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Convergence Club Empirics

Some Dynamics and Explanations of Unequal Growth across Indian States

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Abstract

This paper documents the convergence of incomes across Indian states over the period 1965 to 1998. It departs from traditional analyses of convergence by tracking the evolution of the entire income distribution, instead of standard regression and time series analyses. The findings reveal twin-peaks dynamics—the existence of two income convergence clubs, one at 50 per cent, another at 125 per cent of the national average income. Income disparities across states seem to have declined over the 1960s, only to increase over the subsequent three decades. The observed polarization is strongly explained by the disparate distribution of infrastructure, and that of education, and to an extent by a number of macroeconomic indicators; that of capital expenditure and fiscal deficits.

Keywords: convergence clubs, conditional convergence, distribution dynamics, infrastructure, capital investment, macroeconomic stability, panel data, India
JEL classification: C23, E62, O53

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1 Introduction

One of the paradoxes of our times is the coexistence of extreme economic affluence amidst enormous pockets of poverty. This holds across countries and even more so within countries, and across regions. Cross-country and cross-regional distributions of per capita incomes seem quite volatile. The extremes seem to be diverging away from each other—with the poor becoming poorer and the rich richer. Understanding why economies fail to converge is unquestionably important for welfare. Yet, there have been a series of debates about how convergence, and the lack of it, is best understood. Within the framework of growth economics, some define convergence as a single economy approaching its theoretically derived steady state growth path. Some again, define convergence as a notion of catch-up—whether poor economies are catching up with the rich. Yet, others still consider both notions as identical.

This paper highlights that how one defines convergence can prove to be crucial in revealing the relevant empirical regularities to advance one's understanding of unequal cross-economy growth performances. In particular, we will take the case of the Indian states over 1965-97, and investigate for tendencies of convergence. If we were not to obtain convergence, we are interested in other empirical regularities that the distribution may display. For example, if there are no cohesive tendencies, does one observe any specific distributional pattern? Do rich economies belong to a club of rich countries, while the poor languish behind? And what are the possibilities of the poor overtaking the rich? Finally, we will be interested in what processes may underpin such dynamics.

Some simple statistics reveal the stark disparities in growth across Indian states; Punjab's income has been at least twice that of Bihar's, Orissa's and Rajasthan's since 1965. Some states have doubled their incomes (real GDP per capita) over the period of the mid sixties to the 1990s, while the poorest states have hardly managed to get anywhere close to the national average income. Most of the poverty too, lies within the poorest states of Rajasthan, Bihar and Orissa. Broadly speaking, states of Punjab, Gujarat and Maharashtra are infrastructurally equivalent to that of a middle income group country (like Brazil,) while the poorer states of Rajasthan, Uttar Pradesh and Bihar are similar to that of Bangladesh, Mali and Burkina Faso. If we add to it the fact that adult illiteracy and gender bias at death is a substantial problem in the poorest states, we see a picture of endemic deprivation that is not captured by average income or growth statistics.

Such empirical characteristics are evident—that income differentials between the states have been widely diverging is more than clear. Studies on the Indian states based on the widely popular cross-section regression approach, of Bajpai and Sachs (1996), Cashin and Sahay (1996), Nagaraj et al. (1998), Rao et al. (1999) Aiyar (2001) emphasise such diverging distributional characteristics, which provide us with information no more useful than the statistics discussed earlier. Recent theoretical studies within the growth economics framework—Bernaud and Durlauf (1994); Ben-David (1994); De Long (1994); Esteban and Ray (1994); Galor and Zeira (1993)—allow for explicit patterns of cross-economy interaction, whereby economies cluster together into groups to endogenously emerge. Thus, identifying explicit patterns of cross-economy interaction, may well serve to shed some light on various theories which propose that economies evolve within groups and not in isolation.

Then again, pinning down a theory of growth is not essential to understanding why the poor remain poor and the rich persistently remain rich. There could be other mechanisms driving the rich and the poor apart, with having nothing to do with the economic growth process. What needs to be clarified is that convergence is simply a basic empirical issue, one that reveals patterns of the distribution which may or may not be simple convergence, or divergence, but polarization, stratification, convergence club formation, and the lack of it is a symptom of a deeper problem, which may or may not be the outcome of some 'perverse' growth process. In this paper we are interested in the growth paths of many aggregate economies and the implications those have for the dynamics of the income distribution across these economies. This, of course, leads to the more fundamental question, empirically addressed in this paper: what drives such dynamics of cross-state income distributions? Mechanisms of growth may serve to answer this question, and, then again, may not.

So, what other empirical regularities, other than that of convergence, may interest the reader? If one were to characterize convergence as a notion of catch-up, one could characterize convergence as a situation where the poor catch up with the rich. Will the rich continue to be rich, while the poor remain poor? What are the possibilities of the poor overtaking the rich, or the rich falling behind? Or are the poor languishing behind the rich, caught in a poverty trap? The questions thus asked are different from those asked traditionally by growth empiricists, and those inspired by more traditional 'Kaldorian' 'great ratios', concerning single economy growth dynamics.[1] Uncovering the income dynamics in the sense of convergence as a notion of catch-up will involve tracking the evolution of the entire income distribution over the given period of time. The primary focus is to understand the cross-country patterns of income, rather than explaining only within-country dynamics (i.e. the stability of factor shares—the 'great ratios'—within a single economy, or growth exclusively in terms of factor inputs).

The standard approach for studying convergence derives from such a growth model, proposed by Solow (1957) whose empirical interpretation implies that growth rates of an economy are inversely related to its initial level of income. Testing for this result has involved running cross-section regressions of countries on their initial levels of income. However, such an empirical methodology while can uncover tendencies of divergence, does not prove tenable in uncovering the empirical regularities of the distributional

[1] Kaldor (1963).

patterns that we wish to expose. Similarly, time series approaches (Bernard and Durlauf 1994; Carlino and Mills 1993) which track the univariate dynamics of income also remains incomplete in describing the dynamics we are interested in—while it incorporates the time series dimension, it fails to utilize the cross-section information.

Empirical methods concerning the behaviour of cross-section distributions of income (or productivity, output or welfare) over time, are traditional to the literature on the dynamics of inequality and personal income distributions (Atkinson 1970, Cowell 1985; Shorrocks 1978) In this paper, we intend to examine interstate income inequalities in terms of the behaviour of the entire cross-section distribution. Similar, if not identical, questions are raised in the dynamics of inequality literature, regarding personal income distributions. Is the distribution collapsing, so that everyone shows a tendency to become equally well off? Or do we see the distribution increasingly disperse whereby the rich become richer, and the poor remain behind? Or, instead, do we observe the distribution collate into individual clubs and subgroups, where the distribution thus polarizes or stratifies? These stylized facts describing the patterns of cross-state growth may reveal insights into the dynamics of what determines such growth processes.

In the distribution dynamics approach, Markov chains are used to approximate and estimate the laws of motion of the evolving distribution. The intradistribution dynamics information is encoded in a transition probability matrix (or a stochastic kernel), and the ergodic (or long run) distribution associated with this matrix describes the long-term behaviour of the income distribution. It encompasses both time series and cross-section properties of the data simultaneously and presents itself as an ideal approach for large data sets. Moreover, this method can be extended to identify factors governing the formation of these convergence clubs.

The main results of the paper are outlined as follows: the prominent distribution dynamics revealed are that of persistence and immobility. Strong polarizing tendencies are found to exist, and incomes exhibit twin peaked dynamics—there exist two convergence clubs, a high-income club at around 125 per cent of the national average and another at 50 per cent of the national average. Over the period 1965-70, one does observe some tendencies of convergence, which gradually dissipate over the following decades of the 1970s, 1980s and the 1990s. Cohesive forces within the convergence clubs are observed to 'tighten' over the latter three decades as well. Finally some macroeconomic indicators and some infrastructural indicators, of which fiscal deficits and capital expenditure, and education, are found to explain some of the observed dynamics.

The rest of the paper is organized as follows. Section 2 briefly introduces the distribution dynamics approach. Section 3 presents new stylized facts of the observed polarization. Section 4 discusses the empirical literature on the role of various macroeconomic indicators in explaining cross-country polarization of economic growth. Section 5 presents results of the various conditioning schemes under the distribution dynamics approach to explain the observed stylized facts. Section 6 concludes.

2 The distribution dynamics approach

It is standard in most growth analyses to study how one economy, in isolation, grows quickly or slowly. The insights developed are then used to explain why some countries grow faster than others. Recent analyses in growth economics, however, recognize cross-economy interaction that endogenously generates groups of economies, where countries endogenously select themselves into groups, and thus do not act in isolation. Thus different interaction patterns will generate different coalitions, or convergence clubs.

Consider the following caricature of an income distribution. In time period t, there is an initial income distribution across the given cross-section of economies. Over the given period of time, k units, some economies are better off, some others worse, while still others are unchanged. Still more, overtaking may occur as well—some poor states may overtaken the relatively rich Thus, by time period t + k coalitions, or convergence clubs form, and the distribution breaks up into a bimodal distribution, or in other words is polarized. Such distribution dynamics are commonplace.

What would one observe of the above dynamics described, if one were to apply the standard tools of cross-section regression analysis? First of all, the standard regression approach is unable to uncover the interesting dynamics of club formation. More so, if the researcher were to explain the dynamics by 'controlling' for a number of auxiliary variables, for example levels of investment in physical capital and other observable variables, he or she will conclude that capital investment explains cross-state growth. Such conclusions misguide the reader, because it is instead the patterns of club membership which serve to explain the observed income dynamics, and that capital investment is only responding endogenously to the coalition structures, which are in turn generating 'conditional convergence'.

2.1 Empirical models of distribution dynamics

Intradistributional mobility is estimated by two empirical models: stochastic kernels and transition probability matrices.[2] Of the two models, the transition probability matrix is the discrete model, while the stochastic kernel is its continuous version. The underlying formal structure of these models as a law of motion of the cross-section distribution of income is detailed in Quah (1996a).

[2] See Bandyopadhyay (2000a) for the use of other models to highlight the distribution dynamics. Transition probability matrices and stochastic kernels are, however, the main tools used to describe the distribution dynamics.

The distribution dynamics approach tracks the evolution of the income distribution by estimating probabilities of intradistributional mobility—in having to do so, it treats the income distribution as a random element in a space of distributions, called the random field. The density of the income distribution is estimated at each point of time, and its dynamics of evolution are estimated using transition probability matrices and stochastic kernels. In estimating the dynamics of the income distribution, there are two possibilities for an economy's (in our case, an Indian state) behaviour—over a given period of time, it may have either driven ahead, caught up with the richer states, it may have fallen behind, or even stagnated. Both transition probability matrices and stochastic kernels estimate probabilities of mobility or persistence of a given economy.

Estimating probabilities of intradistributional mobility of an Indian state involves first identifying its location in the initial period, and then tracking its movement to other parts of the distribution. The transition probability matrix divides the initial income distribution into a number of intervals, called 'income states'—for example, let the first income interval (or income state) consist of a range of incomes from a fifth to a third of the average national income. Typically, states like Rajasthan, and Bihar would lie within such an income state. The transition probability matrix would typically estimate the probability of mobility of an economy (an Indian state), moving from its original location to that of following income states. Thus, for instance, we are interested in the possibility that states like Rajasthan and Bihar move to a higher income state. The probabilities obtained, give us the percentages of economies (in our case, Indian states) which given a starting income state, have moved on to a different state. Thus row probabilities add to one. The transition probability matrix also allows us to take a long run view of the evolution of the income distribution. This is tabulated in the row called the 'ergodic distribution'.

A shortcoming of the transition probability matrix is that as the selection of income states is arbitrary—different sets of discretizations may lead to different results. The *stochastic kernel* improves on the transition probability matrix by replacing the discrete income states by a continuum of states.[3] This means that we no longer have a grid of fixed income states, like (0.2 0.5), (0.5 0.75) etc. but allow the states to be all possible intervals of income. By this we remove the arbitrariness in the discretization of the states. We now have an infinite number of rows and columns replacing the transition probability matrix.

Reading the stochastic kernel is as follows. A slice running parallel to the horizontal axis (i.e. $t + k$ axis) sketches a probability density function which describes the transitions from one part of the income distribution to another over k periods. The location of the probability mass within the t axis and $t + k$ axis grid informs us of any possibilities of intradistributional mobility. Concentration of the probability mass along the positive slope indicates persistence in the economies' relative position and therefore low mobility. The

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[3] Such refinement goes beyond the generalization as well. It is well known that discretization may well remove the Markov property from an otherwise well behaved Markov process, Chung (1960).

opposite, i.e. concentration along the negative slope, would imply overtaking of the economies in their rankings. Concentration of the probability mass parallel to the t + k axis indicates that the probability of being in any state at period t + k is independent of their position in period t—i.e. evidence for low persistence. Finally, convergence is indicated when the probability mass runs parallel to the t axis.

3 The stylized facts: twin peaks

Tables 1 to 2a-d present the transition probability matrices estimated over the following subperiods: 1965-70, 1970-80, 1981-9, and 1990-7. Interpretation of the tables is as follows. Each of the defined states for each table is different, such that each distribution is uniform at the beginning year of the sample. The first column of the table accounts for the number of transitions over the time period beginning at each state. The following columns present the calculated probabilities of transition from one specified state to another. A 'heavy' main diagonal is bad news—indicating persistence.

Table 1: Interstate (per capita) income dynamics, 1965-97—first order transition matrix, time stationary

	Upper end point				
Number	0.640	0.761	0.852	1.019	1.393
5	0.40	0.00	0.40	0.00	0.20
5	0.00	0.40	0.20	0.20	0.20
2	0.00	0.00	0.50	0.00	0.50
4	0.00	0.00	0.25	0.25	0.50
1	0.00	0.00	0.00	1.00	0.00
Ergodic	**0.00**	**0.00**	**0.22**	**0.44**	**0.33**

Source: see text.

Table 2a: Interstate (per capita) income dynamics, 1965-70—first order transition matrix, time stationary

	Upper end point				
Number	0.640	0.761	0.852	1.019	1.393
5	0.40	0.00	0.40	0.00	0.20
5	0.00	0.40	0.20	0.20	0.20
2	0.00	0.00	0.50	0.00	0.50
4	0.00	0.00	0.25	0.25	0.50
1	0.00	0.00	0.00	1.00	0.00
Ergodic	**0.00**	**0.00**	**0.22**	**0.44**	**0.33**

Source: see text.

Table 2b: Interstate relative (per capita) income dynamics, 1971-80—first order transition matrix, time stationary

	Upper end point				
Number	0.680	0.730	0.795	1.010	1.489
5	0.40	0.60	0.00	0.00	0.00
1	0.00	1.00	0.00	0.00	0.00
3	0.00	0.67	0.33	0.00	0.00
4	0.00	0.00	0.75	0.25	0.00
4	0.00	0.00	0.00	0.50	0.50
Ergodic	**0.00**	**1.00**	**0.00**	**0.00**	**0.00**

Source: see text.

Table 2c: Interstate relative (per capita) income dynamics, 1981-89—first order transition matrix, time stationary

	Upper end point				
Number	0.533	0.628	0.795	1.010	1.489
6	0.17	0.50	0.33	0.00	0.00
4	0.00	0.00	0.25	0.75	0.00
3	0.00	0.67	0.33	0.67	0.00
2	0.00	0.00	0.00	0.00	1.00
2	0.00	0.00	0.00	0.00	1.00
Ergodic	**0.00**	**0.00**	**0.00**	**0.00**	**1.00**

Source: see text.

Table 2d: Interstate relative (per capita) income dynamics, 1988-97—first order transition matrix, time stationary

	Upper end point				
Number	0.141	0.207	0.241	0.412	0.464
6	1.00	0.00	0.00	0.00	0.00
4	0.00	1.00	0.00	0.00	0.00
3	0.00	0.00	1.00	0.00	0.00
2	0.00	0.00	0.00	0.67	0.33
2	0.00	0.00	0.00	0.50	0.50
Ergodic	**1.00**	**0.00**	**0.00**	**0.00**	**0.00**

Source: see text.

The matrix for the subperiod 1965-70 reveals that probabilities in the main diagonal lie around 50 per cent, indicating that probability of persistence for an economy (Indian state) is around 50 per cent. The off-diagonal values are discouragingly low—with the exception of the above average income group. The long-run view of whether economies will converge over the long run is given by the ergodic distribution. The results suggest that over the long run, the probability that an economy lands up in the fourth state is the highest, a little over 40 per cent. What is encouraging is that the lower income groups vanish in the ergodic distribution.

The second period also reveals tendencies of both persistence and mobility, though persistence is more evident than mobility—this is particularly so for the lower and upper income groups. Again, mobility is observed for some high-income groups states. This trend continues in the next two periods. One should also note, however, that as these estimates are based on time stationary transition matrices, it may not be reliable for long periods due to structural changes.

The stochastic kernel estimates complement and conform with the results of the transition matrices obtained. Figures 1a-d represent the stochastic kernels and contour plots for relative per capita income of 1-year transitions for four subperiods 1965-70, 1971–80, 1981-8, and 1989-97. While the earlier years indicate some tendencies of convergence, later years increasingly reveal tendencies of persistence (in their relative positions) and diverging incomes. Over 1965-70, we obtain some tendencies of convergence—with two sharp peaks at either end of the probability mass, running parallel to the t axis. The two clubs of states lie at 50 per cent (lower) and 125 per cent (upper) of the national average.

Figure 1a: Relative income dynamics across Indian states, 1 year horizon, 1965-70

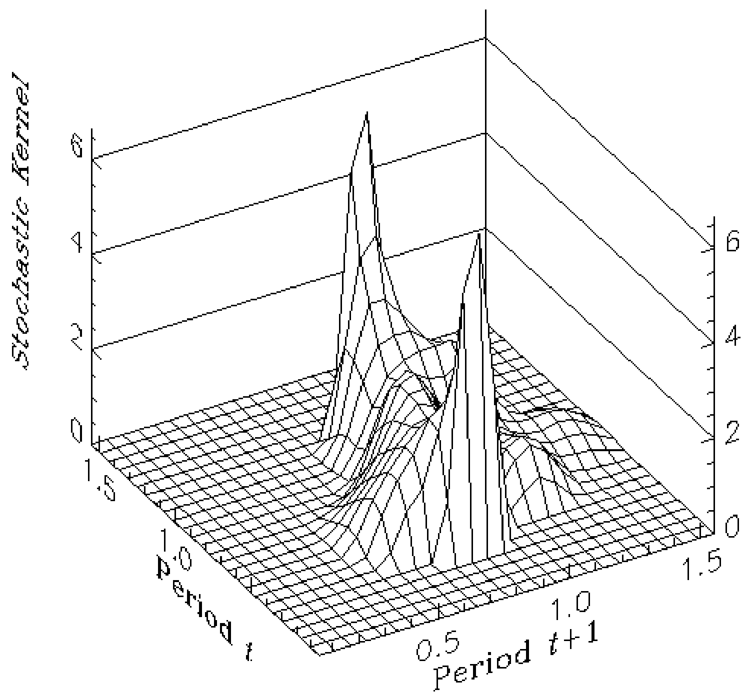


Figure 1b: Relative income dynamics across Indian states, 1 year horizon, 1971-80

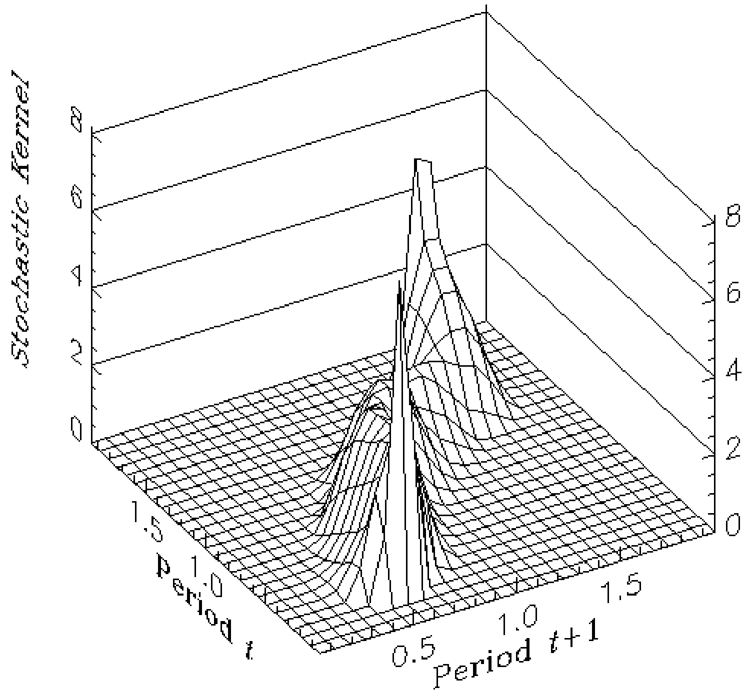


Figure 1c: Relative income dynamics across Indian states, 1 year horizon, 1981-89

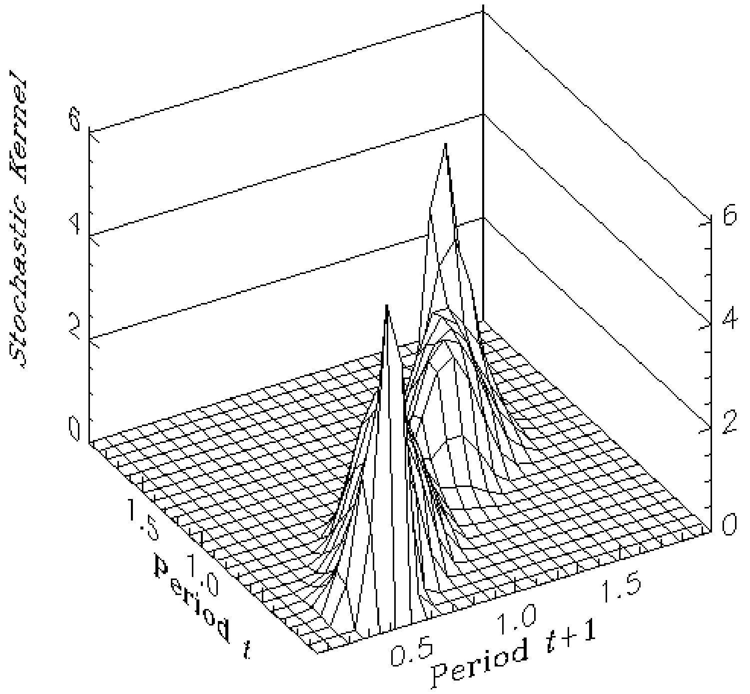
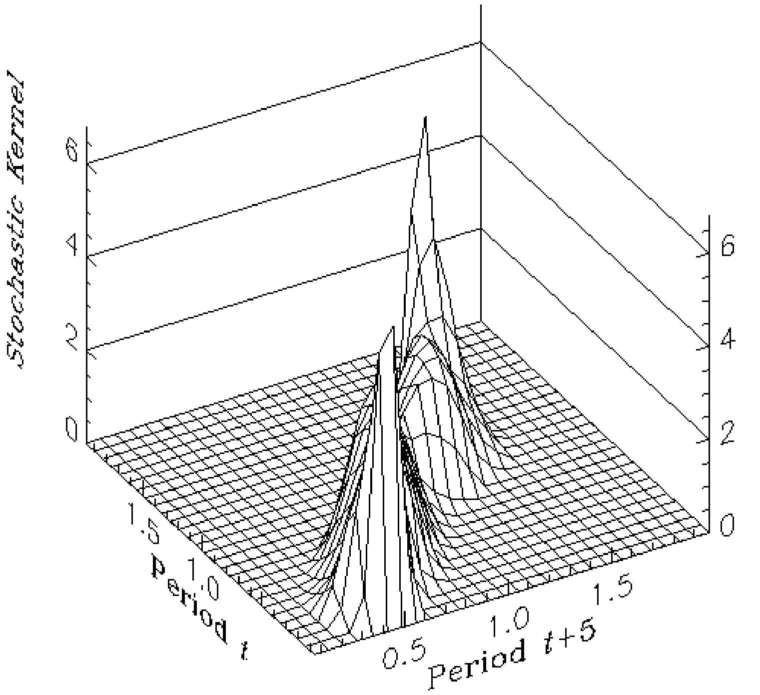


Figure 1d: Relative income dynamics across Indian states, 1 year horizon, 1990-97



Over the following periods, however, one observes increasing tendencies of persistence, and all signs of convergence observed over 1965-70 slowly dissipate. Over the periods 1965-70, 1971-80, 1981-8, 1989-97 we observe in Figures 1a-d the probability mass lengthening and shifting totally in line with the positive diagonal, the two peaks still at the two ends of the mass. One observes empirics of divergence and polarization—with increasing tendencies of the diverging states to cluster with a high-income club, or a low-income club.

4 Conditioning

It is often unclear in such analyses about what kind of conditioning variables are appropriate in understanding the lack of cohesion. It is unclear still as to what may explain polarizing dynamics as obtained in our study. One can intuitively suggest a large number of explanations as to what may underpin such dynamics. In some well-known studies many such variables are included as the right-hand side explanatory variables in a convergence regression, whose inclusion is justified by the intuition that they would influence growth in the long run. Examples are of human capital, physical capital, democracy, composition of GDP, democracy, etc.

In the empirical and theoretical literature, the influence of the stable macroeconomy is considered to be essential (but not sufficient) for sustainable economic growth. Endogenous growth theories have also stressed the role of factors like fiscal policy in determining long run growth (Barro 1991; Rebelo 1991; Stokey and Rebelo 1995). The empirical literature on the other hand, has estimated a number of significant correlations, which have shed light on the complexity of the relationships. Easterly and Rebelo (1992) present convincing evidence of fiscal deficits being negatively related to growth, while Levine and Renelt (1992) show that high growth countries are with lower inflation, have smaller governments and lower black market premia, but the relationships are established to be fragile (with the exception of investment ratio). Fischer (1991) too, extending the basic Levine and Renelt regression, reveals that growth is significantly negatively associated with inflation and positively with budget surplus as a ratio of GDP. The relationship between growth and inflation too has been heavily investigated. Levine and Zervos' (1993) study reveals that inflation is significant, though only for high inflation countries. A composite indicator of (lower) inflation and (lower) fiscal deficit is revealed to be positively related with growth. Similar studies of Bruno and Easterly (1998) also reveal high inflation crises to be associated with output losses.

Again, different countries, states or regions within counties, respond differently to a particular macropolicy framework depending on their market structure, credit markets, and infrastructure, to mention the least. A cursory comparison of some Indian states will clarify the reader on the importance of such issues for the Indian case in particular. Consider, on the one hand, Bihar: with poor basic infrastructure, low industrialization, agriculture based economy, poor infrastructure in terms of schools, health, power, transport and communication, etc. Compare Bihar with Punjab—agriculture highly developed, infrastructure greatly developed in terms of education, health, power and transport. The wide schism separating the rich states from the poor in terms of their average per capita income is indeed great, but is manifold more when one compares their basic infrastructural statistics.

In this paper we empirically investigate the role of a number of few macroeconomic indicators and a few infrastructural indicators in explaining the observed twin peaked dynamics. In the following section we will extend the distribution dynamics methodology for the conditioning exercise, which will be followed by the conditioning.

4.1 Conditioning in distribution dynamics

Given that our fundamental object of study is a distribution, and no longer a conditional average as was the case under standard regression methods, empirically accounting for the patterns of the income distribution involves eschewing standard techniques of conditioning. The approach adopted here, popularized by Quah (1996a), is analogous to constructing a conditional distribution from the unconditional distribution, in classical probability theory. Explaining features such as polarization, means obtaining a conditional distribution such that no such features appear. This compares to the traditional cross-section regression approach in that while in that approach we would be comparing E(Y) and E(Y|X), for the distribution dynamics approach we would be comparing Y and Y|X.

So, how does one estimate the conditional distributions? Given that our auxiliary factors are macroeconomic indicators and infrastructural indicators, one can anticipate issues with endogeneity. This is discussed and the conditional distributions are derived in the following section. Our tools for the distribution dynamics are again the stochastic kernel, where a mapping is obtained from the unconditional distribution to the conditional distribution. If the auxiliary factors were successful in removing the twin peaked features, then the mapping would result in what is commonly called conditional convergence—with the probability mass running parallel to the original unconditional axis.

4.2 Endogeneity

As is often encountered in macroeconomic analyses, endogeneity of macroeconomic variables is common and is treated rigorously. Granger causality tests are performed to confirm such endogeneity.[4] The regressions are obtained by OLS, pooling cross-section and time series observations. Unlike standard panel applications, we do not allow for individual effects, to allow for the permanent differences in growth rates across states. Granger tests for bivariate VARs[5] in GDP (per capita) growth rates and the auxiliary variables we are testing for, indicate significant dynamic inter-dependence between growth and our auxiliary variables. This implies that while the variable, for example, infrastructure, does help to predict future growth, it is itself incrementally predicted by lagged growth. Given that our auxiliary variables are endogenously determined, we need to estimate the appropriate conditional distribution free from the feedback effects.

We will obtain the conditioned distribution by regressing growth rates on a two sided distributed lag of the time varying conditioning variables and then extracting the fitted residuals for subsequent analysis. The residuals will constitute the relevant conditioning distribution irrespective of the exogeneity of the right hand side variables. The method derives from that suggested by Sims (1972),[6] where endogeneity (or the lack of it) is determined by regressing the endogenous variable on the past, current and future values of the exogenous variables, and observing whether the future values of the exogenous variables have significant zero coefficients. If they are zero, then one can say that there exists no 'feedback', or bi-directional causality. Needless to say, the residuals resulting from such an exercise would constitute the variation of the dependent variable unexplained by the set of exogenous variables, irrespective of endogeneity. We present the results for these two-sided regressions in Table 3.

All projections reveal that fiscal deficits at lead 1 though lag 2 appear significant for predicting growth, but other leads and lags, not so consistently. Fit does not seem to improve with increasing lags (or leads). The coefficients of the two-sided projections also

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[4] Results are not presented in paper due to space constraints, and are obtainable from the author.

[5] Vector autoregressions.

[6] This method has been adopted by Quah (1996b) to obtain the conditional distribution.

appear to be fairly stable. The residuals for the second lead-lag projections are saved to be the conditioned distribution of growth on fiscal deficits. We also obtain other conditioned distributions with auxiliary variables of capital expenditure, education expenditure, inflation and interest expenditure and own tax revenue.

Table 3: Conditioning regressions (two-sided projections) of growth rate on fiscal deficits

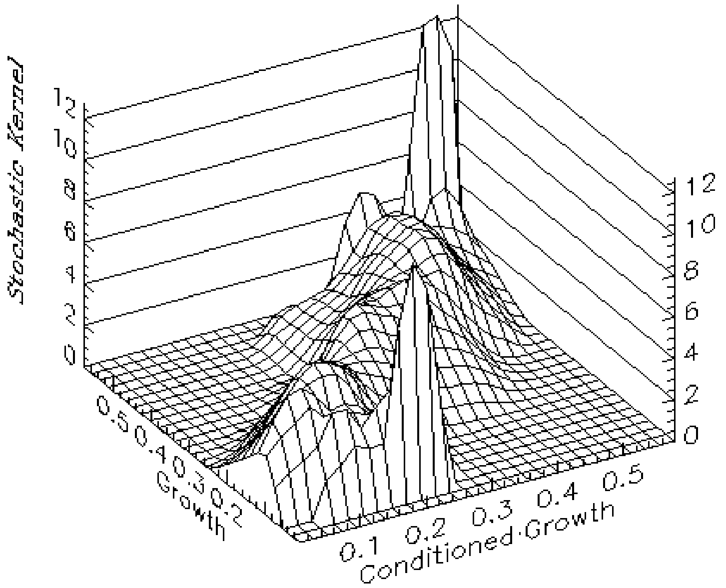
Fiscal deficits		Coefficients in two-sided projections		
Lead	4			-0.00 (0.003)
	3		0.010 (0.008)	0.012 (0.009)
	2	0.013 (0.008)	-0.018 (0.010)	-0.019 (0.016)
	1	0.020 (0.010)	0.021(0.012)	0.024 (0.019)
	0	-0.022 (0.016)	-0.024 (0.018)	-.0.029 (0.019)
Lag	1	-0.021 (0.014)	-0.02 (0.016)	-0.022 (0.015)
	2	-0.01 (0.010)	-0.01 (0.011)	-0.01 (0.011)
	3			-0.00 (0.007)
	4			
Sum of coefficients		-0.01	-0.04	-0.014
R^2		0.10	0.10	0.11

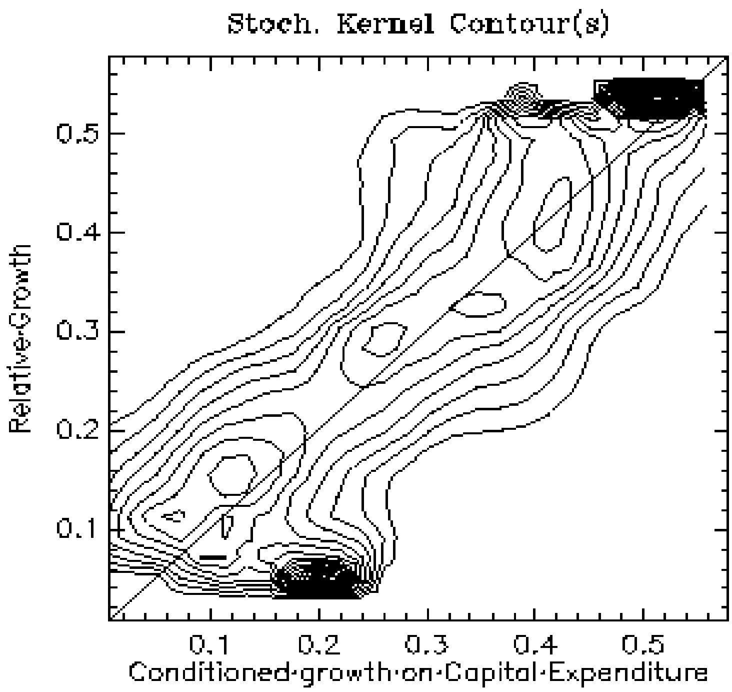
Note: numbers in parentheses are OLS and White heteroskedasticity consistent standard errors.
Source: see text.

5 Conditioning results

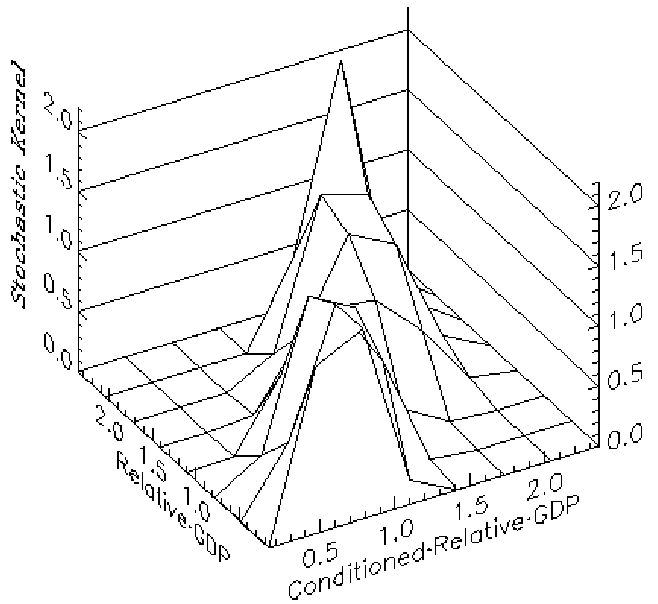
Figures 3 to 8 present the stochastic kernels mapping the unconditioned to conditioned distributions, for the five conditioning auxiliary factors. Figures 3 presents the stochastic kernel representing conditioning with fiscal deficits. Here we observe that while the probability mass lies predominantly on the diagonal, there are some individual clusters of states, at 50 per cent of the national average running off the diagonal, parallel to the original axis. The clusters are clearly identified in the contour plot in Figure 3b. These clusters are evidence that fiscal deficits do serve to explain the formation of the higher income club. Similar mappings conditioning with capital expenditure as auxiliary variable, results in similar observations, Figure 4. Here too one obtains evidence of some conditional convergence. The probability mass runs mainly along the diagonal, while isolated clusters run off the kernel, parallel to the original axis. Inspection of the contour also reveals the kernel to be twisting anti-clockwise at the higher and lower income levels, also indicating tendencies of obtaining conditional convergence at those levels.

Figures 3a and b: Relative per capita incomes across Indian states; capital expenditure conditioning, with contour





Figures 4a and b: Relative per capita incomes across Indian states—state development expenditure conditioning, with contour



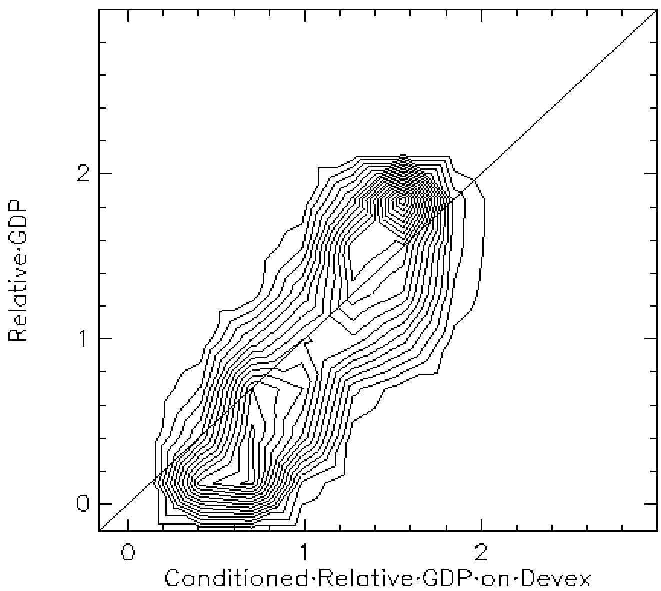
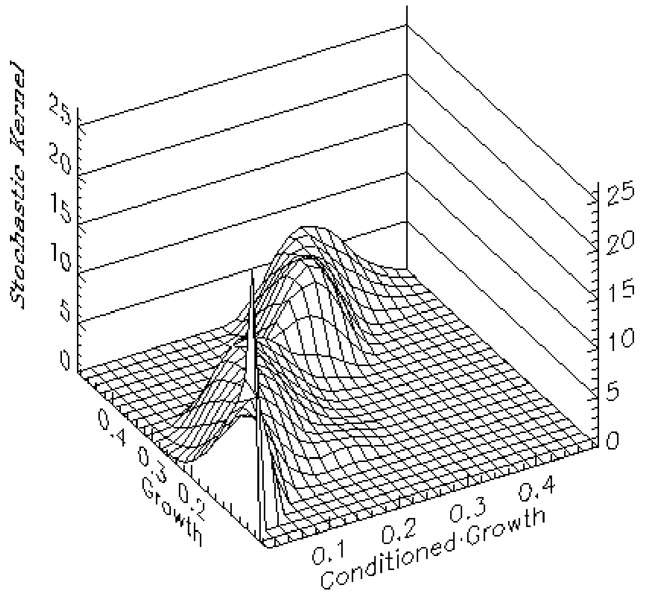
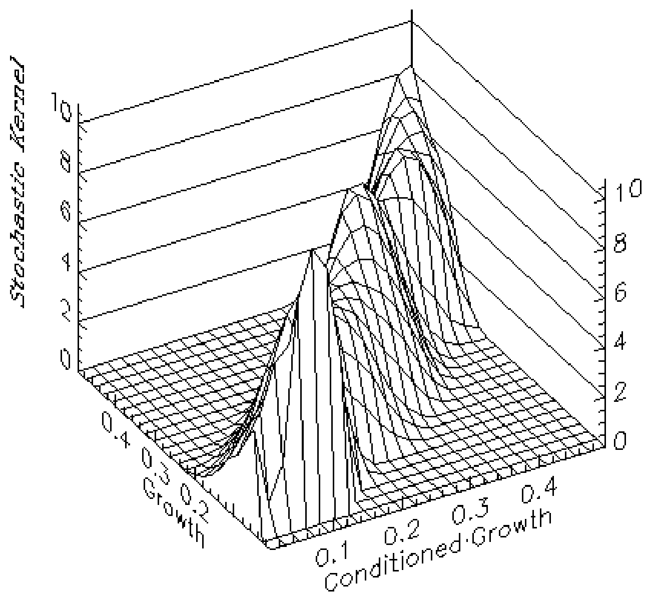


Figure 5: Relative per capita incomes across Indian states—inflation conditioning, with contour



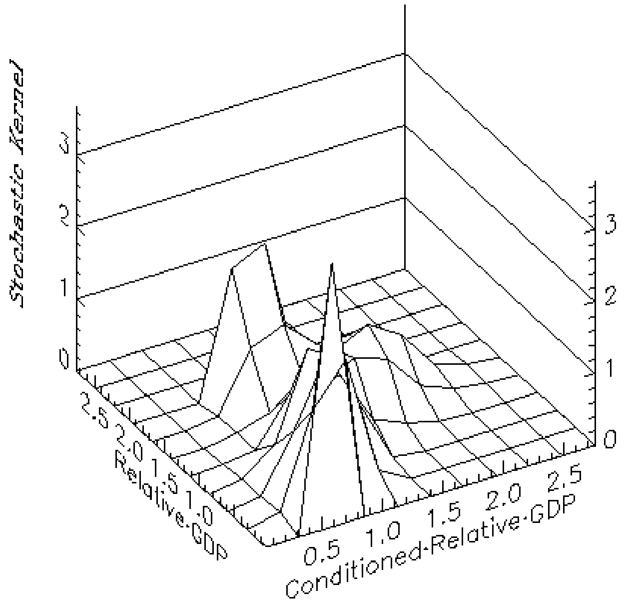
Conditioning with state development expenditure (Figure 5) reveals similar dynamics—dominant features characterising the kernel are that of persistence, while signs of mobility are evident at the tails.

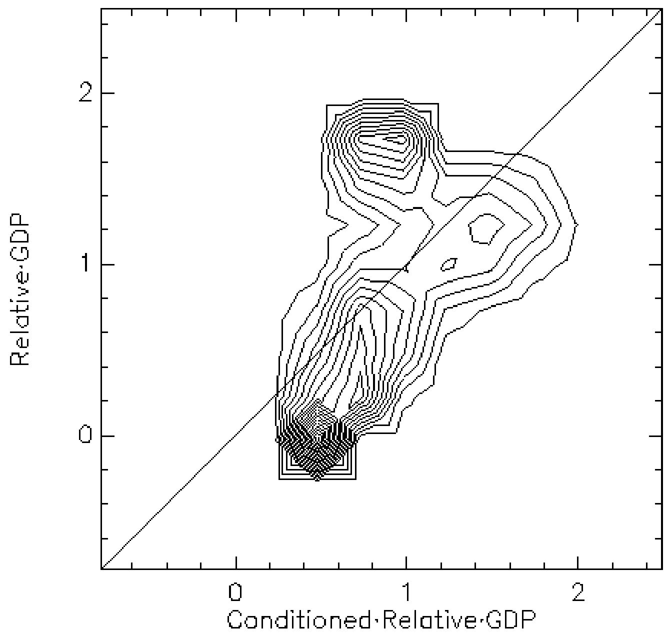
Figures. 6: Relative per capita incomes across Indian states—interest expenditure conditioning, with contour



Conditioning on inflation and interest expenditure reveals no interesting insights in how they explain disparate growth performances—Figures 6 and 7 have the probability mass running decidedly along the diagonal.

Figures 7a and b: Relative per capita incomes across Indian states—infrastructure conditioning, with contour plot





The infrastructure indicators[7] (panel data) which we use for the analysis are the following. The states covered for the analysis are stated in the Appendix, and the period of study is 1977-93. There are no missing observations.

per capita electrical consumption (in kilowatt hours)
per capita industrial consumption of electricity
percentage of villages electrified
percentage if gross cropped area irrigated
road length (in km per 1,000 km^2)
number of motor vehicles per 1,000 population.
rail track length (in km per 1,000 km^2)
literacy rates (in percentage of the age group)
primary school enrolment (age 6-11, in percentage of the age group)
secondary school enrolment (age 11-17, in percentage of the age group)
infant mortality (in percentage)
number of bank offices per 1,000 population
bank deposits as a percentage of the SDP
bank credit as a percentage of the SDP

We construct a single index accounting for the each of the state's infrastructure base. We use factor analysis to obtain the general index of infrastructure. This technique is a method of data reduction and attempts to describe the indicators as linear combinations of a small number of latent variables.[8] Results of the factor analysis are presented in Table 4. We accept the first factor F1 (which has an eigenvalue of 12). To now account for possible endogeneity, we perform similar lead-lag regressions and extract the residuals that now constitute the conditional distribution.

Table 4: Results of factor analysis

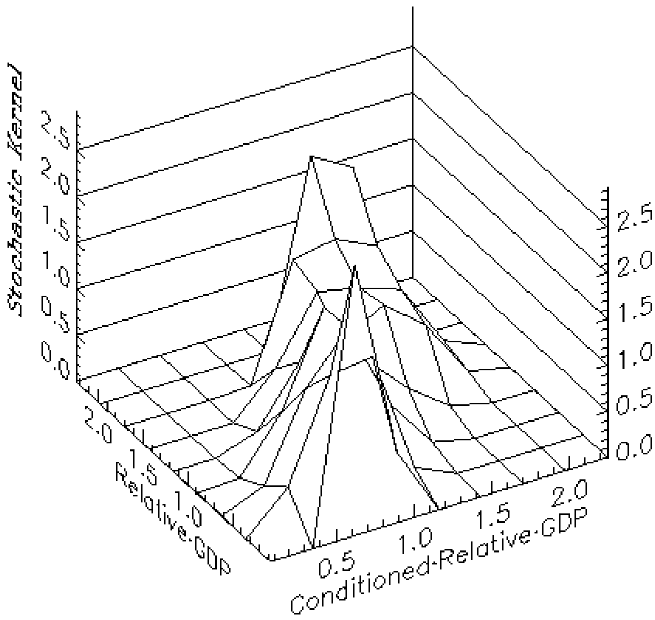
Components	Eigenvalue	Cumulative R^2
f1	12.41	0.83
f2	1.22	0.91
f3	1.00	0.97

Source: see text.

[7] The infrastructure indicators' data set has been provided by the India team, Development Centre, OECD, Paris. The author gratefully acknowledges thanks to Dr A. Varoudakis and Dr M.Veganzones for kindly providing the data set.

[8] This method was first used in development economics by Adelman and Morriss (1967) in an ambitious project to study the interaction of economic and non-economic forces in the course of development, with data on 41 social, economic and political indicators for 74 countries. For further discussion, see Adelman and Morriss (1967), and for more on factor analysis, see Everitt (1984).

Figures 8a and b. Relative per capita incomes across Indian states—education conditioning, with contour plot



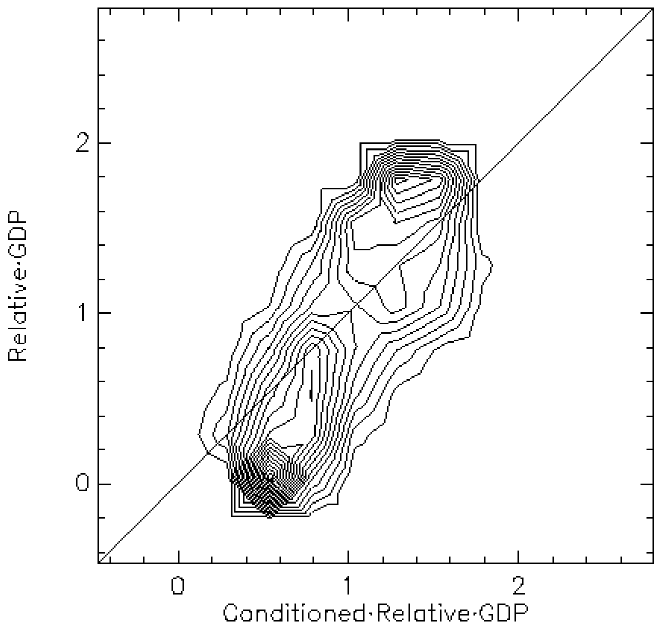


Figure 8 shows the cross-state distributions conditioning on infrastructure—the results obtained are encouraging, particularly so for the higher income and lower income group states. Level of infrastructure, hence, does not appear to be a factor which explains cross-section disparity in middle income group states. Conditional convergence is especially clear for the range of incomes above 1.2 times the national average, and states with incomes below the national average, more clearly revealed in the contour plot. That we observe infrastructure serving to explain the observed dynamics at different levels of the distribution is interesting in that it would not have been revealed so under standard regression techniques**.** Parametric tests confirming conditional convergence with infrastructure are not included in the results here due to the length of the paper, see Bandyopadhyay (2000b).

We finally isolate education (measured as primary and secondary school enrolment) as an auxiliary variable, to observe its role in explaining the income dynamics. First, we construct a similar index of education, applying factor analysis and use the first factor as our index. Similar endogeneity tests are performed, and the residuals from earlier two-sided lead-lag regressions are extracted as the conditional distribution. Figure 8 presents the conditioning results. Here again, one observes tendencies of the lower income club showing signs of convergence, while the higher income group remains unexplained. Once again, one observes that education serves to explain coalition at the lower income levels.

5.1 Conditioning results with transition probability matrices

Table 5a. Interstate conditioning on fiscal deficit; transition matrix

	Upper end point				
Number	0.172	0.235	0.272	0.388	0.536
100	1.00	0.00	0.00	0.00	0.00
320	0.72	0.19	0.09	0.00	0.00
250	0.08	0.20	0.48	0.20	0.04
220	0.00	0.09	0.18	0.50	0.23
230	0.00	0.00	0.04	0.30	0.65
Ergodic	**1.00**	**0.00**	**0.00**	**0.00**	**0.00**

Source: see text.

Transition matrices for fiscal deficits (in Table 5a) exhibit signs of partial mobility—it is at the middle income groups that one observes mobility, but not at the peaks. The values pertaining to these income states are smaller on the diagonals, with off-diagonal values increasing in value. There is, however, no tendency towards conditional convergence.

Table 5b. Interstate conditioning on capital expenditure; transition matrix

	Upper end point				
Number	0.173	0.234	0.276	0.396	0.547
110	0.82	0.18	0.00	0.00	0.00
300	0.73	0.23	0.03	0.00	0.00
310	0.10	0.16	0.35	0.35	0.03
180	0.00	0.06	0.11	0.56	0.28
220	0.00	0.00	0.00	0.27	0.73
Ergodic	**0.731**	**0.179**	**0.015**	**0.036**	**0.038**

Source: see text.

The capital expenditure matrix (Table 5b) reveals a tendency of intradistributional mobility of the middle income group towards lower and higher income states. This adds to our findings of the stochastic kernel—capital expenditure seems to marginally explain the polarization of growth performances for the middle-income group of states.

Likewise, state development expenditure conditioning (Tables 5c) exhibits similar signs of partial mobility—it is at the middle income groups that one observes some mobility, but not at the peaks. The probabilities on the diagonals are significantly smaller, with off-diagonal values increasing in value. The second and third income classes seem to exhibit most of the mobility. There is, however, no tendency towards conditional convergence.

Table 5c: Interstate conditioning on state development expenditure, transition matrix

	Upper end point				
Number	0.274	0.620	0.760	0.926	1.220
84	0.210	0.260	0.370	0.140	0.010
66	0.000	0.140	0.330	0.420	0.110
36	0.000	0.140	0.250	0.530	0.080
33	0.000	0.000	0.120	0.240	0.640
30	0.000	0.000	0.000	0.060	0.940
Ergodic	**0.000**	**0.002**	**0.013**	**0.077**	**0.907**

Source: see text.

Tables 5d-5f once again represent estimates of intradistributional mobility using capital inflation and interest expenditure as the conditioning variables. Here too one observes little evidence of either factor explaining the observed twin-peakedness. These results support standard parametric results where inconclusive results are obtained as well.[9] Finally the infrastructure conditioning matrix too, exhibits signs of mobility, particularly that of the lower income states. These results confirm those obtained with the stochastic kernel.

To summarize the results obtained, one finds that factors of capital expenditure and fiscal deficits partially explain the formation of the higher income club, while infrastructure, and to an extent education, measured as school enrolment, explains the formation of the lower income club. If one were to apply standard regression techniques, one could very well obtain evidence of conditional convergence, on controlling for these auxiliary factors.[10]

[9] These results are not detailed in this paper due to its length.

[10] Panel regressions within the standard regression framework are obtainable from the author, where one does obtain conditional convergence with the auxiliary variables in use for this exercise.

Table 5d: Interstate conditioning on inflation, transition matrix

	Upper end point				
Number	0.113	0.187	0.249	0.308	0.483
0	0.350	0.140	0.350	0.140	0.010
150	0.000	0.250	0.190	0.460	0.090
360	0.000	0.060	0.560	0.260	0.120
290	0.000	0.000	0.130	0.210	0.660
320	0.000	0.000	0.000	0.000	0.000
Ergodic	**0.400**	**0.212**	**0.116**	**0.144**	**0.128**

Source: see text.

Table 5e: Interstate conditioning on interest expenditure, transition matrix

	Upper end point				
Number	0.193	0.240	0.282	0.400	0.531
180	1.00	0.00	0.00	0.00	0.00
270	0.33	0.52	0.15	0.00	0.00
310	0.00	0.13	0.32	0.55	0.00
150	0.00	0.00	0.00	0.80	0.20
210	0.00	0.00	0.00	0.05	0.95
Ergodic	**1.00**	**0.00**	**0.00**	**0.00**	**0.00**

Source: see text.

Table 5f: Interstate conditioning on infrastructure, transition matrix

	Upper end point				
Number	0.208	0.626	0.762	0.916	1.10
89	0.100	0.310	0.400	0.170	0.01
62	0.030	0.080	0.290	0.520	0.08
32	0.030	0.190	0.190	0.410	0.19
31	0.030	0.000	0.320	0.100	0.55
41	0.000	0.020	0.000	0.200	0.78
Ergodic	**0.013**	**0.042**	**0.105**	**0.210**	**0.78**

Source: see text.

The dynamics revealed in this paper clarify how such a conclusion can mislead the reader in deducing that these auxiliary variables explain the cross-state patterns of growth. What is highlighted in the results is that different auxiliary factors serve to explain club membership at different levels. While education, and our general index of infrastructure serve to explain cohesive forces within the lower income club, capital expenditure and fiscal deficits (partially) do so for the higher income club. These empirical regularities both sketch and explain specific income dynamics, particularly that of patterns of distributions, not revealed by standard approaches. It is clear from these empirical facts that different policies are to be targeted for different states, and that a global allencompassing policy for all states would not serve well to bridge the wide disparities in economic growth across Indian states.

6 Conclusion

This paper has examined the convergence of growth and incomes with reference to the Indian states using an empirical model of dynamically evolving distributions. The model reveals 'twin peaks' dynamics, or polarization across the Indian states, over 1965-98—empirics which would not be revealed under standard empirical methods of cross-section, panel data, and time series econometrics. We find that the dominant cross-state income dynamics are that of persistence, immobility and polarization, with some cohesive tendencies in the 1960s, only to dissipate over the following three decades. These findings contrast starkly with those emphasised in works of Bajpai and Sachs (1996); Nagaraj et al. (1998), and Rao et al. (1999). Such dynamics warn on potential misinterpretations of conditional convergence regressions.

A conditioning methodology using the same empirical tools further reveals that such income dynamics are explained by the disparate distribution of infrastructure and to an extent by fiscal deficit and capital expenditure patterns. Unlike standard methods, this model allows us observe the income dynamics at different levels of the distribution. Infrastructure, and education, seems to strongly explain the formation of the lower convergence club, while fiscal deficits and capital expenditure patterns explains club formation at higher income levels. Such stylized facts are interesting for policy purposes in tracking the forces, which govern growth dynamics across the Indian states.

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Appendix

States used in the study:

- Andhra Pradesh
- Assam
- Bihar
- Delhi
- Gujarat
- Haryana
- Jammu and Kashmir
- Karnataka
- Kerala
- Madhya Pradesh
- Maharashtra
- Orissa
- Punjab
- Rajasthan
- Tamil Nadu
- Uttar Pradesh
- West Bengal

Other states were excluded from the study due to the incomplete data available over the given period.