

# Twin Peaks: Distribution Dynamics of Economic Growth across Indian States

by

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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 – known as the distribution dynamics approach in the growth literature. The findings reveal twin-peaks dynamics – the existence of two income convergence clubs, one at 50 per cent, another at 12 per cent of the national average income. Income disparities seem to have declined over the sixties, only to increase over the following three decades. The observed polarisation is strongly explained by the disparate distribution of infrastructure 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

There are few questions more compelling to economists than to explain why some countries grow faster than others. Understanding different patterns of cross country or cross regional growth is important - persistent disparities in income across countries and across regions lead to wide disparities in welfare and is often a source of social and political tension, particularly so within national boundaries.

That regional inequalities of incomes across the Indian states exist has been well documented and studied by many. It is almost common knowledge that the western states are the industrially advanced, while the north-west is agriculturally prosperous. There exist pockets of relative success in agriculture and industry the south and the north, while the north eastern states are yet to excel in either.

Saying that regional inequalities exist is just the starting point - what is of concern is that they continue to persist, particularly that they do so after five decades of concerted state led planning. Such differential development, given widespread inter-state socio-ethnic and political differences, risk the unleashing of highly destructive centrifugal political forces. It is therefore vitally important that policies for containing and counteracting regional disparities are implemented in the early rapid phase of development.

This study documents the dynamics of growth and convergence of incomes (real per capita) across Indian states over the period 1965-1998 and attempts to find some factors underpinning such income dynamics. The framework we will be using addresses a number of specific goals: first, we are interested in the dynamics of equality across incomes across Indian states. In other words, is there any tendency of equality in the cross section income distribution across the Indian states? If not, what distribution pattern do they exhibit?

Second, if cohesive<sup>1</sup> tendencies were not to obtain, we would like to characterise the possibilities for inter-regional mobility – are there any signs of poorer regions overtaking the rich in the future? Are there any signs of initially rich economies falling behind? For example, we would like to know how an economy initially within the poorest 10 per cent of the country can catch up with the rest, or will converge within a median 20 per cent. These facts are important for policy purposes. Characterising the presence of other distribution patterns, e.g. convergence

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<sup>1</sup> By cohesion, we simply mean the tendency towards equality of incomes across the States.

clubs or stratification, will enable the researcher to identify the economic forces governing their formation and their persistence.

Finally, we will investigate causes explaining the persistence of unequal growth performances. I will allow for a number of explanatory factors to examine for conditional convergence properties. In particular, I will examine the role of the disparate distribution of infrastructure across the states, and the role of a number of macroeconomic variables in explaining the divergent growth performances.

This exercise follows from the new wave of empirical growth analyses, following the studies of Barro and Sala-i-Martin(1992), Desdoigts(1994), Quah(1992-98), Nagaraj et al (1998) to name a few. These empirical studies of income dynamics have made powerful and controversial claims, which have instigated yet further empirical techniques of analysing cross-country income dynamics. The ensuing stylised facts of growth dynamics have telling implications for widely accepted theoretical claims. Also, the questions which are addressed in the new empirical growth literature differ from those in earlier empirical works of Kaldor's stylised facts (1963), or of Solow(1957) in a production function accounting exercise. 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 new empirical literature also uses auxiliary explanatory factors to explain the stylised facts, opposed to analysing the production function residual, as done earlier.

Here we intend to examine inter-state income inequalities in terms of the behaviour of the entire cross section distribution. When the cross section distribution exhibits tendencies of collapsing to a point mass, one can conclude of tendencies towards convergence. If, on the other hand, it shows tendencies towards limits which have other properties – normality or twin peakedness, or a continual spreading apart - these too will be revealed. What this approach essentially endeavours is to describe a law of motion of the cross section income distribution over the period of study. Appropriately named, the distribution dynamics approach exposes instances of economies overtaking, or falling behind – it reveals the existence of any intra-distributional mobility, or persistence. Finally, this model will allow the researcher to study not just the likelihood, but also the potential causes, of poorer economies becoming richer than those currently rich, and that of the rich regressing to become relatively poor.

The distribution dynamics approach to studying convergence (Bianchi, 1997, Desdoigts, 1994, Jones, 1997, Lamo, 1996 and Quah, 1995,1997) improves on the existing approaches employed so far. Standard (i.e. beta convergence) regression analysis only considers average or

representative behaviour, and says nothing about what happens to the entire distribution (Barro and Sala-i-Martin, 1992, and Bajpai and Sachs, 1996, Cashin and Sahay, 1996, Nagaraj et al., 1998, for the Indian case, among many others). Neither are both beta and sigma convergence analyses able to inform the researcher of any prospects of inter-regional mobility. They are unable to uncover the long run aspects of the evolving distributional pattern. Such is also the case with time series applications to regional analyses (Carlino and Mills, 1995). The methodology employed in this paper, goes beyond point estimates of dispersion and unit root analyses to highlight two vital aspects of how a distribution evolves over time – intra-distributional mobility and the long run prospects of the distribution (ergodicity). 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.

This paper uncovers the relevant stylised facts of Indian inter-state income distribution over the period 1965-97, over different sub-periods. The main finding is that strong polarising tendencies are found to exist resulting in the formation of two income “convergence clubs”, one at 50% of the national average, another at 125% of the national average. Examining the sub-periods reveal that while cohesive tendencies were observed in the late sixties, these were considerably weakened over the following decades with increasingly polarising tendencies. Further analysis reveals that the disparate distribution of infrastructure strongly explains the observed polarisation, particularly so for the lower income club. Indicators of macro-economic stability provide some evidence of explaining the lack of convergence. Of the different macroeconomic indicators observed, capital expenditure and fiscal deficits do explain some of the polarisation. This is in contradiction to results of using standard techniques (i.e. panel regressions) where the role of both of the above in explaining the lack of convergence are found to be inconclusive<sup>2</sup>.

The rest of the paper is organised as follows. Section 2 introduces the distribution dynamics approach. Section 3 presents new stylised facts of the observed polarisation. Section 4 discusses the empirical literature on the role of various macroeconomic policies in explaining cross country polarisation of economic growth. Section 5 presents results of the various conditioning schemes and techniques to explain the observed stylised facts. Section 6 concludes.

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<sup>2</sup> Results of standard regression approaches are not produced in this paper due to its length. These are available in Bandyopadhyay 2000b, and 2001.

## 2. The Distribution Dynamics Approach

The approach of distribution dynamics originates from recent empirical research on patterns of cross country growth. The focus of research in the new empirical growth literature no longer concerns understanding the behaviour of per capita income or per worker output of a single representative economy but asks questions like, why do some countries grow faster than others. The traditional approach to convergence clarifies whether an economy will converge to its own steady state (income) – this, however, is a less interesting notion of convergence.

We are interested in a more useful notion of convergence here. We would like to know how an economy initially within the poorest 10 per cent of the country can catch up with the rest, or will converge within a median 20 per cent. Extant approaches cannot say anything on whether the poorest economies will stagnate, permanently distant from the richest ones – they remain silent on patterns of stratification and polarisation. It has been argued by many, that convergence as a notion of “catch-up” is not useful when studied by standard regression analysis as it captures only representative behaviour, and uninformative, in general, for the dynamics of the distribution of income across countries (Friedman, 1992, Leung and Quah, 1996). Again, while time series analyses accounting for the univariate dynamics, does not utilise the cross section information, the evolution of income dispersion, (say, in terms of the standard deviation), also does not tell us anything about the underlying cross section growth dynamics.

What existing standard techniques fail to inform the researcher is about the *intra-distributional dynamics* of the income distribution and hence, of a distribution pattern other than convergence. These goals have necessitated going beyond the extant technical tools of studying convergence.

In view of the drawbacks presented above, the approach<sup>3</sup> of distribution dynamics to characterising convergence moves away from a singular treatment of cross section regression or a time series approach. It involves tracking the evolution of the entire income distribution itself over time. Markov chains are used to approximate and estimate the laws of motion of the evolving distribution. The intra-distribution dynamics information is encoded in a transition probability matrix, and the ergodic (or long run) distribution associated with this matrix describes the long term behaviour of the income distribution. Such an approach has revealed empirical regularities such as convergence clubs, polarisation, or stratification – of cross economy interaction that endogenously generates groups of economies; of countries catching up

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<sup>3</sup> See Quah (1996a,b). Similar studies which have focused on the behaviour of the entire distribution have been of Bianchi(1997) where he uses the bootstrap test to detect multimodality and that of Bernaud and Durlauf(1995), where they identify "multiple regimes" across the economies.

with one another but only within sub-groups (Bernaud and Durlauf, 1996, Bianchi, 1997, Quah, 1997a).

## 2.2 *Random Fields and the Random Element*

The distribution dynamics approach is based on treating a single income distribution as a *random element* in a field of income distributions. Figure 1 presents the entire distribution of State income (relative per capita) in India for the period 1965-98. Such structures where both time series and cross section dimensions are large and of equal magnitude are called *random fields* in probability theory. At each point in time, the income distribution is a *random element* in the space of distributions. This approach involves estimating the density function of the income distribution at each point in time and then observing how it evolves over time. These dynamics account for the change in the shape of the distribution and for intra-distribution dynamics which are notable characteristics of convergence. In our analysis, we shall non-parametrically estimate a density function of the given data set as it does not impose a known structure on the distribution, allowing us to detect structures different from parametric forms. To study the distribution dynamics of the Indian income distribution, we shall be using transition probability matrices and stochastic kernels to estimate the density function and observe its evolution.

## 2.3 Models of Intra-distribution Churning

The two main models which highlight the distribution dynamics of an income distribution are stochastic kernels and transition probability matrices<sup>4</sup>. Of the two models, the transition probability matrix is the discrete model, while the stochastic kernel is its continuous version. We present the underlying formal structure of these models as a law of motion of the cross section distribution of income in the technical appendix.

Both stochastic kernels and transition matrices provide an estimate of intra-distribution mobility taking place. In both cases, it is assumed that an economy (in our case, a state) over a given time period (say, one year or five years) either remains in the same position, or changes its position in the income distribution. Such a change in position of an economy in the income distribution is called a transition. Our task is to observe how many such transitions take place in the given time period.

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<sup>4</sup> 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.

First, what needs to be identified is the position of the economy in the income distribution in the starting period. This is done by dividing the income distribution into "income states". Income states are a range of income levels, say between a fifth and a half of the weighted average of the country. Then we observe how many of the economies which are in an income state say, (0.2, 0.5) in the initial period land up in that very state, or elsewhere. If they do end up in another income state, (for example, in the income range of a half to three quarters of the weighted average income) there is said to be mobility. If they end up in the same, there is persistence. We will be interested in the former possibility i.e. of intra-distribution mobility.

In our exercise on India, we have measured these transitions and the results are tabulated in Tables 1 and 2 as *transition probability matrices*. Interpreting the transition matrix is as follows: First, we discretise the space of possible values of income, in  $r$  states. For instance, we define the state  $i = (0.2, 0.5)$  as one which has regions with an income which lying between 0.2 and 0.5 times the average income of the country. The probabilities obtained, give us the percentages of economies (in our case, Indian states) which given a starting state, have moved on to a different state. So, our row probabilities all add up to 1. Of these, the diagonal of the transition probability matrix is of interest to us. A diagonal with high values indicates higher probabilities of persistence - the likelihood of remaining in a particular state when one starts there. Thus, the smaller the diagonal, the greater intra-distribution mobility there exists.

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".

There is, however, a drawback in this measure as the selection of income states is arbitrary - different sets of discretisations 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. 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 discretisation of the states. We now have an infinite number of rows and columns replacing the transition probability matrix. In our exercise on India, such stochastic kernels are presented in Figures 5*ai*–*hi*.

Interpreting the stochastic kernels is as follows. Any slice running parallel to the horizontal axis (i.e.  $t + k$  axis) describes 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 will provide us information about the distribution dynamics, and thus about any tendencies of convergence. Concentration of the probability mass along the positive slope indicates

persistence in the economies' relative position and therefore low mobility. The 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. What has been happening to the inter-state income distribution in India?**

We will now take a look at the distribution dynamics of incomes across Indian states over 1965 to 1998. Figures 2a to 2d represent the stochastic kernels for relative per capita income of 1-year transitions for four sub-periods 1965-70, 1971–1980, 1981-88, and 1989-97.

Observation of the stochastic kernels and the contour plots reveal that the later years provide increasing evidence of persistence and low probabilities of changing their relative position. Over the periods 1965-70, 1971-80, 1981-88, 1989-1997 we observe in Fig. 2a-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. The cluster of States at the two peaks to consist of some low income economies at around 50% of the all India average and another at 150% of the average. Thus, though an overall view of the entire sample period 1965-88 shows some signs of cohesion, the sub-sample periods, particularly during the later years, have shown the cohesive forces substantially dissipating in influence. The result has been more of that of the rich states forging ahead, with the poor making little progress and a dispersing middle income group.

The long run view of whether the economies will converge over the long run is addressed by calculating the transition probability matrices. The results are tabulated in the appendix (Tables 1 and 2a-d). 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. Like the stochastic kernel, a "heavy" main diagonal is bad news - i.e. indicating persistence.

Tables 1 reports results for 1965-97 and they are quite similar to those obtained for the stochastic kernel - the values in the main diagonal are around 50%, which indicates that the probability that an economy remains in its own income state is around 50%. The off-diagonal

values are those which are indicative of mobility, albeit little. Mobility is evident and obvious for the above average income group. The states with incomes in the first two states reveal some low income states which have forged ahead. We also have an estimator of the long run tendencies, named the ergodic distribution, accounted in the last row of the table. This will give us the long run tendency of an economy to land up in a given income range. The results suggest that over the long run, the probability that an economy lands up in the 4th state is the highest, a little over 40%. What is encouraging is that the lower income groups vanish in the ergodic distribution.

Following tables 2a to 2d give us estimates of the transition matrix for the sub-periods. The second period again reveals tendencies of both persistence and mobility, with tendencies of persistence in the lower income group and the high income groups. The probability that the first two income states and last two income states shift anywhere other than their own is zero. Though there are signs of persistence, there is evidence of some inter-state (income state) movement, again in the high income clusters. This trend continues in the next two periods.

It is important to remember that as these estimates are based on time stationary transition matrices, it may not be reliable for long time periods for economic structural changes.

#### **4. What Explains the Polarisation?**

##### *4.1 Macroeconomic stability and Growth*

It is widely accepted that a stable macro-economic environment is required (though not sufficient) for sustainable economic growth. That taxation, public investment, inflation and other aspects of fiscal policy can determine an economy's growth trajectory has been articulated in the growth literature for the last three decades. Endogenous growth models have also stressed the long run role of fiscal policy as a key determinant of growth<sup>5</sup>. Recent cross-country studies also provide evidence that the causation runs in good measure from good macro-economic policy to growth (Fisher 1993, 1991, Easterly and Rebelo, 1993, Barro 1997).

The link between short run macroeconomic management and long run growth, however, remains one of the most controversial areas in the cross-country literature. A number of studies estimating regressions do show significant correlations, with the expected signs, though, it has been perniciously difficult to isolate any particular policy variable and demonstrate a robust correlation with growth, irrespective of endogeneity concerns and other variables. Endogeneity proves to be the hardest of problems to deal with as economic crises do not occur in isolation – inflation typically accompanies bad fiscal discipline, political instability and exchange rate crises.

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<sup>5</sup> See Barro (1990), Rebelo (1991), Jones et al (1993), Ireland (1994), Stokey and Rebelo (1995)

The recent cross country literature deals with much of establishing such correlations, revealing the complexity of the relationships. Levine and Renelt (1992) show that high growth countries are with lower inflation, have smaller governments and lower black market premia. While their results show that the relationship between growth and every other macro-economic indicator (other than investment ratio) is fragile, Fischer (1991) extends the basic Levine and Renelt regression to show that growth is significantly negatively associated with inflation and positively with budget surplus as a ratio of GDP. Easterly and Rebelo (1992) also present convincing evidence of fiscal deficits being negatively related to growth. Links between inflation and growth are particularly controversial. Levine and Zervous (1992) show that inflation is significant, though not robust and relates to only high inflation countries. Their composite indicator of macro-economic performance, a function of inflation and fiscal deficit is shown to be positively related with growth performance (lower inflation, lower fiscal deficit). Bruno and Easterly (1998) also take a short run approach and find that high inflation crises are associated with output losses, but that output returns to the same long run growth path once inflation has been reduced. This may be the reason for the weak inflation and growth relationship.

We will empirically investigate the role of a number of macroeconomic indicators in the following section for the period 1986-1998. We will be using panel data for indicators of capital expenditure, education expenditure, fiscal deficit, inflation, and interest expenditure<sup>6</sup>. We will start the analysis by looking at the role of distribution of infrastructure, where we use a number of indicators (social and economic infrastructure) in composite to explain the observed polarisation.

But first, let us extend the distribution dynamics approach for our conditioning exercise.

#### *4.2 The conditioning methodology under distribution dynamics*

The non-parametric tools which I will be using are those proposed by Quah (1996a). Using this approach is noteworthy in two important aspects - first, it differs from the conventional models of growth and accumulation in the direction of theorising in terms of the entire cross section distribution, and second, it departs from standard techniques. Theoretically, this method draws upon a growing body of literature of growth theories allowing for explicit patterns of cross-economy interaction, whereby economies cluster together into groups to endogenously emerge (Baumol 1986, Ben-David 1994, De Long 1994, Esteban and Ray 1994, Galor and Zeira 1993, to name a few). These new empirical patterns have encouraged the use of yet further empirical

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<sup>6</sup> I am grateful to Shahrokh Fardoust, World Bank, for providing me with the data set.

techniques as standard techniques are not capable of describing the new empirics. The distribution dynamics method is one such technique which describes convergence empirics in terms of the evolution of the entire income distribution.

While conventional methods (of standard regression analysis) explain average representative behaviour, this methodology explains how distributions evolve and tracks the law of motion of such a change. While the auxiliary factors in standard regression explains average behaviour, the distribution dynamics method explains the evolution of the entire distribution, hence exposing and explaining behaviour at different parts of the distribution. In other words, while standard methods compare  $E(Y)$  and  $E(Y|X)$ , thus determining whether  $X$  explains  $Y$ , this approach maps the entire distribution of  $Y$  to  $Y|X$ . If there is no change in the distributions, conditioned and unconditioned, we then conclude that the auxiliary factor does not explain the polarisation (or any other observed distribution pattern). However, if it does explain the polarisation, the distribution will have changed, where all economies in the conditioned distribution have the same income. This will all be revealed in the two models which are used in this method, described in the following section.

#### *How to read the stochastic kernels and transition probability matrices?*

How will all this be revealed in the stochastic kernels and transition probability matrices? These models essentially provide an account of the amount of intra-distributional mobility taking place. Mappings obtained earlier to observe the distribution dynamics characterise transitions over time – Figures 2a – 2d reveal transitions over different periods of time – it shows that income distribution over the period 1980 to 1998 has polarised into two convergence clubs (or income groups) – one at 50 per cent of the national average income, another at 125% of the national average. It can further be shown (see Technical Appendix) that just as stochastic kernels (and transition matrices) can provide information about how distributions evolve over time, they can also describe how a set of conditioning factors alter the mapping between any two distributions. Hence, to understand if a hypothesised set of factors explains a given distribution we can simply ask if the stochastic kernel transforming the unconditional one to the conditional one removes those same features.

One extreme situation would be where we find that the mapping from the unconditional to the conditional distribution would have the probability mass running parallel to the original axis at one. This would mean that all states irrespective of their own income would have their income conditioned by the auxiliary factor close to one. Since all incomes here are relative to the national average, this would mean that income, once conditioned, leads to “conditional convergence” – where all incomes converge to the national average. The conditioning factor

would therefore be deemed as a factor explaining the observed polarisation. This, of course, is our desired outcome.

Another extreme would be where the stochastic kernel mapping the unconditional income distribution to that conditioned has its probability mass running along the diagonal. Unlike the previous case, this now implies the opposite possibility – each state, irrespective of its position in the initial distribution, has its income conditioned by the auxiliary factor unchanged. This renders the conditioning factor as one which does not explain the observed polarisation.

The transition probability matrices are the discrete version of the kernels described above. Here again we map the unconditioned to the conditioned distribution. We divide the income distribution into “income states”, where each income state constitutes a range of incomes. The matrices provide the probabilities with which each economy (in our case, Indian states) moves out of its income state to land up elsewhere, or to remain in its original position. Like the stochastic kernel, a heavy diagonal indicates persistence, while higher probabilities indicating movement into the national average income-state (that is, one) indicates conditional convergence. The auxiliary factor used to derive the conditioned distribution will hence be a factor which explains the observed polarisation.

## **5. The Results**

### *5.1 Conditioning on infrastructure*

The precise linkages between infrastructure and economic growth and development are still open to debate. But it is widely agreed that the adequacies of infrastructure helps determine one country's success and another's failure - in diversifying production, expanding trade, coping with population growth, reducing poverty, or improving environmental conditions. Good infrastructure raises productivity, lowers costs, but it has to expand fast enough to accommodate growth<sup>7</sup>, it must adapt to support the changing patterns of demand. How far does the distribution of infrastructure explain disparate economic growth performance in the Indian case? In this section we will show that the changing pattern of the distribution of infrastructure serves to explain much of the evolution of disparities in economic performance across Indian states.

#### *Construction of an index of general infrastructure*

The infrastructure indicators<sup>8</sup> (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 1977-1993. There are no missing observations.

Per capita electrical consumption (in kilowatt hours)

Per capita industrial consumption of electricity

Percentage of villages electrified.

Percentage of gross cropped area irrigated

Road length (in kms per 1,000 square kms)

Number of motor vehicles per 1,000 population.

Rail track length (in kms per 1,000 sq.kms)

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

To obtain a general idea on the overall provision of infrastructure across the states, and to observe the role of economic and social infrastructure as a whole in explaining the evolution of the income distribution, we construct a single index accounting for each of the state's infrastructure base. One is also faced with the problem of multi-collinearity because of a large number of infrastructure variables, which may result in inconsistent estimates. 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<sup>9</sup>.

The results of the factor analysis are tabulated in Table 3. We accept the first factor (f1, which we will call INFRA) to be the general index of infrastructure, which takes an eigenvalue of over 12. This means that this factor accounts for 12 (out of 17) variables of infrastructure. Our

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<sup>7</sup>Infrastructure capacity grows step for step with economic output - a 1 per cent increase in the stock of infrastructure is associated with a 1 per cent increase in GDP across all countries in the world (World Development Report, 1994)

<sup>8</sup> 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.

<sup>9</sup> 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

results suggest that the indicator INFRA accounts for over 87 per cent of the variation in the 17 infrastructure variables. We will be using this indicator for our analyses.

*Conditioning on infrastructure.*

Does this improvement in the provision of infrastructure have a role to play in explaining the polarisation of income across the states? Our results suggest yes. Fig. 3*ai* plots the stochastic kernel mapping each state's income (relative to the national average) to that relative to the average income of states with the *same level of infrastructure*<sup>10</sup>. The kernel is constructed using 6 groups of states which have the same level of infrastructure, based on the general index of infrastructure constructed earlier. The mapping obtained is encouraging, particularly so for the higher income and lower income group states. For the middle income states, however, one finds that the mass lies close to the diagonal, implying that one does not observe a "group effect". Level of infrastructure, hence, does not appear to be a factor which explains cross section disparity in middle income group states.

The range above 1.2 times the national average, and those below the national average stands out from the rest. This is clearly revealed in the contour in Figure 3*aii* - here we observe a vertical spread of the probability mass centred around one. This suggests that these states have seen similar outcomes. The spike at around 0.5 of the national average in this range corresponds to the states of Bihar, Orissa, Rajasthan and Uttar Pradesh, Madhya Pradesh and Rajasthan, while spike at around 1.2 of the national average corresponds to higher income states of Punjab, Haryana, Gujarat and Maharashtra. Our conclusion hence is that infrastructure does explain the clustering of the lower income states, though does little to explain the higher income club. This is an interesting result in that we can observe infrastructure playing different roles at different levels of the income distribution. It is also worth noting that this result would go surpassed in standard methods of investigating for conditional convergence viz. standard regression analyses. Parametric tests confirming conditional convergence with infrastructure are not included in the results here due to the length of the paper, see Bandyopadhyay (2000b).

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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)

<sup>10</sup>Calculating *same level of infrastructure relative income* entailed calculating calculating each state's income relative to the group average income to which they belong for each year.

## *5.2 Conditioning with indicators of macroeconomic stability*

### *Obtaining the conditional distribution*

Here the conditioning scheme used to derive our conditioned distribution will be slightly different to that used earlier. Unlike many standard convergence regression analyses, here we do not assume the time varying auxiliary variables to be exogenous. We confirm endogeneity of the variables by Granger causality tests. The regressions are obtained by OLS, pooling cross section and time series observations. Unlike standard panel applications, we do not allow for individual effects, precisely for the reason to explain the permanent differences in growth rates across states. Granger tests for bivariate VARs in GDP (per capita) growth rates and capital expenditure – indicate significant dynamic inter-dependence between growth and capital expenditure. This implies that while capital expenditure does help to predict future growth, it is itself incrementally predicted by lagged growth. Thus we cannot include capital expenditure as an exogenous variable in our growth equations, but need to estimate the appropriate conditional distribution free from the feedback effects.

The conditional distribution is obtained 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. This will result in a relevant conditioning distribution irrespective of the exogeneity of the right hand side variables. The method derives from that suggested by Sims (1972)<sup>11</sup>, 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 co-efficients. 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 5.

What is observable in all projections is that capital expenditure 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). We seem to have a fairly stable set of co-efficients of the two-sided projections. The residuals of the second lead-lag projections are saved for the conditional distribution of growth on capital expenditure<sup>12</sup>. Conditioning two sided projections are also derived for the other auxiliary variables – namely – inflation, fiscal deficits, interest expenditure, own tax revenue, and education expenditure.

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<sup>11</sup> This method has been adopted by Quah (1996) to obtain the conditional distribution

<sup>12</sup> Results are found to be unchanged if one uses residuals from other projections

### *The Results*

Figures 3b to 3f present the stochastic kernels mapping the unconditioned to conditioned distributions, for the six conditioning auxiliary factors. Figure 3b presents the stochastic kernel representing conditioning with capital expenditure. The appropriate conditioned distribution has been derived by extracting the residuals from our earlier two-sided regressions. The probability mass lies predominantly on the diagonal, though one can observe some local clusters running off the diagonal at the very low and high ends of the distribution. These clusters are more clearly revealed in the contour plots, Fig 3b. These clusters, running parallel to the original axis at different levels provide evidence of capital expenditure explaining polarisation, quite similar to our earlier results with infrastructure.

Figure 3c, mapping the conditioning stochastic kernel with education expenditure as auxiliary variable, also runs mainly along the diagonal, with the upper and lower tails tending to run off parallel to the unconditioned axis. Both conditioning exercises with capital and education expenditure hence, seem to marginally explain some of the cross section distribution dynamics of growth across Indian states.

Figure 3d maps the conditioning stochastic kernel with fiscal deficit. Though it predominantly lies on the diagonal, there appears to be a number of individual. Of these, one lies way off the diagonal, at a level of 0.5 of the national growth rate. This is suggestive of fiscal deficit in serving to explain growth distribution dynamics for the cluster of States identified at the level.

Conditioning on inflation and interest expenditure, reveals no interesting insights in how they explain disparate growth performances – Figures 3e and 3f have the probability mass running decidedly along the diagonal.

### *Transition probability matrices*

The capital expenditure matrix (Table 6a) reveals a tendency of intra-distributional 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 polarisation of growth performances for the middle income group of states.

Transition matrices for education expenditure and fiscal deficits (in Tables 6b and 6c) exhibit similar 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.

Tables 6d and 6f once again represent estimates of intra-distributional 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.<sup>13</sup>

## **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 polarisation across the Indian states, over 1965-1998 - 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 polarisation, 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 Shand and Kalirajan 1999.

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 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 stylised facts are interesting for policy purposes in tracking the forces which govern growth dynamics across the Indian states.

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<sup>13</sup> Parametric results for conditioning are not produced in this paper for brevity. See Bandyopadhyay (2001) for relevant results

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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.

## Technical Appendix

(A) Here we will present the formal underlying structure for both models (stochastic kernels and transition matrices) highlighting distribution dynamics

Let us first consider the continuous version. The model is one for a stochastic process that takes values which are probability measures associated with the cross section distribution.

Let  $F_t$  be the probability measure associated with the cross section distribution. The following probability model holds:

$$F_{t+1} = T^*(F_t, u_t). \quad (1)$$

Here  $T^*$  is a mapping operator which maps probability measures in one period (with a disturbance term) to those of another. It encodes information of the intra-distribution dynamics: how income levels grow closer together or further away over successive time periods. Our task is to estimate  $T^*$  from the observed data set.

For simplicity in calculations, iterating the above equation one can write, (and leaving out the error term)

$$F_{t+s} = T^{*s} \cdot F_t. \quad (2)$$

As  $s$  tends to infinity it is possible to characterise the long run distribution - this is called the *ergodic* distribution and it predicts the long term behaviour of the underlying distribution.

Handling equation (1) is difficult; hence, the concept of the stochastic kernel was introduced to estimate the long run behaviour of the cross-section distribution<sup>14</sup>.

Let us consider the measurable space  $(\mathbf{R}, R)$ .  $\mathbf{R}$  is the real line where the realisations of the income fall and  $R$  is its Borel sigma algebra.  $B(\mathbf{R}, R)$  is the Banach space of finitely additive functions. Let  $F_{t+1}$  and  $F_t$  be the elements of  $B$  that are probability measures in  $(\mathbf{R}, R)$ . A stochastic kernel is a mapping  $M : \mathbf{R} \times R \rightarrow [0,1]$ , satisfying the following :

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<sup>14</sup>See Stokey, Lucas and Prescott (1989) and Silverman (1986)

- (i)  $\forall a \in \mathbf{R}, M(a, \cdot)$  is a probability measure.
- (ii)  $\forall A \in \mathcal{R}, M(\cdot, A)$  is a sigma measurable function.

Then  $M(a, A)$  is the probability that the next state period lies in the set  $A$ , given that the state now is  $a$ .

For any probability measure  $F$  on  $(\mathbf{R}, \mathcal{R}) \forall A \in \mathcal{R}$ :

$$F_{t+1}(A) = \int M(x, A) dF_t(x) \tag{3}$$

, where  $M(\cdot, \cdot)$  is a stochastic kernel, and  $F_{t+1}(A) = (T^*F_t)(A)$ .  $T^*$  is an operator associated with the stochastic kernel that maps the space of probabilities in itself, (adjoint of the Markov operator associated to  $M$ ). The above equation (12) measures the probability that the next period state lies in the set  $A$ , when the current state is drawn according to the probability measure  $F_t$ .  $F_{t+1}$  i.e.  $T^*F_t$  is the probability measure over the next period state, when  $F_t$  is the probability measure over this period. Hence we can consider the  $T^*$  in the previous equations as being generated by the above differential equation. Our empirical estimation will involve in estimating a stochastic kernel as described above.

Such stochastic kernels though satisfactory as a complete description of transitions, are however, simply point estimates and we are yet to have a fitted model. It is thus not possible to draw inferences and derive long run estimates. However, it is possible for us to infer whether income levels have been converging and diverging. For these computations, we turn to the discrete formulation of the above.

#### *Transition probability matrices*

Now let us consider the discrete version. Given that using the stochastic kernel it is not possible for us to draw any inferences about the long run tendencies of the distribution of income, we now turn to a discrete version of the above calculation. Here we calculate  $T^*$  from the above equation (1.15) and to compute the values using (1.14).  $T^*$  is calculated assuming a countable state-space for income levels  $Y_t = \{y_{1t}, y_{2t}, \dots, y_{rt}\}$ . Thus  $T^*$  is a transition probability matrix  $Q_t$ , where

$$F_t = Q_t(F_{t-1}, u_t)$$

$Q_t$  encodes information of the short run distribution dynamics and the long run information is summarised by the ergodic distribution - it gives the distribution across states that would be achieved in the long run. Here, convergence takes place when the ergodic distribution

degenerates towards a mass point. The transition matrix and the stochastic kernel together expose the deep underlying short run and long run regularities in the data.

(B) Here we shall explain how the stochastic kernel comes useful in explaining distribution dynamics. The idea is that, to understand if a hypothesised set of factors explains a given distribution dynamics we will simply be asking whether the stochastic kernel transforming the unconditional distribution to a conditional one removes the same features which characterised income distributions as distorted. The following explains the above.

We consider the definition of the stochastic kernel, once again.

Consider the measurable space  $(R, \mathcal{R})$ .  $R$  is the real line where realisations of income fall and  $\mathcal{R}$  is its Borel sigma algebra.  $B(R, \mathcal{R})$  is the Banach space of finitely additive functions. Let  $\nu$  and  $\mu$  be elements of  $B$  that are probability measures in  $(R, \mathcal{R})$ . A Stochastic Kernel is a mapping  $M: R \times R \rightarrow [0,1]$ , satisfying:

- (i)  $\forall x \in R, M(\mu, \nu)(x, \cdot)$  is a probability measure.
- (ii)  $\forall A \in \mathcal{R}, M(\mu, \nu)(\cdot, A)$  is a sigma measurable function.

Then  $M(\mu, \nu)(x, A)$  is the probability that the next state period lies in set  $A$ , given that in this period the state is in  $x$ .

For any probability measure  $\mu(A)$  on  $(R, \mathcal{R}), \forall A$  in  $\mathcal{R}$ :

$$\mu(A) = \int M(\mu, \nu)(x, A) d\nu(x)$$

$$\text{or, } (T^* \nu)(A) = \int M(x, A) d\nu(x) \dots (iii)$$

where,  $M(\cdot, \cdot)$  is a stochastic kernel, and  $\mu(A) = (T^* \nu)(A)$ .  $T^*$  is an operator associated with the stochastic kernel that maps the space of probabilities in itself (adjoint of the Markov operator associated to  $M$ ). Conditions (i) and (ii) simply guarantee that interpretation of (iii) is valid. By (ii), the right hand side of (iii) is a well defined Lebesgue integral. By (i), the right hand side of (iii) is weighted average of probability measures. It however, nowhere requires that  $\nu$  and its image  $\mu$  under  $T^*$  be sequential in time. Thus the stochastic kernel  $M$  representing  $T^*$  can be used to relate *any* two different distributions - sequential in time, or not. In the distribution dynamics case, we specify  $\nu$  and its image  $\mu$  to be  $F_t$  and  $F_{t+1}$ , which are sequential in time. For the conditioning exercise, we use the stochastic kernel  $M$  representing  $T^*$  (with  $\nu$  and its image  $\mu$  under  $T^*$ ) to relate two different distributions - distributions of which  $\nu$  and its image  $\mu$  are two realisations of the random element - the unconditional distribution and the conditional distribution in the income distribution space.

**Table1: Inter-State ( per capita) income dynamics, 1965-97**  
**First Order transition matrix, Time stationary**

(Number )	Upper end point				
	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

**Table2a: Inter-State ( per capita) income dynamics, 1965-70**  
**First Order transition matrix, Time stationary**

(Number )	Upper end point				
	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

**Table2b: Inter-State relative ( per capita) income dynamics, 1971-80**  
**First Order transition matrix, Time stationary**

(Number )	Upper end point				
	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

**Table2c: Inter-State relative ( per capita) income dynamics, 1981-89**  
**First Order transition matrix, Time stationary**

(Number )	Upper end point				
	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

**Table 3****Results of Factor Analysis**

Components	Eigenvalue	Cumulative R <sup>2</sup>
f1	12.41	0.83
f2	1.22	0.91
f3	1.00	0.97

**Factor Loadings**

	f1	f2	f3
total power consumption	0.97	-0.16	0.10
power consumption in industrial sector	0.95	-0.12	0.04
percentage of villages electrified	0.99	0.04	-0.08
percentage of net area operated with irrigation	0.95	-0.20	0.18
length of road network per 1000 sq kms.	0.97	-0.12	0.10
number of motor vehicles per 1000 inhabitants	0.89	0.07	-0.37
length of rail network per 1000 sq.kms	0.61	-0.47	0.60
literacy rate of adult population	0.98	-0.04	-0.15
primary school enrolment rate	0.97	0.04	-0.08
secondary school enrolment rate	0.98	-0.13	-0.02
infant mortality rate	-0.96	0.05	0.22
bank offices per 1000 people	0.91	0.24	-0.30
bank deposits as a percentage of SDP	0.75	0.57	0.28
bank credit as a percentage of SDP	0.58	0.68	0.40

**Table 4. Inter-state conditioning on infrastructure transition matrix**

Number	Upper end point				
	0.208	0.626	0.762	0.916	1.1
89	0.10	0.31	0.40	0.17	0.01
62	0.03	0.08	0.29	0.52	0.08
32	0.03	0.19	0.19	0.41	0.19
31	0.03	0.00	0.32	0.10	0.55
41	0.00	0.02	0.00	0.20	0.78
<b>Ergodic</b>	<b>0.013</b>	<b>0.042</b>	<b>0.105</b>	<b>0.21</b>	<b>0.78</b>

**Table 5. Conditioning regressions (two sided projections) of growth rate on capital expenditure**

capital expenditure		Co-efficients 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 (0.01)	-0.019 (0.016)
	1	0.020 (0.01)	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			
<b>Sum of co-efficients</b>		-0.01	-0.04	<b>-0.014</b>
<b>R<sup>2</sup></b>		0. 10	0. 10	0. 11

Note: Numbers in parentheses are OLS and White heteroskedasticity consistent standard errors.

**Table 6a. Inter-state conditioning on capital expenditure**  
*transition matrix*

Number	Upper end point				
	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
<b>Ergodic</b>	<b>0.731</b>	<b>0.179</b>	<b>0.015</b>	<b>0.036</b>	<b>0.038</b>

**Table 6b. Inter-state conditioning on education expenditure,**  
**transition matrix**

Number	Upper end point				
	0.190	0.227	0.273	0.400	0.572
170	0.76	0.12	0.06	0.06	0.00
220	0.36	0.36	0.23	0.05	0.00
290	0.21	0.38	0.14	0.28	0.00
230	0.04	0.09	0.14	0.28	0.00
210	0.00	0.00	0.00	0.05	0.95
<b>Ergodic</b>	<b>0.305</b>	<b>0.129</b>	<b>0.093</b>	<b>0.126</b>	<b>0.346</b>

**Table 6c. Inter-state conditioning on fiscal deficit, transition matrix**

Number	Upper end point				
	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
<b>Ergodic</b>	<b>1.00</b>	<b>0.00</b>	<b>0.00</b>	<b>0.00</b>	<b>0.00</b>

**Table 6d. Inter-state conditioning on inflation, transition matrix**

Number	Upper end point				
	0.113	0.187	0.249	0.308	0.483
0	0.35	0.14	0.35	0.14	0.01
150	0.00	0.25	0.19	0.46	0.09
360	0.00	0.06	0.56	0.26	0.12
290	0.00	0.00	0.13	0.21	0.66
320	0.00	0.00	0.00	0.00	0.00
<b>Ergodic</b>	<b>0.400</b>	<b>0.212</b>	<b>0.116</b>	<b>0.144</b>	<b>0.128</b>

**Table 6e. Inter-state conditioning on interest expenditure,  
transition matrix**

Number	Upper end point				
	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
<b>Ergodic</b>	<b>1.00</b>	<b>0.00</b>	<b>0.00</b>	<b>0.00</b>	<b>0.00</b>

Fig.1: Relative GDP per capita of Indian States  
1965-1998

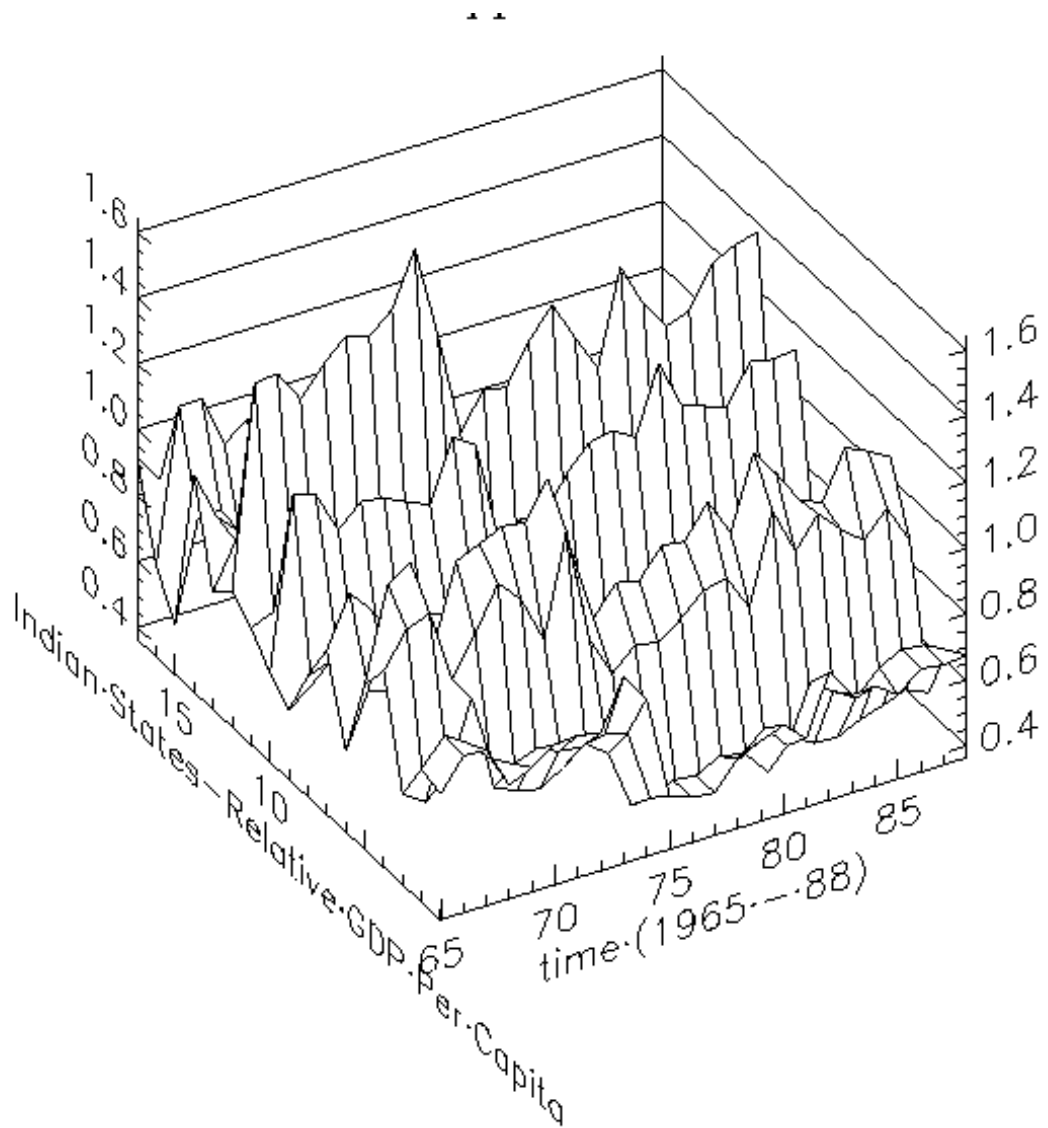


Fig.2a: Relative Income Dynamics across Indian States, 1 year horizon,  
1965-70

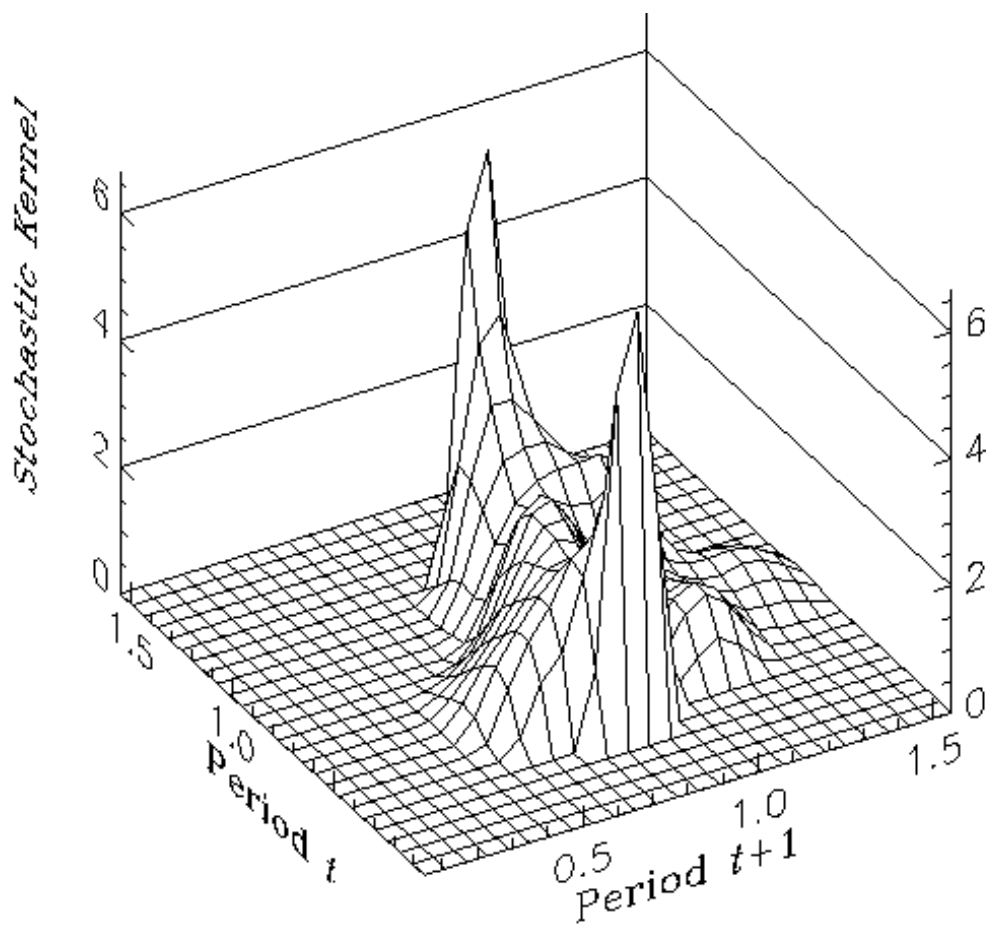


Fig. 2b: Relative Income Dynamics across Indian States, 1year horizon  
1971-80

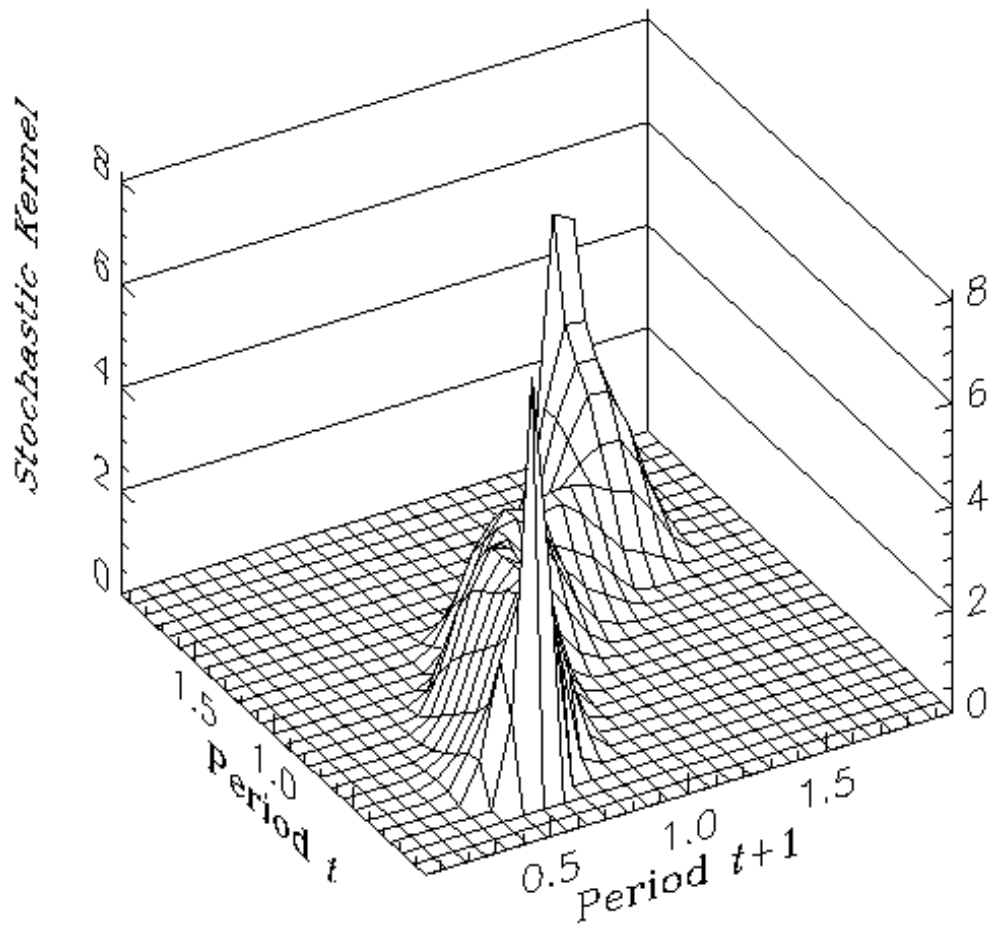


Fig. 2c: Relative Income Dynamics across Indian States, 1 year horizon  
1981-89

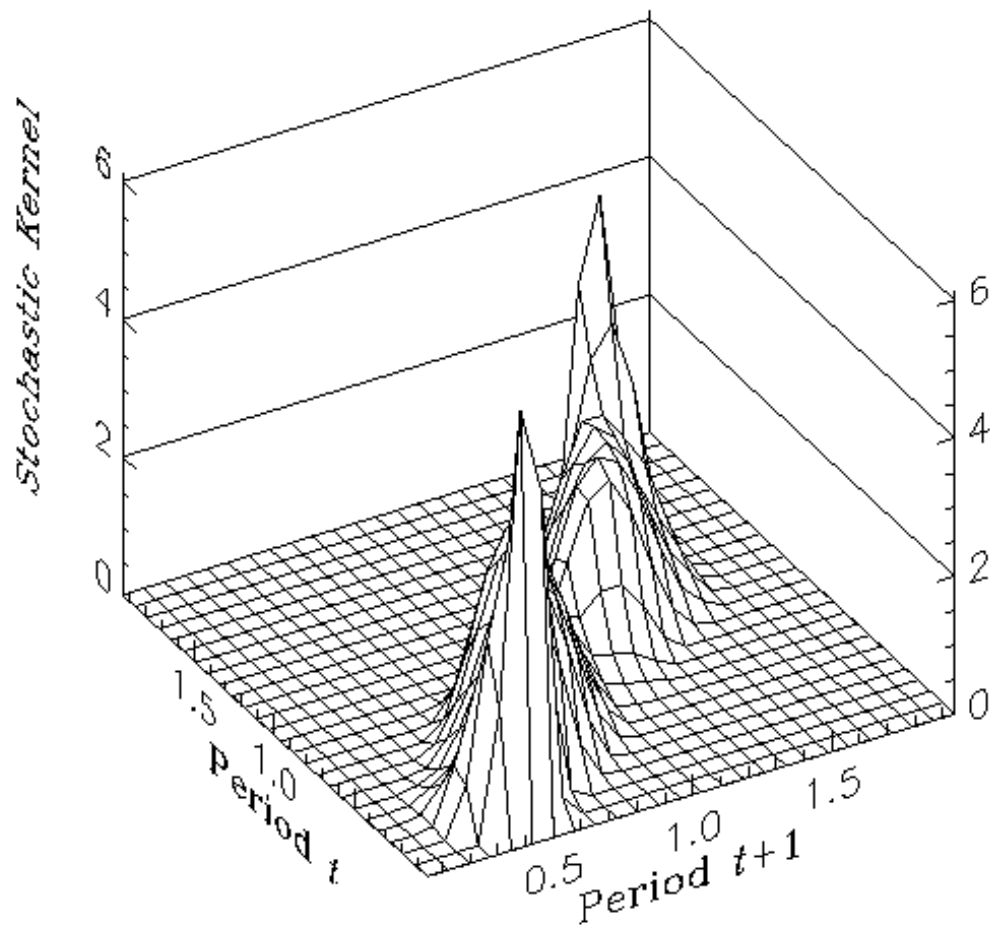
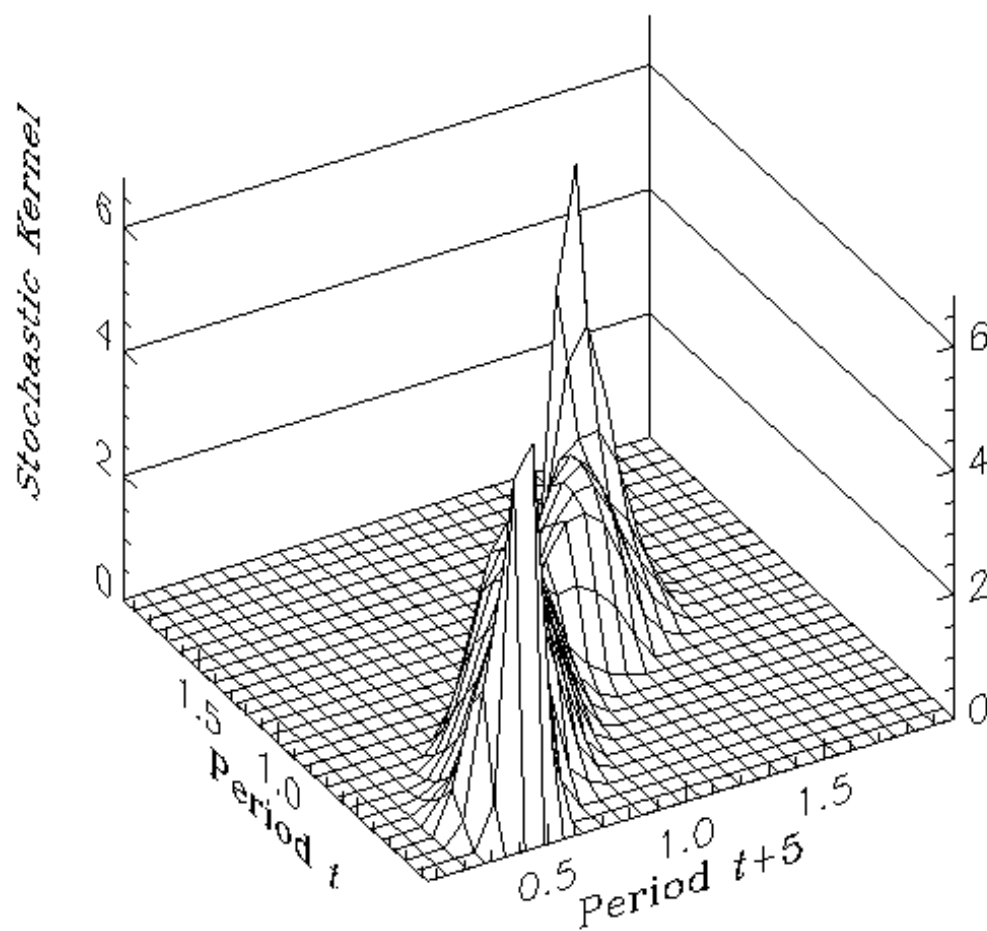
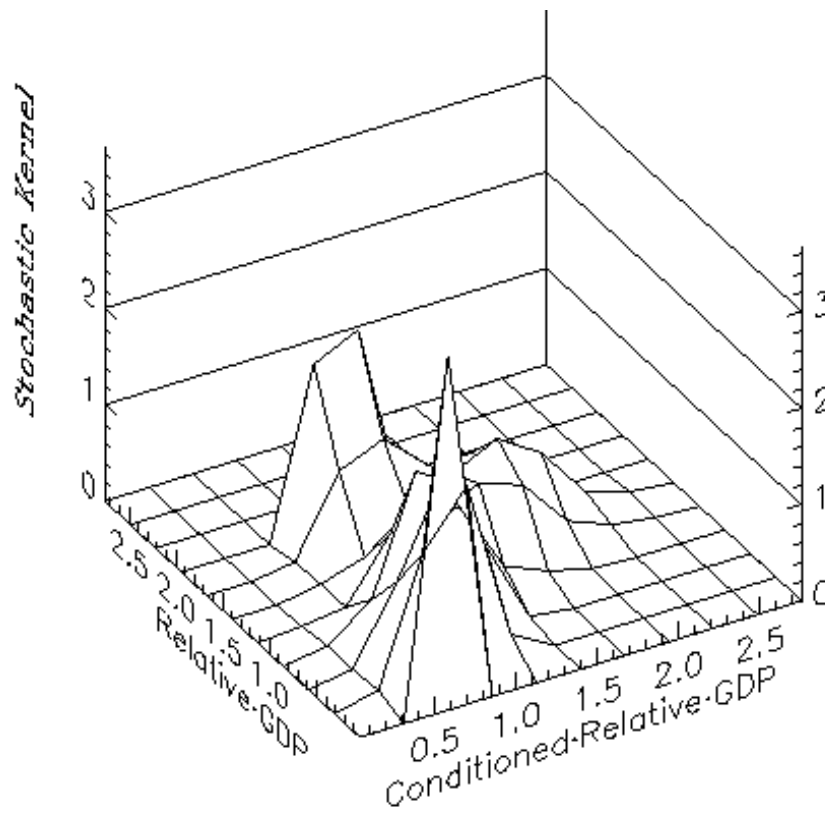


Fig. 2d: Relative Income Dynamics across Indian States, 1 year horizon  
1990-97



**Fig.3a i. Relative per capita incomes across Indian states**  
**Infrastructure conditioning**



**Fig.3a ii. Relative per capita incomes across Indian states**  
**Infrastructure conditioning, contour**

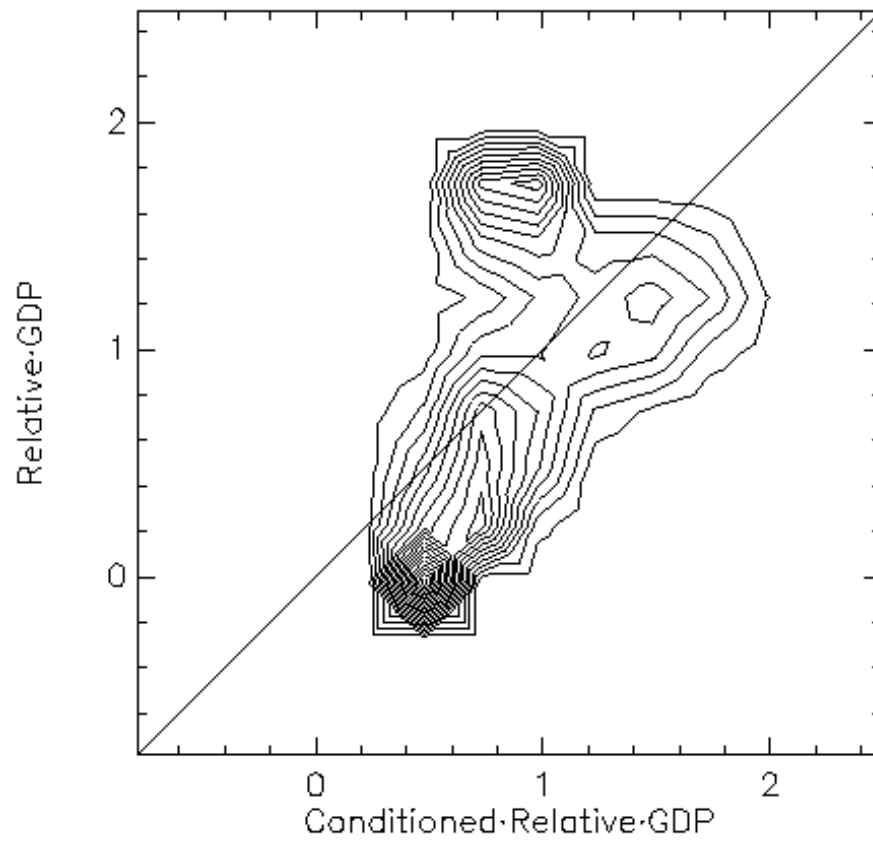


Fig.3b. Relative per capita incomes across Indian states  
Capital Expenditure conditioning.

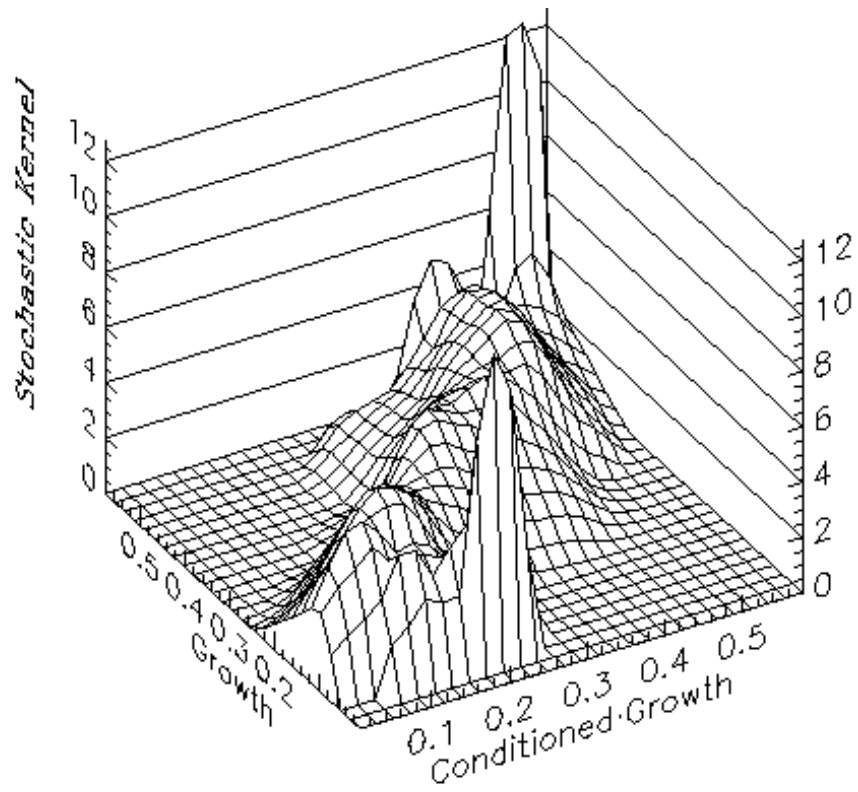


Fig.3c. Relative per capita incomes across Indian states  
Education Expenditure conditioning.

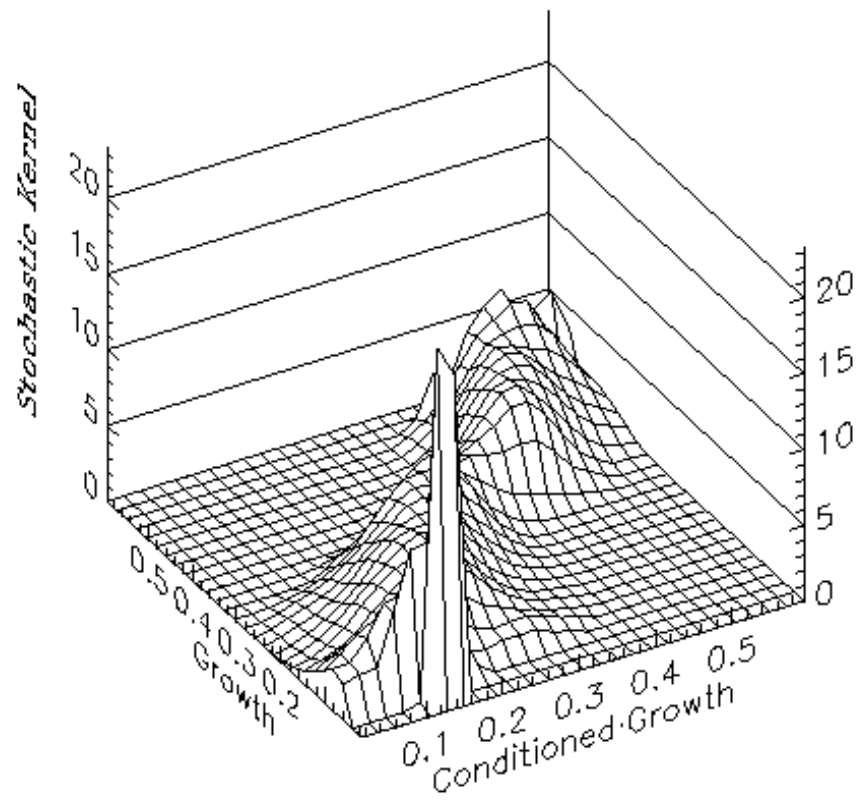


Fig.3d. Relative per capita incomes across Indian states  
Fiscal deficit conditioning

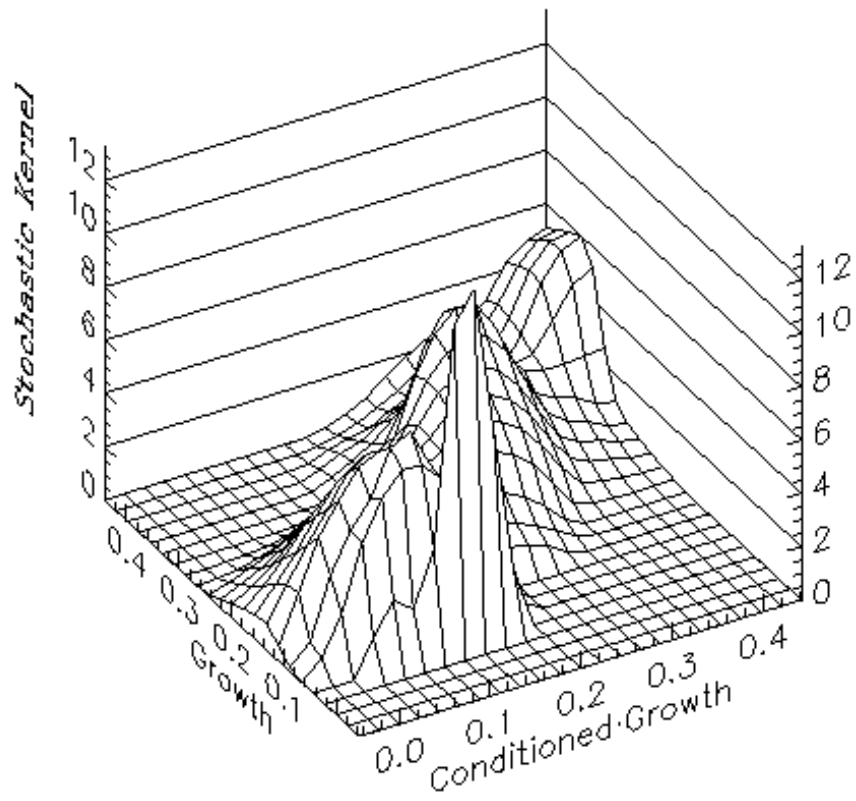


Fig.3e. Relative per capita incomes across Indian states  
Inflation conditioning

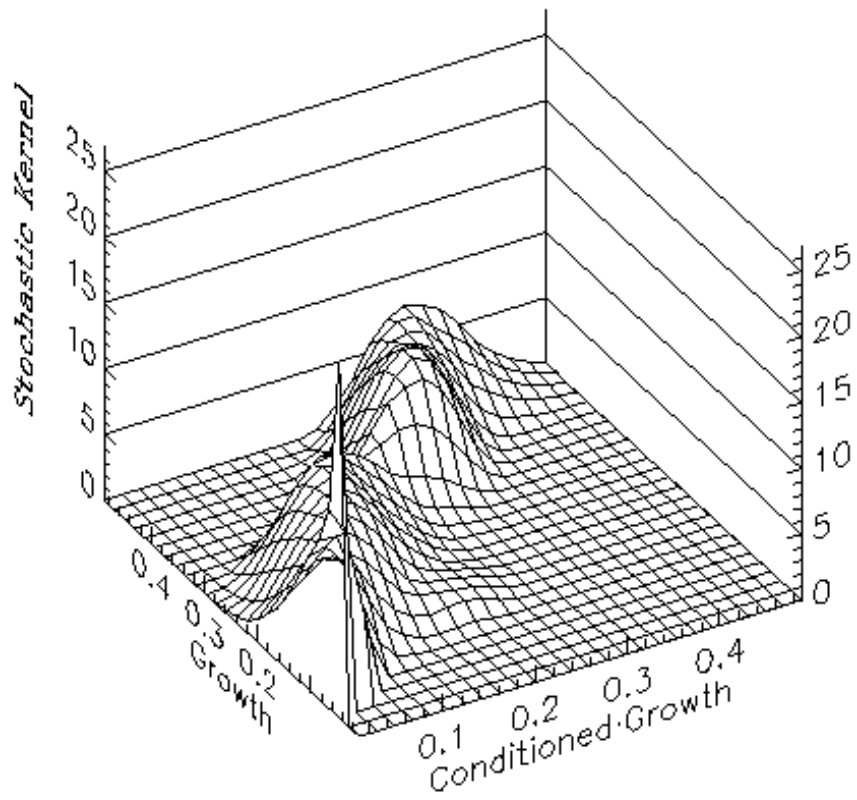


Fig.3f. Relative per capita incomes across Indian states  
Interest expenditure conditioning

