Business Analyst, ISSN 0973 - 211X, 41(2), 3-23, ©SRCC

HETEROGENEOUS GROWTH TRAJECTORIES OF INDIAN STATES: GROWTH REGRESSIONS THROUGH THE LENS OF CLUB CONVERGENCE

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ABSTRACT

This paper examines the growth trajectories of Indian states. We find that not only is the disparity among states increasing, there is evidence that the distribution of the per-capita income of states is becoming bimodal. We use the methodology of Phillips and Sul (2007) to identify convergence clubs among Indian states and find three clubs. Furthermore, in a novel application of this methodology we use the identified clubs to run separate growth regressions for different clubs of states and find significant differences in the regression coefficients. This vindicates our approach and shows that combining data from all states at the same time to study growth dynamics can be misleading in a heterogenous country like India.

Keywords: Club Convergence, Conditional Convergence, Growth Econometrics, Growth Experience of Indian States.

INTRODUCTION

This paper draws on two strands of empirical literature on growth. The first is the growth regression tradition of Barro (1991) and specifically the literature on conditional convergence. In this literature regressions are run using panel data on nations or sub-national units to determine whether there is a tendency of cross-

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[**] The author would like to thank seminar participants at Sri Venkateswara College and Centre for the Study of Regional Development, JNU and an anonymous referee for their valuable comments.

sectional units to converge and to understand the determinants of economic growth. The second strand of literature that we draw upon is the literature on club convergence. This literature tries to develop methods of identifying convergence clubs, which are defined to be clusters of cross-sectional units with similar growth trajectories. The novel contribution of this paper lies in taking an algorithm developed for identifying club convergence and using it further as an input into growth regression analysis to overcome problems arising from heterogeneity in growth dynamics among cross sectional units.

Conditional convergence and growth regressions

Neoclassical growth theory begins with the Solow-Swan model which considers a single-good economy with a constant savings rate, constant returns to scale and diminishing returns to capital. The Solow-Swan economy has a unique steady state determined by technology, the savings rate and the population growth rate. Regardless of its starting point the economy asymptotically converges to that steady state. Therefore, a set of identical economies starting from different initial conditions will ultimately converge to the same steady state level of per-capita income and capital stock. Moreover, during this process of convergence countries with lower initial per-capita income will grow faster in order to catch up with the countries with higher initial per-capita income. Similar properties continue to hold in extensions of the Solow-Swan model that introduce additional forms of capital such as human capital and endogenous or exogeneous technological change.

These predictions of the Solow model have formed the basis of a large literature that empirically studies convergence of per-capital income between countries or between sub-national regions. A number of different convergence concepts have been used in this literature. The first, unconditional convergence or absolute convergence, requires that the poorer countries (or regions) grow faster than the richer ones so that they converge to a common steady state. This kind of convergence would be a consequence of Solow-like models only if all the countries were identical except for their initial level of per-capita income and capital, something which seems unlikely to hold true. It is therefore not surprising that evidence of unconditional convergence has been hard to find.

The next convergence concept, conditional convergence, on the other hand only requires only that countries converge after controlling for some set of exogeneous variables. These variables serve as a proxy for the technological and institutional determinants of the steady state in Solow-type models. Therefore, knowing the set of exogenous variables which ensure conditional convergence is interesting in itself since this allows us to form an idea about the long-run prospects of countries and the means by which these prospects may be improved.

The definition of convergence we have been using in terms of poor countries growing faster than rich ones is known as β convergence. The most basic test for β convergence is the log-linear version of the neoclassical growth model with the growth rate of per-capita income as the dependent variable and per-capita income as the independent variable.

$$\log(y_{it}/y_{i,t-1}) = \alpha_{it} + \beta \log y_{it} + \mu_{it}$$

This model is estimated and a null hypothesis of $\beta = 0$ is tested against the alternative $\beta < 0$,. A rejection of the null is taken as evidence of convergence since a negative β implies that richer countries have slower growth. Now if in the above equation if we add a vector of exogenous explanatory factors that might determine the steady state of output per capita, say *X*, then the same hypothesis test on β gives us a test for conditional convergence.

Thus, we see that the concepts of absolute and conditional convergence are related. Absolute convergence is the special case of conditional convergence in which the set of exogeneous variables is empty, that is, there is common steady state across regions/countries. On the other hand conditional convergence does not imply absolute convergence. A set of countries converging conditionally can fail to converge absolutely if they differ greatly in their values of *X*.

Along with this notion of β convergence, another notion of convergence which has been discussed in the literature is that of σ convergence. A set of cross-sectional units is said to σ converge if the standard deviation of their per-capita incomes decreases over time.

Studies of developed countries, have found evidence for both absolute convergence and conditional convergence. Barro and Sala-i-Martin (1992) found unconditional convergence for the 48 states of the US for the period between 1840-1988. However, for a sample of 98 countries they found only conditional convergence after adding factors like school enrollment rates at primary and secondary level, ratio of government consumption to GDP and political stability as control variables. Rodrik (2013) found strong unconditional convergence in labour productivity for manufacturing industries, regardless of geography, policies, or other country-level influence.

Coulombe and Day (1999) carried out a comparative analysis of regional disparities in per capita production in Canada and 12 US states by examining three factors—dispersion of productivity, the dispersion of employment rates and the dispersion of participation rates. They found convergence between Canadian provinces and the bordering U.S states. Persson (1997) found similar results for 24 Swedish regions for the period 1911-93. Gezici and Hewings (2000) examined the interregional disparities and core-periphery relations in Turkey for the period 1980-97. They analyzed both β and σ (absolute and conditional) convergence, but their empirical work does not show convergence across either provinces or functional regions in Turkey. Yao and Weeks (2003) examined income convergence between China's coastal and interior provinces between the two periods, 1953-1977 and 1978-97, taking into account the province specific factors, such as initial technology and technological progress. Their finding was that income diverges during the latter reform period because of the difference in the rate of technological progress between the coastal and the interior provinces. Petrakos and Saratsis (2000) examined regional inequalities in Greece between for the 1970s and 1980s on the basis of beta and sigma convergence by taking into account specific factors like the quality of human capital, tourism development, structure of local industry, process of EU expansion as important factors explaining regional growth. Another important finding was that in Greece regional inequality was procyclical, that is, it increased during expansion phase and decreased during recessions.

Club convergence

An influential strand of literature starting with Durlauf and Johnson (1995) takes seriously the possibility of multiple growth regimes and club convergence where countries form "clubs" such that countries within a single club converge over time but there is no tendency for the different clubs to converge. Durlauf and Johnson showed that such behaviour is possible if there are nonconcavities in the production function, in which case different initial conditions not only produce different asymptotic steady states but also different dynamics for different countries. Further they showed that if the real data is generated through such a process then trying to fit a single growth regression over all countries will not give a true picture of actual convergence behaviour.

Durlauf and Johnson empirically substantiated their argument by first splitting the cross-section of countries under study on the basis initial output and literacy rates and fitting growth regressions separately to each group of countries. They found a substantial difference in the regression coefficients for different groups of countries, thus proving that it would be incorrect to fit models that assume the same law of motion for all countries.

Next, they adopted the regression tree approach of Breiman (1984) to discover data-driven splits in the set of countries that best produces homogeneous behaviour within each group. The algorithm yielded four groups of countries within which once again they found a big difference in coefficients of growth regressions.

Later literature has used time-series methods to identify convergence clubs. These methods take the entire trajectory of some macroeconomic time series (say the series of per-capita income) for each cross-sectional unit and cluster together those units whose time-series trajectories remain together in some sense.

For example, Pesaran (2007) suggested testing for convergence among some set of N cross-sectional units by considering all possible $N(N - 1)/2$ pairs of units and testing for the stationarity of the output gap for each such pair. If there is no convergence the null hypothesis of non-stationarity will be rejected for approximately α proportion of the pairs where α is the size of the significance test being run on each pair. On the other hand, if non-stationarity is rejected for a proportion of pairs greater than α then this provides evidence of convergence.

Hobijn and Franses (2000) use multivariate stationarity tests and clustering algorithms to identify convergence clubs. Their clustering algorithm is initialized by placing each country in a separate cluster by itself. Then a coalescing step is run multiple times which combines pairs of clusters as long as there is strong evidence of two clusters converging together. The clusters which survive till the end of the process constitute the final convergence clubs.

In contrast to this "bottom up" approach, Beylunioğlu, Stengos and Yazgan (2018) propose a "top down" approach to clustering. They describe their clustering algorithm in the language of graph theory, with the countries forming vertices and there being an edge between a pair of countries if the pair converges according to Pesaran's pairwise convergence criteria discussed above. They then use algorithms from computer science to identify "maximum cliques", i.e. maximal sets of countries each of whose elements is connected to each other element pairwise. These they identify as convergence clubs.

Phillips and Sul (2007) use a nonlinear time varying factor model to analyze club convergence. They decompose a time series into a time-varying common factor and an idiosyncratic trend. They develop a non-parametric statistical test to test for the idiosyncratic factor converging to a constant, which would mean that the cross-sectional units under consideration converge to a common trend. In turn they use this test to identify clusters (clubs) of cross-sectional units which converge to each other, even though there may be no convergence across these different clusters. This is the approach we will follow in this paper. We shall discuss their method in greater detail in Section 3.

Literature on the growth experience of Indian states

In India there have been several studies on regional inequality and convergence. Most of these studies have found evidence of conditional convergence but not of absolute convergence. Also, most of these studies have found that confirmed that the regional divergence in terms of per capita income has been going up in India.

There are number of studies that have found the evidence of conditional convergence in India (Nagraj 2000, Aiyar 2001, Sachs, Bajpai, Ramiah 2002). Nagraj (2000) examined the growth performance of Indian states during 1970-94 and found evidence for conditional convergence. He found infrastructure, primary education, health conditions to be important specific factors determining states' steady states. Aiyar's work on regional disparity examined absolute and conditional convergence of 19 Indian states for the time period 1971-96. His results do not confirm absolute convergence but find evidence of conditional convergence. He identified literacy and private investment as an important factor in determining regions' steady state.

Sachs, Bajpai, Ramiah (2002) carried out a comparative analysis of the regional disparity between fifteen major states in India between the pre- and post-liberalization period based on α and β measures of convergence. They found that the disparity of income among states, during the time period 1980-1998, as well as between the pre- and the post-reform period has increased. For the post-reform period their work shows convergence within the rich states but divergence among the poor states.

Trivedi (2003) examined the regional convergence of per-capita income in levels as well as growth for Indian states from 1960 to 1992, using OLS, the within-group

LSDV estimator, Re-Weighted Least Squares, and Least Trimmed Squares estimators. His results show no evidence for unconditional convergence but strong and robust evidence of conditional convergence, i.e after controlling for the factors like education, human capital and physical capital, poor states grow faster than the rich states. His analysis of the income distribution of states found the emergence of an incipient bimodal distribution. Another paper that has analyzed the relative performance of 15 major states in India was by Ghosh (2006). His study period was between 1981-2001 in which he found that states have been converging in terms of per-capita income but diverging in terms of HDI.

The club convergence phenomenon has also been studied in the Indian context. Though the study by Baddeley, Kirsty and Cassen (2006) did not find club convergence among Indian states but did find evidence of conditional convergence. Also, according to them the 1991 economic reforms have intensified the growth differential between the states. But the two studies, one by Bandyopadhyay (2011) and another by Ghosh, Ghoshray and Malki (2013) have identified the club convergence in India. Bandyopadhyay's study (2011) that cover the period between1965 to 1997 has identified two convergence clubs, one at 50% and another at 125% of the national average income. Also, they found that this increasing clustering is correlated with the unequal distribution of infrastructure. by Ghosh, Ghoshray and Malkin (2013) paper studied club convergence both at aggregate and sectoral level for 15 major states for the time period 1968-69 to 2008-09 using the same Philips and Sul method that we use. They identified three clubs at the aggregate level. At sectoral level, they identified three clubs at the industrial level, two clubs at the agriculture and services sectors.

DATA

We use annual data on NSDP for the period 1970-71 which we use in our exploratory analysis and for identifying convergence clubs.[3] We run our growth regression for the

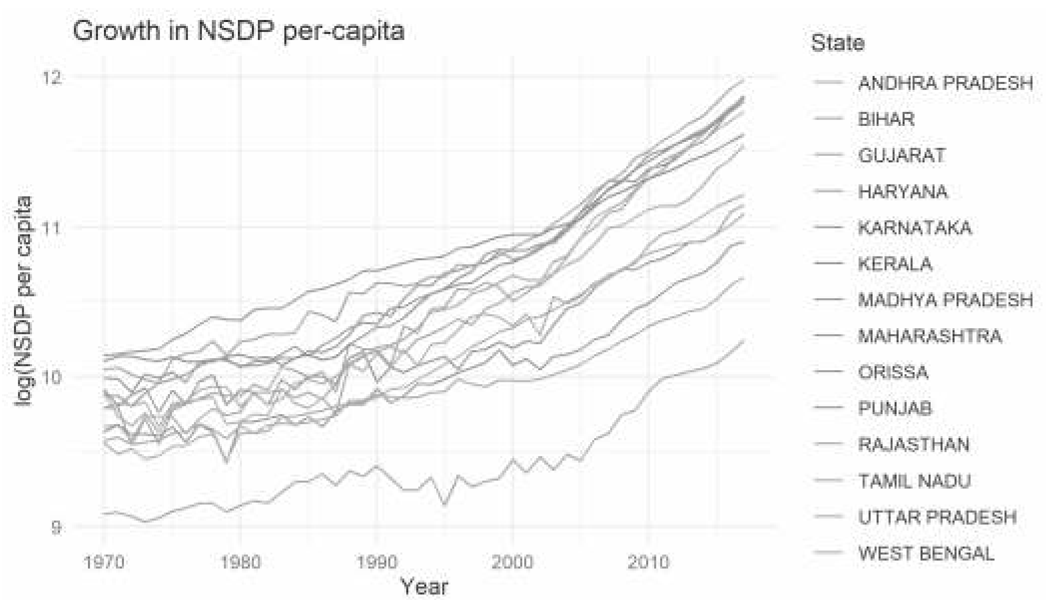
[3] The data is sourced from RBI's Database on the Indian Economy

period 1991-92 to 2017-18. These regressions use additional control variables which we describe later. Both these studies are carried out for fourteen major Indian states.[4]

Descriptive Statistics

Figure 1 plots NSDP per-capita for the major states of India from 1970-71 to 2017-18. The great disparity between the states of India in terms of per-capita income is quite clear from this figure. And this disparity has only been growing. For instance, in 1970-71 the income differential between the richest and the poorest (Punjab and Bihar) was about 2 times, which rose to 5 times (Haryana and Bihar) in 2017-18. It is clear from figure that the relative position of states has not changed much. To a large extent the states which were initially rich have remained rich and those which were poor have remained poor.

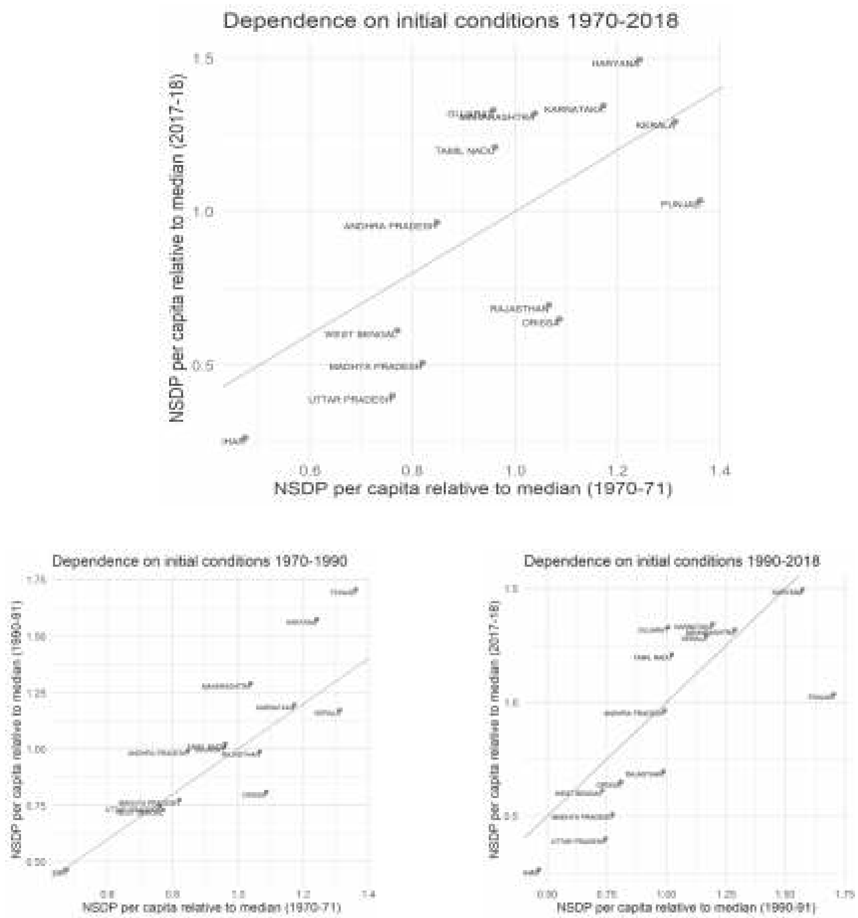
Figure 1 : Growth in NSDP per capita



[4] The states are Andhra Pradesh, Bihar, Gujarat, Haryana, Punjab, Karnataka, Kerala, Maharashtra, Tamil Nadu, Madhya Pradesh, Orissa, Rajasthan, Uttar Pradesh and West Bengal.

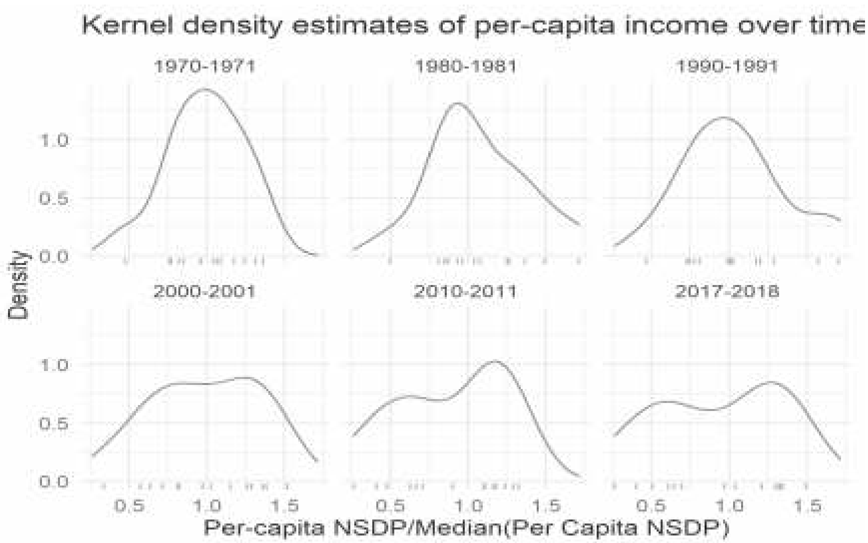
To show the absence of mobility in the income distribution we plot NSDP per-capita of states in an initial year against NSDP per-capita in a later year. In the top panel of Fig 2 the initial year is 1970-71 and the final year is 2017-18. The orange line is the 45° line. The data is clearly clustered in an upward rising direction, showing that states that were poor in earlier periods also were poorer in the later periods and vice-versa. The two subfigures in the bottom panel show that the lack of convergence persists even when we look at the subperiods 1970-71 to 1990-91 and 1990-91 to 2017-18. The lack of convergence is thus a phenomena of both the pre- and post-liberalization periods.

Figure 2 : Dependence on initial conditions



Next, we visualize the changes in distribution of per-capita income across states by plotting kernel-density estimates of per-capita income at decadal intervals. Since we are interested in the distribution of per-capita income and not in its overall level, we normalize each year's income by dividing by the median across states for each year.

Figure 3.4 : Kernel density estimates of per-capita income over time



The figures again show the growing disparity in per-capita income across states. But a further issue now comes to light. Not only is the distribution of income becoming wider, its shape is changing. In the post-liberalization period, the distribution of per-capita incomes is moving from a unimodal to a bimodal distribution. Not only are the states growing more disparate, there seems to be a segregation happening between the rich and the poor states.

CLUB CONVERGENCE

One objective of our study is to understand the convergence behaviour and growth dynamics of Indian states. But as the literature discussed above shows, it might be misleading to apply a single growth regression to the entire set of states in case the states differ in their growth dynamics and the steady state depends on the initial conditions.

Therefore, we use the methodology of Phillips and Sul (2007) to first cluster the states into convergence clubs and then fit growth regressions on each of the convergence clubs separately.

In the framework of Philips and Sul a time series X_{it} for the cross sectional unit i is decomposed into a common factor μ_t and a loading coefficient δ_{it} according to $X_{it} = \delta_{it}\mu_t$

In above equation, δ_{it} is allowed to depend on time to account for idiosyncratic shocks as well as other heterogeneities between cross sectional units. In this framework Philip and Sul study the question of convergence by investigating the null hypothesis $H_0 : \delta_{it} \to \delta$ for some δ as $t \to \infty$ for which they develop a novel a test statistic.

Further they used this test statistic to develop the automatically clustering algorithm for discovering convergence clubs as well as divergent cross-sectional units. The algorithm works as follows:

1. The cross-sectional units are ordered by the value of the variable of in the last period.

2. An initial core convergence cluster is identified from among the cross-sectional units with the highest final values of the variable using the convergence test statistic.

3. Cross-sectional units not in this initial core are added one by one to the core as long as the test statistic of the convergence test does not go outside an acceptable bound.

4. From the remaining cross sectional units, the algorithm tries to form a second

core convergence group. If such core group can be found the procedure is repeated from step 3 onwards. Otherwise the remaining cross-sectional units are considered to be divergent.

This method has the advantage over others that it does not require any assumption regarding the stationarity in trend. Also, the non-parametric nature of the method allows for a wide range of variations over time and across individuals to be accommodated.

We apply the Phillips and Sul clustering algorithm to the per-capita NSDP at constant prices of major Indian states for the period 1970-71 to 2017-18. The algorithm yields the following clubs:

Table 3.2 : Convergence clubs

Club 1	Club 2	Club 3	Divergent
Punjab, Kerala, Haryana, Karnataka, Maharashtra, Tamil Nadu, Gujarat, Andhra Pradesh.	Orissa, Rajasthan, West Bengal.	Uttar Pradesh, Bihar	Madhya Pradesh

The first club captures the relatively high-income states and their forming a convergence club is consistent with our earlier observation of the richer clubs forming a cluster giving the distribution of income a bimodal shape.

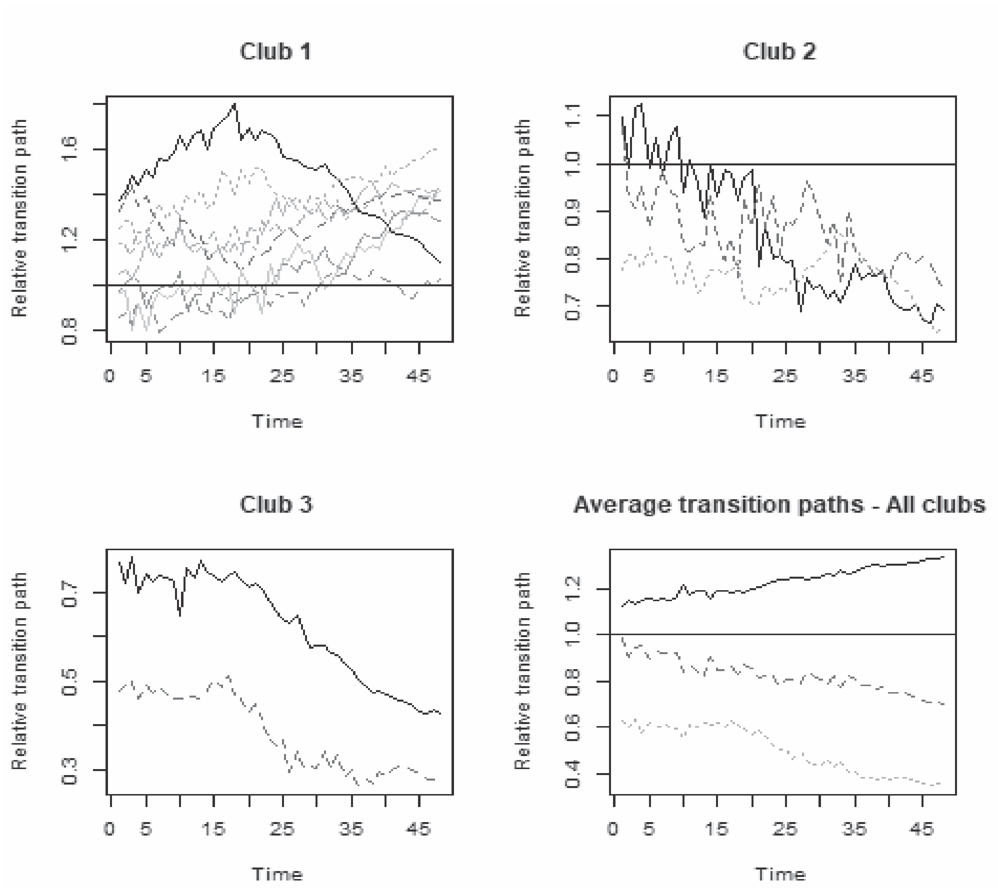
More interestingly, the poor states do not form a single convergence club. Instead, they split into three groups. Thus our convergence club analysis produces evidence of incipient stratification among the poorer states, something which was not obvious from our previous analysis.

These trends are illustrated in Figure 3 which shows the transitional trajectories for the convergence clubs by plotting the per-capita income of each state relative to the national average.

Club 1 contains states with a wide range in terms of per-capita income (though most of them do better than the national average for most of the period of study). States in this club change their relative position in our period of study. Yet, they remain clustered together, justifying their inclusion in the same convergence club.

As we can see from the trajectories, club 2 and club 3 are falling further and further behind the national average while at the same time tending to grow apart from each other.

Figure 3 : Transition paths



Growth Regressions

Next, we fit growth regressions to panel data for each of the clubs separately for the years 1991-92 to 2017-18. The regressions are dynamic panel regressions of the form:

$$Y_{it} = \alpha + (1+\beta)Y_{i,t-1} + \beta_2 X_{it} + \mu_{it}$$

where Y_{it} is the log per capita GSDP, X_{it} is the control variables, and μ_{it} is the error term.

Our control variables include various economic and social factors: the share of agriculture in GSDP *(agrishare)*, log of per capita gross fixed capital formation (in constant prices), log of per capita total government capital expenditure (at constant prices), log of per capita total government revenue expenditure (at constant prices) and the literacy rate. Data on the literacy rate is interpolated by the author from census data. The other data are from the RBI databases *Handbook of Statistics on Indian States* and *State Finances: a study of budgets.* We also include two political control variables: *Match* is a dummy variable which is one for a state-year combination if the chief minister of the state in that year belong to a party that is a member of the ruling coalition at the Centre. This variable captures the political alignment between the centre and the state government, since such alignment might give the state a greater share of central transfers and more favourable treatment from the Centre. *Fragcoalition* is a dummy variable which is one if the government in the state is the coalition government in which more than one party is pivotal. This is used a proxy for the degree of political competition. The series for these two political variables were constructed by the author based on Election Commission data.

In above analysis if $1 + \beta < 0$, will indicate conditional convergence, since we have the per-capita income and not the growth rate on the left-hand side

Since the model includes the lagged value of the left-hand variable on the right hand-side we must take into account the possibility of endogeneity bias. We therefore estimate the model using both Arellano and Bond (1991) and Blundell and Bond (1998) methods.

The estimates obtained are reported in the tables below, where the first column gives estimates on the data set containing all states while the next three columns give regression results for estimates restricted to each of the three convergence clubs identified in Table 3.2:

Table 3.3 : Estimation results: growth regressions (Arellano-Bond). The dependent variable for all the regressions is log GSDP per capita. Figures in brackets are p-values.

	All India	**Club 1**	**Club 2**	**Club 3**
First lag of Log GSDP-per capita (p-values are for the test of the null hypothesis of the coefficient being equal to 1)	0.848*** *(0.00)*	0.834*** *(0.000)*	0.525*** *(0.000)*	0.612*** *(0.009)*
Match	0.014** *(0.04)*	0.006 *(0.354)*	0.008 *(0.623)*	0.046* *(0.054)*
Frag coalition	0.020** *(0.02)*	0.0005 *(0.951)*	0.012 *(0.615)*	0.004 *(0.891)*
Literacy rate	0.006*** *(0.00)*	0.01086*** *(0.00)*	0.017*** *(0.001)*	0.0128** *(0.021)*
Agrishare	0.0019** *(0.02)*	6.88e-06 *(0.994)*	0.003** *(0.022)*	0.008** *(0.046)*
Log GFCF	0.020*** *(0.00)*	0.0277*** *(0.000)*	0.022** *(0.027)*	0.009 *(0.554)*
Log total govt. capital expenditure	0.029*** *(0.001)*	0.024*** (0.006)	0.014 (0.502)	0.023 (0.676)
Log total govt. revenue exp	0.039 *(0.103)*	-0.0080 *(0.706)*	0.222*** *(0.003)*	0.053 *(0.678)*
Constant	0.426* *(0.010)*	0.750*** *(0.000)*	1.54*** *(0.001)*	2.206* *(0.068)*

Table 3.3 Estimation results: growth regressions (Blundell-Bond). The dependent variable for all the regressions is log GSDP per capita. Figures in brackets are p-values.

	All India	**Club 1**	**Club 2**	**Club 3**
First lag of Log GSDP-per capita (p-values are for the test of the null hypothesis of the coefficient being equal to 1)	0.824^{***} *(0.00)*	0.841^{***} *(0.00)*	0.657^{***} *(0.00)*	0.724^{***} *(0.00)*
Match	0.015^{**} *(0.017)*	0.011^{*} *(0.077)*	0.021 *(0.163)*	0.054^{***} *(0.005)*
Frag coalition	0.023^{***} *(0.006)*	0.006 *(0.497)*	0.000 *(0.965)*	0.028 *(0.145)*
Literacy rate	0.005^{***} *(0.00)*	0.009^{***} *(0.00)*	0.003 *(0.221)*	0.011^{***} *(0.00)*
Agrishare	0.001^{*} *(0.08)*	0.000 *(0.932)*	0.003^{**} *(0.041)*	0.009^{***} *(0.004)*
Log GFCF	0.023^{***} *(0.00)*	0.022^{***} *(0.00)*	0.032^{***} *(0.00)*	0.021^{***} *(0.009)*
Log total govt. capital expenditure	0.031^{***} *(0.00)*	0.029^{***} (0.00)	0.015 *(0.499)*	0.079^{**} (0.037)
Log total govt. revenue exp	0.072^{***} *(0.00)*	0.008 *(0.647)*	0.281^{***} (0.00)	*-0.032* *(0.747)*
Constant	0.502 *(0.00)*	0.664^{***} *(0.00)*	*0.591** *(0.064)*	*1.406**** *(0.008)*

Since the coefficient of log PCY_{it-1} for all India as well as for all the three clubs is less than one and statistically different from zero, this indicates that there is a strong evidence of conditional convergence. But this overall picture of conditional convergence hides two important features of the actual growth trajectory of Indian states. First, the fact that the states are becoming polarized into different convergence clubs, which is seen both in the kernel density estimates of the distribution of per capita income of the states India and in the more formal Philips and Sul clustering analysis. Second the separate estimates of the groups of states shows considerable heterogeneity in the estimated regression coefficients, even for the same model specifications. Though all the three clubs and the overall India picture is showing convergence, the rate of convergence is quite different across clubs. This reconfirms the existing criticism in the literature of Barro type regression that impose a common model on the heterogenous set of cross-sectional units.

In the above table, fiscal variables are measured through log of total capital and log of total revenue government expenditures. Fiscal variables are positive and statistically significant in for all the categories except for club 3. But different fiscal variables are significant for different clubs: the log of total capital expenditure is statistically significant for overall India and club 1, but the log of total revenue expenditure is statistically significantly for club 2. This shows that government expenditure works differently for states at different level of development, possibly because government capital expenditure can be effective only in the presence of other complementary inputs and a conducive institutional environment.

Our socio-demographic factors literacy rate and share of agriculture in total GSDP is statistically significant for all most all the three clubs (except that the share of agriculture is statistically insignificant for club 1).

Lastly we come to the political factors which are captured by *Match* and *Fragcoalition*. While both these variables are significant when all states are considered in one model, they are mostly statistically insignificant when regressions are run separately for each club. Given the heterogeneity of the regression models for the different clubs we should therefore consider the result for the overall sample to be spurious and the true conclusion to be that these political variables have no impact on growth once the level of government expenditure is controlled for.

CONCLUSION

The convergence club analysis of our paper shows that the states of India are becoming stratified into distinct clusters in terms of their growth trajectories. This has serious consequences not only for policy formulation but for the future of the Indian union itself since it is quite possible that the states in each cluster would come together to push national policies in particular directions, thus putting the India federal structure and national unity under strain.

Methodologically we find that trying to encompass the growth process of such a heterogenous set of cross-sectional units in a uniform law of motion can be extremely misleading. We show that club convergence algorithms can be effective tools to cut through this heterogeneity and to identify clusters of cross-sectional units with commonalities which can be studied together to identify their laws of motion.

We show that when this methodology is applied to the states of India, the growth rates of rich and poor states map very differently to the economic and social control variables. We hope that future work would trace back these differences to the socioeconomic mechanisms underlying economic growth.

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