Is India Shining?

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Abstract

In India, the popular perception is economic reforms have benefited the rich more than the poor leading to an unequal income distribution, as in Quah's twin peaks hypothesis. In this article we test this hypothesis by studying the spatial dynamics of income distribution. Using district-level per-capita income we find that the income distribution has not changed. The perception about economic reforms having benefitted only the rich is not correct because income growth across districts is positively correlated spatially. Thus there is a positive spatial multiplier effect on income and growth. In addition, we also identify physical infrastructure, human capital, and factories, as factors responsible for increase in income for both the rich, and the poor districts.

Key Words: Districts of India, Income, Moran's Index, Spatial Analysis

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1. Introduction

The present debate about India's development strategy is inclusive growth. Inclusive growth emphasizes a more equitable distribution of income, and building capabilities for attaining better health and education. The general notion about the success of inclusive growth is pessimistic. The argument generally made is that the poor are getting richer, but the rich are getting richer faster. [3]

Apparently such an outcome is not surprising. Free market reforms entail unequal payoff to economic agents. People with better skill stand to gain more compared to people with lesser skill. The perception about economic reforms only benefitting the rich might have been one of the factors responsible for the ouster of the National Democratic Alliance (NDA) government; paving the way for United Progressive Alliance (UPA) government initially during 2004, and subsequent re-election in 2009. To address this perception about increase in income inequality, the UPA government, started several market interventions. Schemes such as Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) is a classic example of a labor market intervention.[4] Capital market intervention through microfinance also emerged substantially. However, the notion about the poor not benefitting from economic reforms still exists.

How true is this perception? We answer this question by looking at the dynamics of income distributional pattern in India. If reforms are pro-rich then we would see the emergence of twin peaks in the underlying income distribution function: clustering of the

[3] The Economic Times News Service. Available at: http://articles.economictimes.indiatimes.com/2011-02-01/news/28424869_1_mckinsey-households-income.

[4] The Mahatma Gandhi National Rural Employment Guarantee Act enacted by legislation on August 2005, aims at enhancing the livelihood security of people in rural areas by guaranteeing 100 days of wage-employment in a financial year to a rural household whose adult members volunteer to do unskilled manual work.

rich people, and clustering of the poor people with pockets of economic growth pulling-up the national average income. On the other hand, a uniform growth process at a pan-India level would lead to a disappearance of such clusters. Considering district-level per-capita income data from the Planning Commission, Government of India, in 1999/2000 and 2004/05, we find that the income distribution has not changed, thus the perception about economic reforms having benefitted only the rich is not supported by the data. Results suggest that between 1999/2000 and 2004/05 there is no statistically significant difference in the median adjusted income distribution functions. In fact, the income density function for 2004/05 has become more platykurtic (with fewer extreme values) than it was during 1999/2000, suggesting that there has been a reduction in inter-district per-capita income disparity.

This idea is in the spirit of work done by Quah (1993, 1996), and Jones (1997), which introduces the notion of twin peaks in the cross-country distribution of incomes. Quah (1993, 1996) finds evidence about persistence, and stratification of income density functions. Jones (1997) observes that clustering can be a temporary phenomenon, as might happen with high frequency growth miracles data. Emergence of twin peaks implies polarization of the cross-country income distribution into rich and poor convergence clubs.

Our study makes two important contributions.

First, we capture interaction among neighboring districts. Economies of neighboring districts are interdependent. This can happen through economic agents such as firms located in different districts trading among themselves; or through peer-group effects where externalities in local labor market due to production, matching, and other market interaction involve movement of labors from one district to another; and even through network externalities of infrastructure. We capture interaction among neighboring districts using Moran's Index (***I***). A higher spatial correlation (***I***) for a particular variable, say per-capita income, would indicate that all the districts in India are more or less similar in terms of economic well-being (read, per-capita income). On the other hand, a lower, or a negative spatial correlation would indicate some districts have higher per-capita income relative to others leading to stratification in the income density function. We find that the Moran ***I*** for both per-capita income, and growth of per-capita income, are significantly positive indicating that the growth process has been uniform across India. There is no evidence supporting an emergence of twin peaks in the underlying income distribution function. This is in line with our earlier result indicating that income growth has been spatially correlated. Growth in one district has helped growth in others, and there has been no increase in income inequality among districts.

Second, while analyzing interaction between growth and development indicators, we separate out, and quantify, the direct and the indirect neighborhood effect. A direct neighborhood effect reflects how the level of development (captured through development indicators) in any particular district *i* affects the income variable of that district. Whereas, the indirect neighborhood effects capture how the level of development in any neighboring district (say, *j*) affects the income level of district *i*. We find that opportunities to earn income (measured in terms of district-level per-capita income) in the neighboring districts positively affect income in district *i*. As there is free movement of labor and capital across districts in India, it may be responsible for a uniform income distribution in the country, resulting in more balance regional growth. In general, better development indicators, such as physical and social infrastructure, including, electricity, hospitals, closed drainage system, drinking water, and banks, positively affect income in any particular region.

To our knowledge this study is the first scientific attempt that makes use of district-level data from India, and quantifies the neighborhood effect using spatial econometric techniques.

2. Earlier studies

There are a number of studies that indicate India is spatially heterogeneous in terms of opportunities to earn income. Singh et al. (2010) gives a detailed account of this literature. Broadly speaking this literature can be divided into two groups.

The first group comprises studies that merely stop at classifying districts and/or states on the basis of some development indicators without quantifying the linkages between the growth and the development indicators. For instance, on the basis of the 1991 Census (Government of India, 1991), Kurian (2000) finds evidence about widening regional disparities in India when measured in terms of sex ratio (females per 1000 males), female literacy, infant mortality, and level of infrastructure development. He finds the forward group of states (Andhra Pradesh, Gujarat, Haryana, Karnataka, Kerala, Maharashtra, Punjab and Tamil Nadu), with higher per-capita income, have move ahead in terms of performance of the aforementioned parameters relative to the backward group of states (Assam, Bihar, Rajasthan, Uttar Pradesh and West Bengal), that is, the states with lower per-capita income. On the basis of data obtained from Planning Commission (Government of India, 2000), Mehta (2003) finds spatial inequalities exist at all level of disaggregation – a given state may perform extremely well on all indicators but there may be districts within that state that are among the most deprived in the country, or a state may have very high levels of attainment on certain specific development indicator(s) but not on all of them.

The second group of studies examines whether income growth across states in India has converged, or diverged over time. These papers find mixed evidence. After controlling for the difference in initial economic conditions (such as initial level of per-capita income, share of agriculture and manufacturing sector in the state-level income), Cashin and Sahay (1996), Aiyar (2001), and Purfield (2006) find evidence in favor of convergence, whereas, Rao et al. (1999), and Bajpai and Sachs (1996) find evidence in favor of divergence.[5] These studies typically use a growth accounting equation, such as the one suggested by Barro and Sala-i-Martin (1992), and attempt to explain long-run growth rates of any state conditional upon its initial output, and development indicators. The conflicting results about convergence or divergence may results from failure to capture patterns of growth at a sub-regional level, smaller than the states. This is because growth accounting literature typically assumes that states are similar in terms of long-run steady state level of income. This assumption is based on the fact that states in India have access to similar level of technology. However, as Aiyar (2001), and Purfield (2006), point out long run steady state level of income can differ because of factors such as spatial variation in demography, development, and state-level policies.

More specifically, as to whether economic reforms in India has widened the gap between the richer, and the poorer states, here also we find mixed evidence. While examining the growth performance of 14 major states during the pre-reform period (from 1980/81 to 1990/91) with the post-reform period (from 1991/92 to 1998/99), Ahluwalia

[5]The time periods, and the number of states, considered to analyze the convergence, or divergence of state-level per-capita income, vary. Cashin and Sahay (1996) look at a sample size of 20 states between 1961 and 1991; Aiyar (2001) consider 19 states between 1971 and 1996; Purfield (2006) considers 15 states between 1973 and 2002; Rao et al. (1999) considers 14 states between 1965 and 1994; and Bajpai and Sachs (1996) consider 19 states between 1961 and 1993.

(2002), finds that not all the rich states has become richer relative to the poorer states. Except for the three poorer states (Bihar, Uttar Pradesh and Orissa), all other states have narrowed the distance between themselves, and two of the richest states (Punjab and Haryana) during the nineties. Middle-income states such as Karnataka, Kerala, Tamil Nadu and West Bengal, actually grew faster during the post-reform period relative to their growth rates during the pre-reform periods. Ahluwalia (2002) finds private sector investment, physical infrastructure (such as irrigation facilities, electrification, roads, ports and rail transportation), and literacy rates, as factors responsible for variation in state-level income.

However, Bhattacharya and Sakthivel (2004) find evidence in favor of increase in regional inequality, with the state domestic product (SDP) widening more drastically during the post-reform period. Arguing that the comparison in Ahluwalia (2002) is based on two different sets of SDP data, [6] Bhattacharya and Sakthivel (2004) extend the new SDP data series backward to compare growth and regional variation across states with a common database. They find the coefficient of variation in the per-capita SDP growth rate has increased from 0.19 during the eighties to 0.29 during the nineties, and the correlation coefficients between the average growth rates of SDP between the eighties and the nineties is 0.50. This means that the states with higher SDP growth rates in the eighties continued to experience higher growth rates in the nineties. This paper finds higher population growth rates is responsible for slower SDP growth rate in poorer states such as Bihar and Uttar Pradesh.

[6] The new 1993/94 base year SDP data series used for doing post-reform period analysis is different than the old 1980/81 base year SDP data series used for analyzing performance of states during pre-reform period. There has been a change in product classification in the new SDP data series, with more sectors included from the financial services, the real estate and the agricultural allied services, than there are in the old SDP data series (See, Bhattacharya and Sakthivel, 2004).

Our study fits well to this strand of literature, and address the limitation of the earlier studies. First, we use district-level data to capture spatial variation in income and development indicators that are observed at a sub-state level. Second, we use this district-level per-capita income data to examine the dynamics of the income distribution function. This we do to analyze whether during the post-reform period (that is, between 1999/2000 and 2004/05) there has been any statistically significant change in the district-level income density function. Finally, to capture the potential for observational interaction across region, such as through technological spillovers, or through good governance, we model the neighborhood effect. This is because, a regression based approach (cross section, time series, or panel) typically do not capture the neighborhood effect, and failure to capture neighborhood effect can result in major model misspecification (Anselin, 1988).[7]

3. Empirical model

The empirical analysis has three parts.

In the first part of the analysis we see how per-capita district level income distribution (absolute, and median (relative) adjusted) has changed between 1999/2000 and 2004/05; and between 2001/02 and 2004/05. To examine the dynamics, we draw density of district per-capita income for the fiscal years, 1999/2000, and 2004/05. To check for the robustness we repeat this exercise for the time period between 2001/02 and 2004/05. We ran Kolmogorov-Smirnov (KS) test to ascertain whether there is any

[7] Even the attempt to control for regional variation using binary dummy variables, as is often done in regression, might not yield satisfactory results in terms of capturing intricate geographical relationship. For instance, Gautam Budh Nagar (one of the more progressive district in the State of Uttar Pradesh) can be treated as one of the richest districts in the country despite being part of Uttar Pradesh, which is classified as a poor state. Using district dummy for this region will fail to capture how elements of prosperity gradually spread from the core (say, Noida, the district headquarter of Gautam Budh Nagar) to the rest of Uttar Pradesh.

statistically significant difference in the median adjusted per-capita income distribution between different fiscal years: from 1999/2000 to 2004/05, and from 2001/02 to 2004/05. For a given cumulative density function *F(X)* the KS statistic is given as:

$D_{n,n'} = \sup_x \left| F_{1,n}(x) - F_{2,n'}(x) \right|$, where $\sup_x$ is the supremum of the set of distances given by $D_{n,n'}$. Under condition when $D_{n,n'}$ converges to zero it implies no significant change in *F(X)* between the time periods 1, and 2. Under this condition, there is no change in moment conditions for the cumulative density functions plotted at two different time periods. On the other hand, a statistically significant difference in median adjusted per-capita income distribution at two different time periods are indication towards the fact that among the districts there has been an increase in income disparity. To visually inspect formation of twin peaks (if any), we compute the density estimates using the Epanechnikov kernel with a bandwith chosen for optimizing normal densities.[8]

To complement the analysis we did in the first part, in the second part we test for the nature of spatial relation. Many of these spatial (cross sectional) relationships are captured by Tobler's first law of geography: “Everything is related to everything else, but near things are more related than distant things.” We test for Tobler’s principle of spatial interaction using Moran’s Index (***I***). The Moran's ***I*** introduced in 1950 is the first measure of spatial autocorrelation in order to study stochastic phenomena, which are distributed in space in two or more dimensions. We capture interaction among the neighboring districts by weighting the income variable with a contiguity matrix, *W*. We define *W*, such that $W_{ij} = 1$, if district *i* is adjacent to district *j*, and zero otherwise (for the districts that are not adjacent). In that case, the diagonal elements will be zero ($W_{ii} = 0$). Using geographical

[8] Compared to other kernels (Gaussian, Uniform, Triangular, and Bi-weight), Epanechnikov kernel minimizes the asymptotic mean integrated square error, and hence is chosen for this analysis.

information system we create this *W* matrix for all the districts in our sample. Emergence, or clustering of growth and development centers would yield a low, or even negative spatial-correlations among regions, but if all regions are on average similar then there will be positive spatial correlations among the regions.

We imagine India as a network, with each district as a node in the network. Moran's correlation of a variable *y* is defined on a spatial network (*W*) with *n* - nodes (districts) as:

$$I\left(y\ :\ W\right)=\frac{\sum_{i,j=1}^{n} w_{ij}\left(y_i-\bar{y}\right)\left(y_j-\bar{y}\right)}{trace(W'W)*\sigma\left(y\right)}$$

where $\sigma(y)$ is the standard deviation of *y*. Like a correlation coefficient the values of Moran's ***I*** range from +1 indicating a strong positive spatial autocorrelation, to 0 indicating a random pattern, to -1 indicating a strong negative spatial autocorrelation. For statistical hypothesis testing, Moran's ***I*** values can be transformed to Z-scores in which values greater than 1.96, or smaller than -1.96, means that the spatial autocorrelation is significant at a 5 per cent level of significance.

The third part of our analysis is a follow-up from the first two parts. We ask the question: What are the factors that might have led to an increase in per-capita district income in India, with or without any change, in the underlying income distribution function? In particular, we consider the following spatial income level model:

$$\begin{aligned}
Y_1 &= X_0\beta_1 + WX_0\gamma_1 + \varepsilon_1 \\
\varepsilon_1 &= \rho_1 W\varepsilon_1 + u_1 \\
Y_2 &= X_0\beta_2 + WX_0\gamma_2 + \varepsilon_2 \\
\varepsilon_2 &= \rho_2 W\varepsilon_2 + u_2 \\
\begin{pmatrix} u_1 \\ u_2 \end{pmatrix} &\sim N\left(0, \sigma^2\begin{pmatrix} 1 & \psi \\ \psi & 1 \end{pmatrix}\right)
\end{aligned}$$

where Y_1 and Y_2 are the $n \times 1$ vector of cross sectional observations on the log of district level per-capita income for the fiscal 2001/02 and 2004/05, respectively. X_0 is a matrix of development indicators data that are mostly obtained from the Census 2001 (Government of India, 2001).[9] W is the contiguity matrix. The coefficients β measure the direct effect. The coefficients γ captures the indirect neighborhood effects. A negative γ implies spillover effects from the neighboring district *j* have detrimental effect on the income of district *i*. A positive γ implies otherwise. For instance, it is expected districts in the neighborhood of big cities will enjoy some positive externalities, and hence will tend to have higher income as compared to districts located further away. Gautam Budh Nagar (a district bordering Delhi), and Gurgaon (a district in Haryana in the neighborhood of Delhi) is expected to have a positive γ. It is also possible that being in the neighborhood of a highly developed district can suffer from negative externality due to moving away of productive resources to the more developed district, therefore a negative γ.

The cross equation correlation coefficient between income in 2001/02 and 2004/05 is given by ψ. The residual errors are spatially autocorrelated, that is, any positive or negative shocks in any specific district, is likely to affect the neighboring districts. The extent of spatial correlation is captured through ρ_1 and ρ_2. As we are considering a system of equations, we use Seemingly Unrelated Regression (SUR) to generate efficient estimates. The estimation of the model is done by the method introduced by Kelejian and Prucha (2004). [10]

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[9] It is to be noted that Census of India 2001 was conducted in two phases. Information related to the development indicators were collected during April and September, 2000. Hence, our model does not have any endogeneity problem.

[10] This methodology can be extended to panel formulation if the cross sectional observation extend beyond a single time period, with time dimension smaller than the cross sectional dimension. Under condition when the time dimension is large compared to the cross sectional dimension one has to follow methodology outlined in Baltagi (1995).

Finally, we examine whether the development indicators have any effect on growth of income (as oppose to level of income). For this we use the following spatial model.

$$\Delta Y = \rho W \Delta Y + X\beta + WX\gamma + \varepsilon$$
$$\varepsilon \sim N\left(0, \sigma^2 I\right)$$

Here, ΔY is the annualized growth of per-capita income between 2001/02 and 2004/05. Like in the earlier case, the coefficient β measures the direct neighborhood effect, and coefficient γ captures the indirect neighborhood effect. The coefficient ρ captures the spillover effect of growth from the neighboring district(s). This creates a *spatial multiplier effect*. The development indicators are same as considered earlier. As Ordinary Least Squares method yield unbiased estimate in presence of non-spherical errors we use maximum likelihood method to estimate our model parameters.

4. Data, and the results

The data on district per-capita income is taken from Planning Commission, Government of India. We include districts from 29 states and 6 union territories in India. We consider the time period between 1999/2000 and 2004/05. Data for the years after 2004/05 are not available for all the districts, resulting in significant drop in the number of observations. Also many districts are newly formed, and information about per-capita income for them is not available for the earlier years. [11] Therefore, to maintain uniformity, and to get a more robust result, we consider the aforementioned time period. For the fiscal 1999/2000 an important omission in the Planning Commission data is

[11]In 2000 there are 585 districts, and in 2011 there are 627 districts in India. Many of these districts are newly formed, and for some of them information about the income variable is not available. The case in point is Delhi. The Census 2001 contains information about many variables related to north, north-east, north-west, south, south-west, west, east, and central Delhi. However during 2001, when it comes to per-capita income we find information only relating to Delhi as a whole, and not its constituent districts. Source: Planning Commission, Government of India<http://districts.nic.in/dstats.aspx>. Accessed (02/04/2011).

district-level income for the State of Gujarat, and Delhi. During 1999/2000, we have 508 data points (out of 585 districts) in India. For the latter fiscal years (2001/02, and 2004/05), we have data points covering 536 districts. This increase in number of observation is due to the inclusion of per-capita district income data from Gujarat and Delhi, which are not available for 1999/2000. The per-capita district income data for Gujarat and Delhi are taken from Indicus Analytics, Delhi.[12] Data relating to the development indicators are mostly taken from the 2001 Census (Government of India, 2001). These development indicators are: number of factories per 1 lakh population, percentage of households using electricity as a source of light, percentage of households with closed drainage system in their neighborhood, school enrolment as a percentage of total population, number of hospitals and dispensaries per 1 lakh population, percentage of households availing banking service, and percentage of households with tap drinking water within the household premise. The data on number of murder by use of fire arms for the year 1999 in each district are collected from National Crime Record Bureau, Ministry of Home Affairs, Government of India. We have calculated the gini coefficient data from the Lorenz ratio obtained from Chaudhuri and Gupta (2009).[13] To merge the data suitably across indicators missing observations for certain districts are dropped from the final data set. In total we have 485 observations. For 51 districts we do not have complete information for all the development indicators, and we drop them from the final data set. The results are generated using MATLAB.

Results

[12] Indicus Analytics collect data from the Central Statistical Organization (CSO), Ministry of Statistics and Programme Implementation, Government of India. CSO collate data from respective state governments. Planning Commission database also uses the CSO database. Therefore introducing per-capita district-level income data for Gujarat and Delhi for 2001/02 and 2004/05 is not going to affect (bias) our results.

[13] Chaudhuri and Gupta (2009) use Consumer Expenditure Data obtained from 61st Round of National Sample Survey (2004/05) conducted by Ministry of Statistics and Programme Implementation, Government of India.

We find some interesting results. We do not find evidence in support of twin peaks: clustering of the rich income districts, and clustering of low income districts, across India. There has been uniform increase in income among all the districts.

Table 1: Per-capita income summary statistics (in 1999 Rupees)

	1999/00	2001/02	2004/05
Mean	15512.3	16882.7	19600.8
Median	14029.5	15154.5	17084.5
Standard Deviation	7660.9	9126.5	12093.4
Skewness	1.5	2.0	3.0
Kurtosis	7.3	12.1	23.3

We notice from Table 1 that there is an increase in the mean, and in the median per-capita district income. We also notice that there is an increase in standard deviation, skewness, and kurtosis measures of income. In fact, as kurtosis has become very high during the latter period, that is, during 2004/05, the assumption of normality might not be valid. So we use the non-parametric sign test to test for the increase in income across different time periods. The results in Table 2 show that there is a significant increase in the mean and median per-capita district-level income between 1999/2000, and 2004/05, as well as between 2001/02 and 2004/05. Since the income distribution is skewed as well has a high kurtosis (evident from Table 1), we perform the same set of tests for the log per-capita income. Here also, we get similar results, indicating that there is an overall increase in the level of income.

Table 2: Tests for significance in mean and variance of Income

	1999/00 and 2004/05 (without Gujarat and Delhi)	2001/02 and 2004/05
T-test of Mean Difference: Income	19.41 (0.00)[a]	16.08 (0.00)
T-test of Mean Difference: Log Income	23.22 (0.00)	22.11 (0.00)

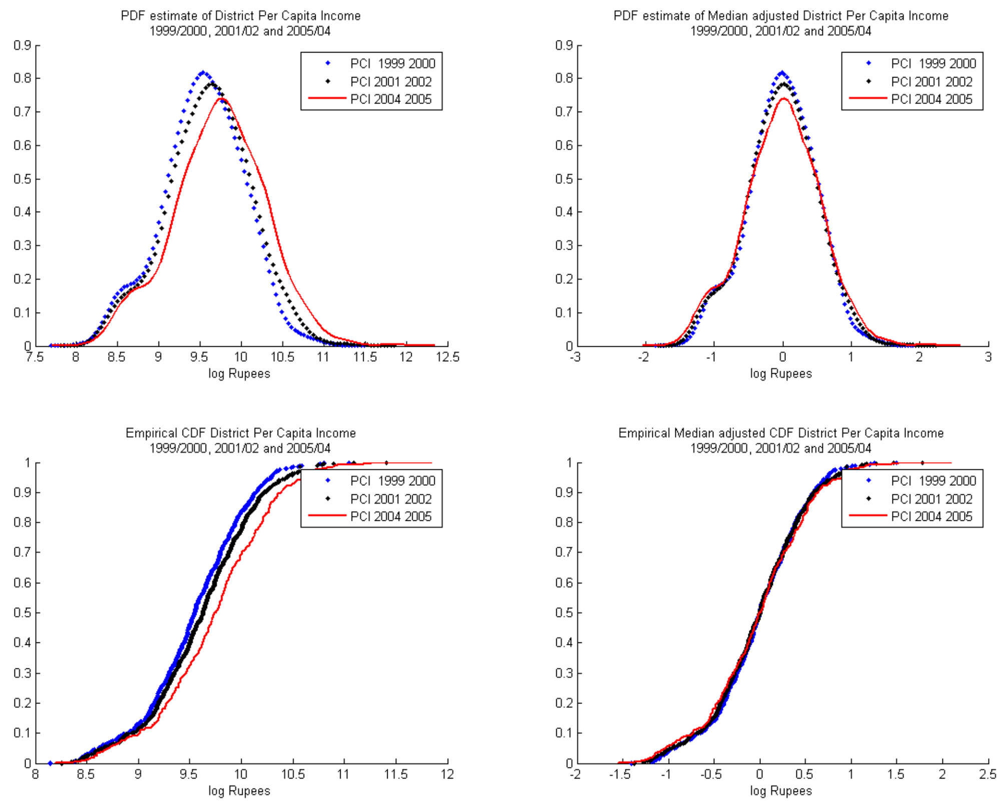
Z-Value of sign test of median: Income	6.87 (0.00)	4.98 (0.00)
Z-Value of sign test of median: Log Income	6.78 (0.00)	4.99 (0.00)

[a] *P*-values are in the parenthesis

Since there has been an increase in the mean and the median per-capita income, does it indicate that districts with high per-capita income have become well-off relative to the districts with low per-capita income? In other words, do we find any evidence in favor of cluster, or divergence of income between the richer and the poorer districts? To analyze this we plot income density function for 1999/2000, 2001/2002 and 2004/05, in Figure 1.

We observe that considering districts income data there is definitely no evidence about emergence of twin peaks in any of these periods. There is a shift in the per-capita income density function during these time periods. This is due to a significant increase in the mean, and the median per-capita income, from 1999/2000 to 2004/05.

Figure 1: Median adjusted densities and distribution of district-level log-income in 1999/2000, 2001/02, and 2004/05.



The income distribution functions also show evidence about first-order stochastic dominance: Income distribution function for 2004/05 lies everywhere below (that is, to the right of) income distribution drawn for 2001/02.[14] Similarly, income distribution for 2001/02 lies to the right of income distribution drawn for 1999/2000. This implies that between 1999/2000 and 2004/05, poverty has fallen. This result is not surprising. It is widely documented that when economic growth happens absolute poverty falls. [15] What is more interesting is to examine whether among districts there is any significant change in the median adjusted per-capita income distribution function between 1999/2000 and 2004/05, and between 2001/02 and 2004/05? This is relevant, especially, because we

[14] An income distribution function stochastically dominates another if the percentage of people below any given income change amount is smaller in the first than in the second. The income distribution function that stochastically dominates the other also has less poverty than the other.
[15] For an excellent discussion on this topic see, Fields (2001) pp.102-104.

observe income density function for 2004/05 has become more platykurtic (with fewer extreme values) than it was during 1999/2000. We ran KS test to ascertain this.

Table 3: Tests of Distributional Difference of median adjusted Log Income

	1999/00 and 2004/05 (without Gujarat and Delhi)	2001/02 and 2004/05
Kolmogorov-Smirnov (KS) one sided test statistics	0.042 (0.38)[a]	0.036 (0.48)

[a] *P*-values are in the parenthesis

Results suggest that between 1999/2000 and 2004/05 there is no statistically significant difference in the median adjusted income distribution functions. We arrive at a similar conclusion while comparing the income distribution functions for 2001/2002, and 2004/2005. In fact, a glance at the median adjusted per-capita income densities drawn for 1999/2000, 2000/01, and 2004/05, suggest that these distribution functions are more or less similar (Figure 1). The data suggests that both the rich, and the poor districts, has equally become well-off. There has been a reduction in income disparity among districts.

To visually compare the effects, we divide India into high, medium and low income regions using the 33rd and 66th percentiles of the income data from 2001/02 (Rs 13484.8, and Rs 20897.2, respectively). Figure 2b shows these different income regions for 2001/02. Using the same values we obtain the high, medium, and low income regions for the year 2004/05 in Figure 2a. The striking observation is that some of the districts from Madhya Pradesh, Orissa, and Rajasthan have moved from the low income category to the middle income category.

Figure 2a: District per-capita income for 2004/05 subdivided into high, middle, and low, income categories, according to 33rd and 66th percentiles (using 2001/02 as base income).

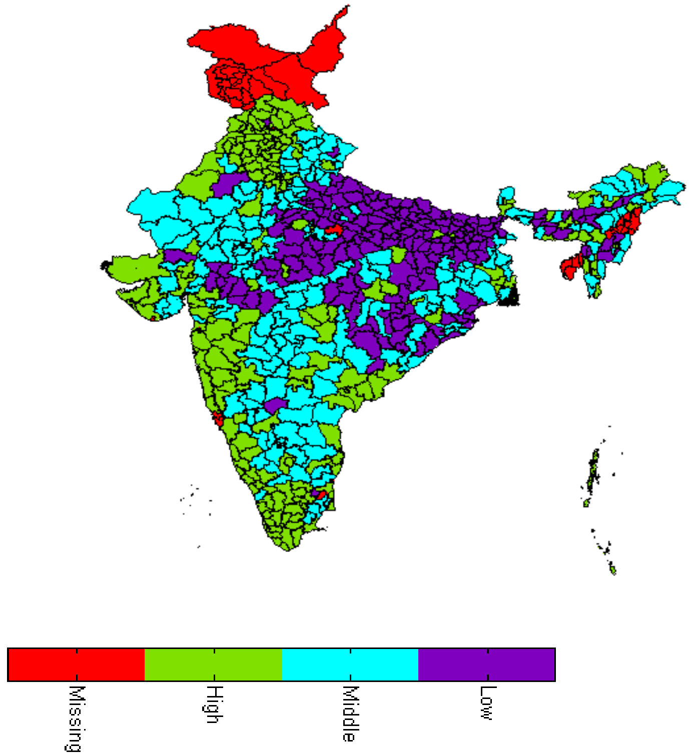
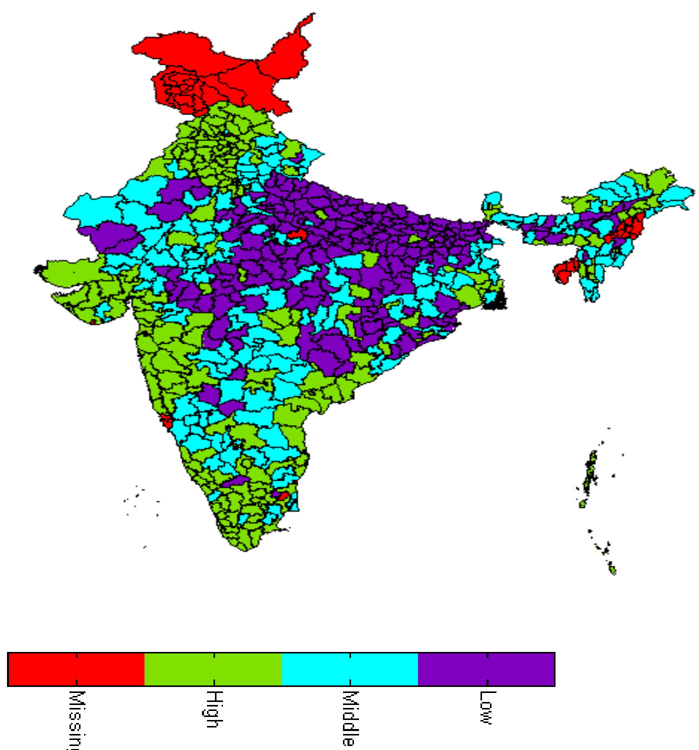


Figure 2b: District per-capita income for 2001/02 subdivided into high, middle, and low, income categories, according to 33rd and 66th percentiles (using 2001/02 as base income).



It is quite evident from the above two maps that for 2004/05, there are more number of districts in the middle and the high income categories, than there were during 2001/02. These mini-district-economies interacted with each other, and manage to grow together. We argue that as inter-income disparity has fallen among districts between 2001/02 and 2004/2005, going forward there is a likelihood of this income disparity even falling further. This is because active labor and capital market intervention have started only post 2005; when in addition to MGNREGA, government introduced other schemes such as mid-day meal schemes for primary school going children, Indira Awas Yojana (building houses for the poor), Pradhan Mantri Gram Sadak Yojana (scheme for building rural roads), and other microfinance activities. Hence, if there has been a fall in inter-district per-capita income disparity for the period before these schemes were started, there is a likelihood that the process of income generation to be more uniform once these schemes are in place.

As there is indication about the per-capita district-level income growing together, we use Moran ***I*** to test for the degree, and the nature of spatial relation between them.

Table 4: All India Moran Indices for income and growth

Variable	Moran Index (I)	*t*-statistics
'Per-capita Income 1999/2000'	0.54	19.74
'Per-capita Income 2001/02'	0.53	20.33
'Per-capita Income 2004/05'	0.48	18.51
'Per-capita Annualized Income Growth 1999/00-2004/05'	0.38	13.88
'Per-capita Annualized Income Growth 2000/01-2004/05'	0.26	10.05

Table 4 indicates Moran ***I*** for both the growth, and the income variables are significantly positive. Highly significant *t*-statistics implies that the regression errors are spatially auto-correlated. For instance, Moran ***I*** for 1999/2000 is 0.54 implying during that particular year 54 per cent of the income in district *i* is influenced by incomes in the neighbouring districts. Considering districts as the unit of account, we find that the growth process has been uniform across India. Moran ***I*** is positive when economic characteristics of nearby objects (districts) are similar. We do not find any evidence about emergence of growth centers, that is, clustering of the high income districts, and clustering of the low income districts. In general, there is positive reinforcement of the growth process.

In the next section we examine the common externalities of income processes, if any, across geographical boundaries. Put differently, we want to find out the channel through which growth is translating to development, and vice versa. To select the appropriate variables we take note of various growth models, [16] and existing literature on India's income, and development dynamics.

For instance, we consider gini coefficient on the basis of the study by Tendulkar (2010). He admits that there has been a rise in summary measures of relative inequality (gini coefficients) during the Eleventh Five Year Plan (2007-12). Similarly, following Rosenzweig and Wolpin (1982), and Rosenzweig (1990), we choose number of hospitals, water and sanitation infrastructure, and school enrollment, respectively, as these variables have significant effect on growth and development indicators of a region. Rosenzweig and Wolpin (1982) find child mortality in India falls in presence of more clinics per-capita, and in presence of better water and sanitation infrastructure (such as closed drainage system). Rosenzweig (1990) finds that higher male wages have a positive income effect on schooling, and raise school enrollment. As a proxy for access to finance, we choose bank branch, and as a proxy for governance and institution, we choose

[16] Solow growth model, endogenous growth models, or models dealing with micro-foundation of macroeconomics like rational expectation type models.

numbers of murder. Burgess and Pandey (2004) finds that the rural bank branch expansion program in India has a significant effect in terms of reducing rural poverty, and to increase non-agricultural output. Kochar et al. (2006), finds that states with weaker institutions and poorer infrastructure have experienced lower GDP, and lower industrial growth. Finally, as Aiyar (2001), Ahluwalia (2002), and Purfield (2002) find investment in productive capacity (especially, private sector investment) as an important factor explaining variation in state-level income, we include number of factories per one lakh population as an explanatory variable as a proxy for productive capacity.

Therefore, the independent variables[17] that we consider for our study are gini coefficient (proxy for income inequality); school enrollment (proxy for human capital); banks, electricity, closed drainage system, drinking water, and hospitals (proxy for social and physical infrastructure); factories (proxy for investment in productive capacity and opportunities to earn income), and murder (proxy for governance). Our dependent variable is log of per-capita income for 2001/02, and 2004/05. All these data are at a district level.

[17] One limitation of the data is failure to capture the quality issue for the services that are provided. For example, there are issues relating to teacher absenteeism, quality of drinking water, healthcare services, etc. Modeling this quality aspect requires experiment such as randomized controlled trial – something outside the scope of this paper.

Table 5: SUR Estimates of Income Distribution.

	Equation 1 Dependent Variable		Equation 2 Dependent Variable	
	Log income 2004/05		Log income 2001/02	
System R-square	0.553			
Cross-equation correlations (ψ)	0.919			
R-bar Square	0.679		0.685	
No. observations, No. Variables	485, 19		485, 19	
Independent Variables (2001 Census)	Coefficient	t-stat	Coefficient	t-stat
Constant	8.3647**	86.48	8.2919**	93.94
No. of factories total	0.0004*	2.38	0.0004*	2.44
Gini coefficient[a]	0.6409*	2.31	0.6116*	2.42
Murder[b]	0.0003	0.76	0.0003	0.98
Electricity connection	0.003*	2.28	0.0031*	2.54
Closed drainage	0.0057**	2.95	0.0044*	2.52
School enrolment	0.009**	3.72	0.0085**	3.83
Hospitals and dispensaries	0.0034**	3.65	0.0031**	3.67
Banking services	0.0064**	2.92	0.0062**	3.12
Tap drinking water	0.0029**	2.81	0.0023*	2.41
[!] W*No. of factories total	0.0002**	4.37	0.0002**	3.18
W*Gini coefficient	0.108	1.20	0.1064	1.30
W*Murder	0	-0.23	0	0.29

W*Electricity connection	0.0004	1.16	0.0008**	2.63
W*HH closed drainage	0.0003	0.40	-0.0002	-0.27
W*School enrolment	-0.0002	-0.40	-0.0002	-0.38
W*Hospitals and dispensaries	-0.0003	-0.80	-0.0003	-0.83
W*Banking services	-0.002**	-3.53	-0.0019**	-3.56
W*Tap drinking water	-0.0003	-1.32	-0.0004	-1.78
ρ_1 , ρ_2	0.096*	10.48	0.094*	10.10

*Indicates the coefficient is significant at a 2.5 per cent level, and ** indicates the coefficient is significant at a 1 per cent level. [a] On the basis of 61st Round of National Sample Survey conducted in 2004/05. [b] Figures for 1999.
! W is the weighting matrix.

Our findings suggest that with the exception of total murder (proxy governance); direct effects of the development variables are statistically significant, and are of expected signs. The significant gini coefficient indicates that for any district income inequality is good for income generation. However, as the KS test in the earlier section indicates, income inequality within any given district is not contributing to divergence in median income across districts. As both the coefficients on factories, and school enrollment, are statistically significant it might indicate that availability of skilled labor force increases income. Similarly, better development indicators, such as physical and social infrastructure, including, electricity, hospitals, closed drainage system, drinking water, and banks, help business to grow in any particular region. This in turn creates opportunities to earn more income. The coefficient on murder rate is statistically not significant. This may be because of poor conviction rate in India.[18] While analyzing the effect of indirect neighborhood effect we find the coefficients on factories and electricity are significantly positive, whereas, the coefficient on bank is significantly negative. There is a positive influence on income of district *i* if there is income generating potential in the

[18] Between 2005 and 2009 the average conviction rate for murder is only 36.2 per cent. Out of nearly 1.27 hundred thousands murder only 44601 people were convicted. See, Times of India News Service. Available at: http://timesofindia.indiatimes.com/india/Conviction-rates-for-murder-abysmal/articleshow/8720229.cms.

neighboring districts (captured as W*No of factories total). Similarly, better electricity, by facilitating growth of business in the neighboring districts may contribute to income generation in district *i*. A negative neighborhood coefficient in the banking variable implies banks in the neighboring districts can lure away productive investment from district *i*, and hence adversely affect its income. The coefficient ρ_1 and ρ_2 are significantly positive with values, 0.096 and 0.094, respectively. It means that the spillover effect of income generation from one district to another adjacent district is around 10 per cent. The cross-equation income correlation is around 0.91, that is, income in both the time periods (2001/02 and 2004/05) are highly correlated. High cross-equation income correlation also implies that the districts with higher per-capita income will continue to perform better relative to the districts with lower per-capita income. However, as is evident from the KS test results in the earlier section, a higher cross-equation income correlation does not automatically imply an increase in income disparity between the richer and the poorer districts, something suggested by Bhattacharya and Sakthivel (2004) in their paper while doing state-level analysis.

We next examine whether the development indicators affect growth of income. We notice, in general development indicators does not affect income growth. The initial level of income (2001/02) is not statistically significant. However, the spillover effect of income growth (ρ) is significantly positive, implying that around 5 per cent of the income growth in one district is affected by income growth in the neighboring districts. A significantly positive neighborhood factor which affects income growth is the number of factories in the adjacent districts. The policy implication is that to facilitate convergence of income among districts there is a necessity to create more employment opportunities. Rapid industrialization is the only way to improve growth convergence. This result is similar to that of Ahluwalia (2002), where he finds private sector investment in productive capacities, and in social (such as human capital) and physical infrastructure (such as ports, airports, national highways, telecommunication, etc.), are positively related to the variation in state-level income.

Table 6: Spatial autoregressive Model Estimates of the Growth Model

Spatial autoregressive Model Estimates

	Dependent Variable Income Growth 2001/02-2004/05	
R-squared	0.179	
Rbar-squared	0.143	
sigma^2	0.015	
No. observations, No. variables	485, 21	
Log-likelihood	499.37	
Independent Variables (2001 Census)	Coefficient	t-stat
Constant	-0.00699	-0.03
Log income 2001/02	-0.01793	-0.79
No. of factories total	0.001846	0.10
Gini coefficient [a]	0.007674	0.27
Murder[b]	-0.01078	-1.15
Electricity connection	0.00411	0.45
Closed drainage	0.023684	2.15
School enrolment	0.055874	1.16
Hospitals and dispensaries	0.046039	1.44
Banking services	-0.02304	-0.79
Tap drinking water	0.001156	0.11
[!] W*Log income 2001/02	0.003265	0.60
W*No of factories total	0.015465*	2.80
W*Gini Coefficient	-0.00407	-0.48
W*Murder	-0.00075	-0.27
W*Electricity connection	-0.00747	-2.17
W*Closed drainage	-0.00265	-0.81
W*School enrolment	-0.01621	-1.30
W*Hospitals and dispensaries	-0.01256	-1.34
W*Banking services	0.002735	0.36
W*Tap drinking water	0.002991	1.10
ρ	0.051977*	4.42

* Indicates the coefficient is significant at a 2.5 per cent level, and ** indicates the coefficient is significant at a 1 per cent level. [a] On the basis of 61st Round of National Sample Survey conducted in 2004/05.[b] Figures for 1999.
[!] W is the weighting matrix.

4. Conclusion

This paper finds that during the post-reform period, India has not only managed to grow fast but has also performed well in terms of providing quality life (measured in terms of per-capita income) to its citizen. Working with district-level data for the period between 1999/2000 and 2004/05, results suggest no divergence in income across districts in India. The income dynamics provide no evidence in support of the twin peaks hypothesis: clustering of the rich income districts, and clustering of the poor income districts at a pan-India level. Income growth has been spatially correlated – growth in one district aids growth in others, and there has been a reduction in income disparity among districts. For the time period between 1999 and 2005, districts in the State of Rajasthan, Madhya Pradesh, and Orissa have done particularly well, whereas we find evidence for pockets of deprivation in the states of Uttar Pradesh and Bihar. Most of the variables explaining growth and development of a region, such as human capital, physical, and social infrastructure, are all contributing to the Indian growth story. As active labor and capital market interventions have started only post 2005, we argue that going forward, this inter-district income disparity is likely to fall further in comparison to what we have observed between 1999/2000 and 2004/2005.

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