is the difference between the states in terms of price index, higher are the chances that they are in the same income cluster. Market per cropped area and deflator were highly correlated so we have controlled for market and deflator interchangeably in our models.

To summarize, smaller is the difference between the two states in state pair on policy variables like state expenditure on agriculture, mechanization substituted by per capita tractor ownership, infrastructure like markets, roads, irrigation and electricity consumption, price index substituted by deflator and deviation of actual rainfall from their normal levels, higher is the probability they will be in the same cluster.

Sub-sample results: Column 4 in table 3 gives the results of a similar regression when performed on contiguous states. Tractors again are a significant driver of states to common income clusters and so are markets, state expenditure on agriculture, growth of total road density and share of cropped area covered with fiber in the final year. Columns 5 and 6 show that the factors which drive non-contiguous states to common income clusters are tractors, irrigation, state expenditure, cropping pattern (share of fiber)and percentage deviation of actual rainfall from the normal levels are also significant. Here, it is the initial road density and not its growth which is significant driver of states to common clusters. Unlike contiguous state-pairs price deflators are significant drivers in this sub-sample (column 6).

Comparing the results for non-contiguous states with the contiguous states, we find that factors like tractor ownership, expenditure by state governments, markets, roads and cropping pattern are common to both sets of models. The factors which differentiate non-contiguous and contiguous states are deviation of actual rainfall from normal levels, irrigation and price differentials between state pairs.

[Table 3]

5. Conclusion

Disparity across states has been a perennial feature of Indian agriculture. Past studies on Indian agriculture such asChatterjee (2014) have found evidence of beta convergence but not sigma convergence. Such a difference in the conclusions is not uncommon in the empirical

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[5]Deflator = NSDP per rural person from agriculture in current prices/NSDP per rural person from agriculture in constant 2004-05 prices

literature on convergence, and this has led some studies to explore the possibility of the existence of multiple steady-states resulting in club convergence.

In this paper, we examine club convergence in Indian agriculture in terms of Net State Domestic Product (NSDP) per rural person over the period 1966 -67 to 2010-11 and trace if over time states have converged to form multiple clusters. Further, we also examined the factors that drive the formation of clusters. The analysis has been done for three sub-phases to understand the temporal and spatial dynamics of cluster formation in Indian agriculture. The entire time period from 1966-2010 was sub-divided into three sub-phases: first sub-phase (1966-2010), second sub-phase (1978-89) and third sub-phase (1990-2010).

Using the PS methodology we found evidence that both the number and constitution of the clubs have changed over the sub-phases. All the states converged to four clusters in sub-phase one while in sub-phase two only had one cluster with 11 states, while all other states diverged from one another whereas sub-phase three had three clusters and two divergent states. Our results also highlight that (a) clusters comprise of both contiguous and non-contiguous states, and (b) not all contiguous states are in the same cluster.

What drives cluster formation, and in particular, why do some non-contiguous states are members of a particular cluster while not all contiguous states are members of a particular cluster? To study these questions we created a new binary variable which takes the value one if both states in a particular state pair are in the same income cluster and zero if not and estimate a logistic model with state fixed effects for the full sample and for two sub-samples, viz., for the contiguous and non-contiguous states. The explanatory variables in these logistic regressions were constructed for a pair of states as the absolute difference between them in the levels of the variable. Further, the widening / narrowing of the gap over time between these states is also captured in the form of ratio of the difference in the variable in the final year to that in the initial year.

The results show that smaller is the relative difference between two states in a state pair in tractor ownership, infrastructure variables like irrigation, power consumption, roads and number of markets, state expenditure on agriculture, price-differentials and rainfall, higher is their probability of being in the same cluster. The results for the two sub-samples for the contiguous and non-contiguous states show that factors like tractor ownership, expenditure by state governments, markets, roads and cropping pattern are common to both of them. Factors such as deviation of actual rainfall from normal levels, irrigation and price differentials between state pairs matter only for the non-contiguous states.

The empirical evidence presented here highlights the importance of mechanization, infrastructure, market integration and state support in growth in agriculture. Therefore, economic policy measures targeting improvement and expansion of infrastructural support, mechanization in agriculture, efficient water management to control the dependence on vagaries of monsoon and incentives for market integration can have a significant 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. Choice of length of the sub-phases and the years chosen as the beginning and end years of the sub-phases might influence the results on cluster constitution. And due to multi-collinearity impact of irrigation and power consumption could not be estimated simultaneously however independently we find that they have a significant impact.

Appendix

Philips and Sul (2007) test is based on an innovative decomposition of the variable of interest. Usually panel data for the variable of interest (y_{it}) is decomposed in the following way:

$$\log y_{it} = \varphi_i \mu_t + \varepsilon_{it} \quad (1)$$

Where, φ_i represents the unit characteristic component, μ_t, the common factor and ε_{it}, the error term. Here, a time varying representation of $\log y_{it}$ can be derived from equation 1 and can be written as follows:

$$\log y_{it} = \left(\varphi_i + \frac{\varepsilon_{it}}{\mu_t}\right)\mu_t = \delta_{it}\mu_t \quad (2)$$

Where both the error term and the unit specific component are condensed into δ_{it} which then represents the idiosyncratic part that varies over time. It represents the share (δ_{it}) of the common growth path μ_t that the i-th economy goes through. This transition coefficient (δ_{it}) is modeled in such a way that the common growth path is eliminated. A relative transition coefficient, h_{it} is constructed from δ_{it} as follows:

$$h_{it} = \frac{\log(y_{it})}{N^{-1}\sum_{i=1}^{N}\log(y_{it})} = \frac{\delta_{it}}{N^{-1}\sum_{i=1}^{N}\delta_{it}} \quad (3)$$

Hence, h_{it} represents the transition path of i-th economy relative to the cross-section average that is it measures the individual behavior in relation to other economies. In case of convergence, i.e. when all economies move towards the same transition path, $h_{it} \rightarrow 1$, for all i as $t \rightarrow \infty$. Then the cross sectional variance of h_{it}, denoted by $V_t^2 = N^{-1}\sum_i (h_{it} - 1)^2$, converges to 0. In order to specify the null hypothesis of convergence, PS model δ_{it} in a semi-parametric form:

$$\delta_{it} = \delta_i + \frac{\sigma_i \varepsilon_{it}}{L(t)t^{\alpha}} \quad (4)$$

Where δ_i is fixed, σ_i is an idiosyncratic scale parameter, ε_{it} is iid (0, 1), L (t) is a slowly varying function (such that L (t) $\rightarrow \infty$ when t $\rightarrow \infty$) and α is the decay rate. The null hypothesis of convergence can be written as: $H_0: \delta_i = \delta$ and $\alpha \geq 0$ and it is tested against the alternative $H_A: \delta_i \neq \delta$ for all i or $\alpha<0$. Under this null hypothesis of convergence various transitional patterns of economies i and j are possible, including temporary divergence, which refers to periods where $\delta_i \neq \delta_j$. Therefore, this method can detect convergence even in the case of transitional divergence, where other methods such as stationary tests for e.g. Hobijn and Franses, 2000 fail (Bartkowska and Reidl, 2012). PS show that under convergence the cross-sectional variance of h_{it} has the limiting form,

$$V_t^2 \sim \frac{A}{L(t)^2 t^{2\alpha}} \text{ as } t \rightarrow \infty \text{ for some } A>0 \quad (5)$$

The following regression based convergence test can be derived from above:

$$\log\left(\frac{V_1^2}{V_t^2}\right) - 2\log L(t) = a + b\log t + u_t \quad (6)$$

for t= [rT],[rT]+1……T where r is the initiating sample fraction and general r Є (0,1) and L(t) is a slowly varying function. The log t procedure depends on the choice of the slowly varying function L (t) and 'r'. Rejection rates of the log t test depend on combinations of r, α, N and T. The authors suggest that since value of α is not known so for purposes of empirical application, value of r must be chosen in such a way so that firstly, size will be accurate when α is close to zero, secondly, for which size is not too conservative when α is larger and thirdly for which power is not substantially reduced by the effective sample size reduction. Their Monte Carlo simulation results indicate that r=0.3 seems to be a preferable choice when sample size is below T=50 to secure size accuracy in the test for small α. Simulation tests involving varying the L(t) function showed that the test is conservative when L(t) = log t is used in the regressions. Hence, in this study with a sample size of less than T=50, suggestions by authors have been strictly followed and r=0.3 and L (t) =log t have been used for the analysis. Using $\hat{\beta} = 2\hat{\alpha}$ for the log t regression, a one sided t-test robust to heteroscedasticity and autocorrelation (HAC) is applied to test the inequality of the null hypothesis α≥0.The null hypothesis of convergence is rejected if $t_{\hat{b}} < -1.65$ (at 5 per cent level of significance). PS state that in case null of convergence is rejected, many possibilities exist for example possible existence of convergence clusters around separate points of equilibria or steady state growth path or cases where there may be possibility of coexistence of convergent clusters and divergent members in the full panel.

If the null hypothesis of convergence is rejected for the overall sample, PS suggests applying the following step-wise cluster mechanism to subgroups:

1. The cross-sectional units are ordered by final observation in descending order as according to them, when there is evidence of multiple club convergence as $T \rightarrow \infty$, this is usually most apparent in the final time series observations.
2. Core group is identified- The first k units of the panel are taken such that $2 \leq k < N$ and log t regressions (as discussed above) are run and $t_{\hat{b}}$ is calculated for the k selected units each time adding further units one by one. These log t regressions are run as long as $t_{\hat{b}}$ keeps on increasing and is larger than -1.65. Once, a smaller value of $t_{\hat{b}}$ is obtained, it can be concluded that the core group with $k^*=k-1$ members is formed. If that $t_{\hat{b}}>-1.65$ does not hold for the first two units, the first unit is dropped and the log t regression is run again for the second and the third unit and so on till $t_{\hat{b}}>-1.65$ is reached for the two units and then again the same process is repeated. If there are no two units for which $t_{\hat{b}}>-1.65$, it can be concluded that there are no convergence clubs in the panel.
3. New club members are added to the core group- One additional unit is added to the core group and the log t regression is run. This is repeated for all the units outside the core group. Units where $t_{\hat{b}}>c$ where c is critical value ($c \geq 0$) are selected and added to the core group. The authors suggest using conservative critical value as it reduces the chances of including a false member into the group. There is a problem with this approach i.e. chances are that more number of converging groups are identified than what exist. To correct this problem Philips and Sul (2009) suggest a merging procedure[6]. Then the log t regression is run for the whole group. If $t_{\hat{b}}>-1.65$, it can be concluded that all these members are part of the same convergence club otherwise, the critical value is increased for the club membership selection and the process is repeated till $t_{\hat{b}}>-1.65$ for the entire group. Then it can be concluded that these units

[6]Philips and Sul (2009) suggest a test for merging between the groups formed according to the clustering algorithm (steps 1 to 4) where the log t test is run on the first two groups. If the t-statistic is larger than -1.65 (5 per cent level of significance), both the groups are merged to form a group. The test is repeated after adding the next group until the t-statistic indicates that the convergence hypothesis is rejected and the step is repeated until it is concluded that the remaining groups do not merge with each other.

form a convergence club. If there are no units apart from the core group that result in $t_{\hat{b}}>-1.65$, it can be concluded that the convergence club consists only of the core group.

4. Recursive and stopping rule- A second group is formed consisting of all units outside of the convergence club, i.e. where $t_{\hat{b}}<c$. The log t test is run for the entire group to check whether $t_{\hat{b}}>-1.65$ and the group converges. If not steps 1 to 3 are repeated on this group to determine whether the panel includes a smaller subgroup that forms a convergence club. If there is no k in step 2 for which $t_{\hat{b}}>-1.65$, it can be concluded that the remaining units diverge.

FIGURES

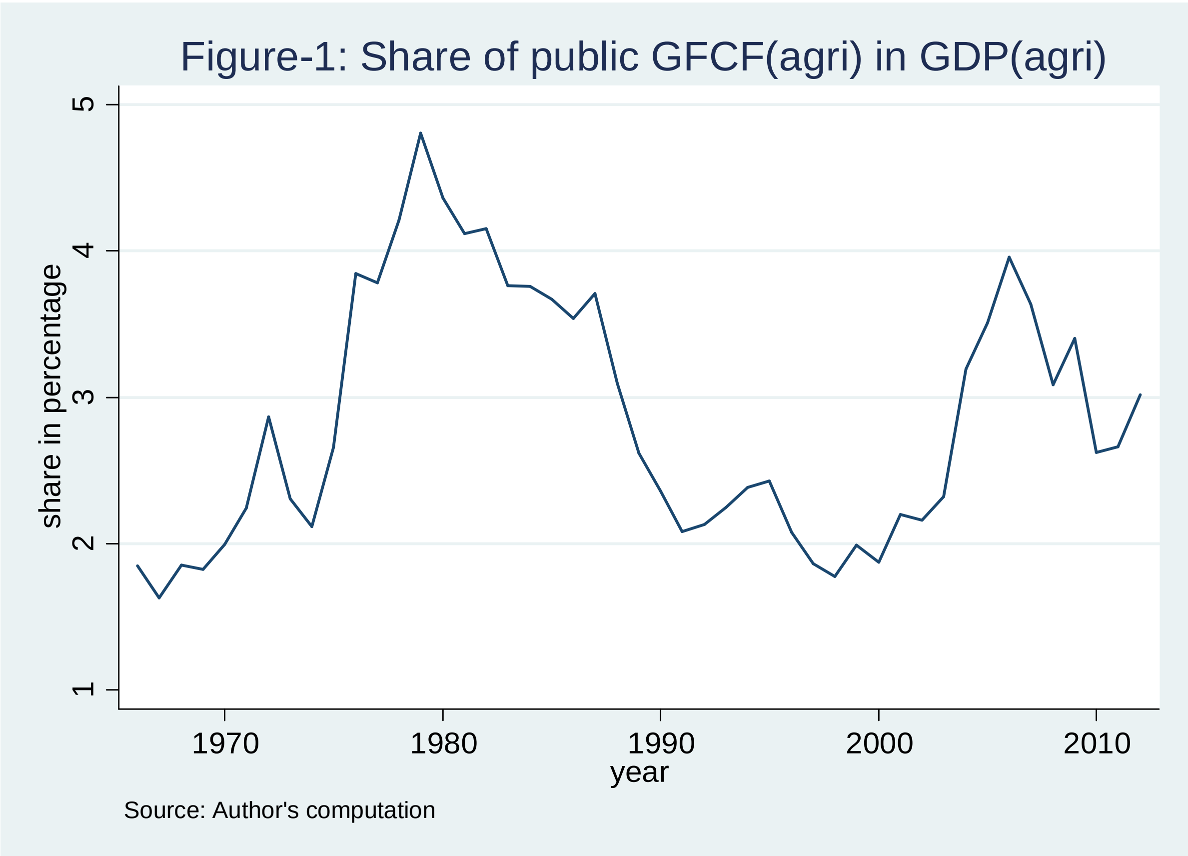


Figure-1: Share of public GFCF(agri) in GDP(agri)
share in percentage
1
2
3
4
5
1970
1980
1990
2000
2010
year
Source: Author's computation

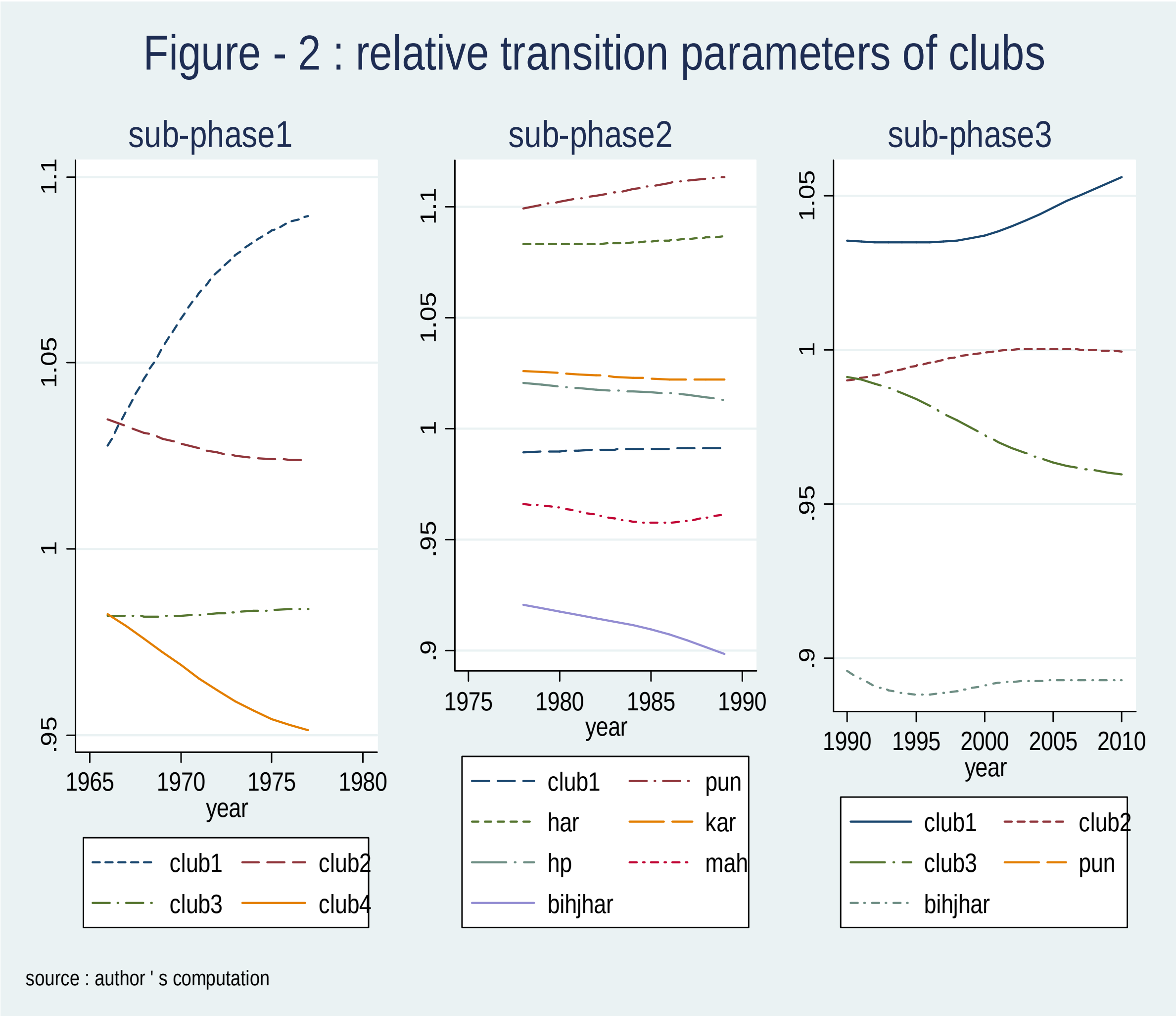
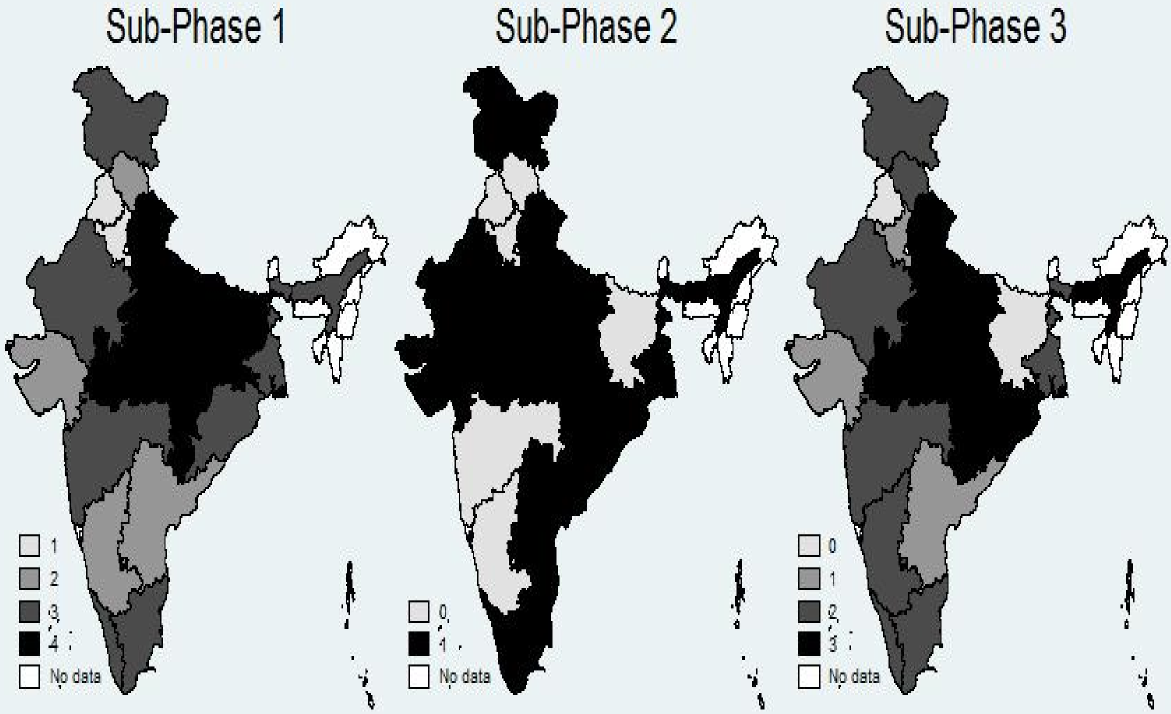


Figure - 2 : relative transition parameters of clubs
sub-phase1
sub-phase2
sub-phase3
1.1
1.05
1
.95
.9
1965
1970
1975
1980
1985
1990
1995
2000
2005
2010
year
club1
club2
club3
club4
pun
har
kar
hp
mah
bihjhar
source : author ' s computation

Figure - 3 : Spatial pattern of Clusters



Same colour scheme indicate same income clusters and 0 implies divergent states

Source : author ' s computation

TABLES

TABLE 1- Agricultural performance across states in India								
	per capita income levels (in Rs.)				Compound growth rate(%)			
State	1966	1977	1989	2010	1966-2010(total time period)	1966-77(sub-phase1)	1978-89(sub-phase2)	1990-2010(sub-phase3)
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	3.5	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	2.2	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	0.5
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	41.3	40.04	49.22	46.77	39.26	51.75	78.37	49.87
Source: author's computation								

Table 2: Members of the clusters-phase wise					
Sub-phase1					
club	**no of states**	**members**	**t-stat**	**per capita income in Rs. (final year)**	**average annual growth rate (%)**
one	2	Punjab, Haryana	-0.3333	9871	17.33
two	4	Gujarat, Karnataka, HP and AP	2.2039	5779	10.56
three	8	JK, Assam, Rajasthan, TN, Kerala, WB, Orissa, Maharashtra	1.7193	4269	9.98
four	3	UP, MP and Bihar	7.9422	3371	8.66
Sub-phase2					
one	11	AP, Gujarat, MP, JK, Assam, Orissa, Rajasthan, WB, UP, TN, Kerala	-0.1062	5138	3.43
divergent states	6	Punjab, Haryana, Karnataka, HP, Maharashtra and Bihar			
Sub-phase 3					
one	3	Haryana, AP, Gujarat	2.1818	12191	3.53
two	8	Karnataka, Maharashtra, Kerala, HP, WB, TN, JK, Rajasthan	2.4131	7403	2.59
three	4	MP, Orissa, UP, Assam	6.8639	5251	0.89
divergent states	2	Punjab, Bihar			
source: authors computation					

Table 3: Results of the logistic models

	all state-pairs			contiguous state-pair	non contiguous state-pair	
Variable	irri_deflator	irri_market	power	market	market	deflator
Variable	[1]	[2]	[3]	[4]	[5]	[6]
per capita tractor	-5.549***	-5.269***	-7.742***	-8.341@	-5.692***	-6.296***
market per cropped area(final)		-11.358***	-11.122***	-21.701**	-8.776*	
irrigation	-2.270***	-1.774**			-2.255***	-2.639***
power per cropped area			-1.356@			
per cap agri exp(final)	-0.137***	-0.147***	-0.115***	-0.587***	-0.091*	-0.082*
growth in total road density	-2.48e-4*	-2.51e-4*	-2.14e-4*	-2.37e-4***		
total road density					-0.350**	-0.265
share of fibre(final)	-8.438***	-8.686***	-6.364**	-13.840***	-6.254**	-5.632*
deflator	-5.731*					-9.648***
abs. deviation of rainfall	-0.027**	-0.030**	-0.025**		-0.030**	-0.026*
state3	-2.382***	-2.587***	-2.264***			
state5	-2.512**	-2.539**				
state7	2.275***	2.234***	2.182***		2.365***	2.533***
state8	-1.419**	-1.486**				
state9	1.048**	1.118**	1.441***		1.215**	1.234**
state14			1.824*			
constant	1.544***	1.703***	1.038***	1.768**	1.598***	1.513***
STATISTICS						
No. of observations	408	408	408	96	312	312
AIC	409.735	406.69	422.456	101.249	334.95	331.014
BIC	461.882	458.836	470.591	116.635	372.38	368.444
log-likelihood	-191.868	-190.345	-199.228	-44.625	-157.475	-155.507
pseudo-R-sq.	0.249	0.255	0.219	0.218	0.204	0.214

@: p<0.15, *:p<0.10, **:p<0.05, ***:p<0.01. Final year values were used for market and state expenditure as data prior to year 1976 and 1972 respectively is not available

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