Review of Development Economics, 18(1), 59–72, 2014
DOI:10.1111/rode.12069

Is India Shining?

*Anurag Banerjee and Nilanjan Banik**

Abstract

The popular perception about economic reforms having benefitted only the richer districts of India between 1999/2000 and 2004/2005 is investigated. Using the spatial dynamics of district-level per-capita income it was found that income distribution did not change between the years examined. It is argued that this is because of per-capita income across districts being spatially positively correlated. Physical infrastructure, human capital, and factories are identified as factors responsible for increase in income for both the rich as well as the poor districts. Infrastructure, physical or social, is a key component of growth in India. A policy impact analysis shows development of better drainage and potable water systems has a large impact on income. For the year 2001/02, it was found that for every 1% increase in closed drainage system and potable water, district-level median income increases by 1.39% and 0.21%, respectively.

1. Introduction

In 2004, the Congress-led United Progressive Alliance (UPA) government came to power after defeating the BJP-led National Democratic Alliance (NDA) government. This defeat for the NDA government came in spite of the fact that Indian economy was growing fast, at 8.5% in 2003/2004. A popular perception explaining the ousting of the then ruling NDA government lay in its inability to check rise in regional income inequality. How true then, is this perception about economic reforms enhancing regional income disparity? We answer this question by studying the dynamics of income distributional pattern in India. If reforms are favoring rich-income districts then we would see the emergence of twin peaks in the underlying income distribution function: clustering of the rich-income district, and clustering of the poor-income district with pockets of economic growth pulling-up the national average income. In contrast, 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 2004/2005, we find that the income distribution has not changed, thus the perception about economic reforms having benefitted only the rich-income district is not supported by the data. Results suggest that between 1999/2000 and 2004/2005 there was no statistically significant difference in the median adjusted income distribution functions. In fact, the income density function for 2004/2005 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.

* Banerjee: Department of Economics and Finance, Durham University, 23/26 Old Elvet, Durham, UK. Tel: +44-(0)191-33-46356; Fax: +44-(0)191-33-46341; E-mail: a.n.banerjee@durham.ac.uk. Banik, 24 Kothari Road, Institute for Financial Management Research, Chennai, India. Support of the research grant from South Asia Network of Economic Research Institute (SANEI) is gratefully acknowledged. The authors thank an anonymous referee, Mia Mikic, Sajal Lahiri and Sharon Barnhardt, for useful comments on an earlier draft of this paper. The authors acknowledge data provided by Savita Sharma from Ministry of Statistics and Programme Implementation, Government of India, and research assistantship provided by Jyoti Prasad Mukhopadhyay. The usual disclaimer applies.

This idea is in concurrence of Quah (1993, 1996), and Jones (1997),who introduce the notion of twin peaks in the cross-country distribution of incomes. Quah (1993, 1996) found evidence about persistence and stratification of income density functions.[1] Jones (1997) observed that clustering can be a temporary phenomenon, as may happen with high frequency growth miracles data. The emergence of twin peaks implies polarization of the cross-country income distribution into rich and poor convergence clubs.

As there has been no evidence in favor of change in the underlying income distribution in spite of the fact that median level of income has increased, we endeavor to investigate why this has happened, and the factors (as captured through development, and other policy indicators) responsible. In the process of analyzing the interaction between income and policy variables affecting income, such as education, health, and other development indicators, we separate out, and quantify the direct (own) effect, the direct neighborhood effect and indirect neighborhood effect. A direct effect reflects how the level of development (captured through development indicators) in any particular district i affects its own income. The direct neighborhood effect captures how the level of development in any neighboring district (say j) affects the income level of district i. The indirect neighborhood effects captures how the increase in income in neighboring district j affects income in 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.[2] The indirect neighborhood effect results in spillovers of income from one district to the other, thereby resulting in concurrent movement in per-capita income across districts. The Indian constitution guarantees free movement of labor and capital across districts in India, thereby, guaranteeing a more balanced spatial distribution of income. In general, development indicators, such as physical and social infrastructure including, electricity, hospitals, closed drainage system, drinking water and banks positively affect income of any particular region; thereby implying infrastructure, physical or social, is a key component of growth.

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

Whether economic reforms in India has widened the gap between the richer and the poorer states, the evidence is mixed. 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 (2002), finds that not all the rich states have become richer relative to the poorer states. Except for 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 1990s. 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 (2013) reinforces this finding where he finds evidence about growth rates of the erstwhile BIMARU states comprising of Bihar, Madhya Pradesh, Rajasthan and Uttar Pradesh are converging with the national average more than what has been reported in his 2003 paper. Ahluwalia (2002, 2013) 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.

Bhattacharya and Sakthivel (2004), in contrast, 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,[3] 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 1980s to 0.29 during the 1990s. The paper by Barua and Chakraborty (2010) also find evidence in favor of widening interregional income inequality during post-1991 reform period. The authors attribute the cause of cross-regional inequalities to disproportionate growth of manufacturing activities across region.

Our study fits well to this strand of literature. We also address the limitation of earlier studies in our analysis. 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. We do this to analyze whether during the post-reform period (i.e. between 1999/2000 and 2004/2005) 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 does not capture the neighborhood effect, and failure to capture neighborhood effect can result in major model misspecification (Anselin, 1988).[4]

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 2004/2005; and between 2001/02 and 2004/2005. To examine the dynamics, we draw density of district per-capita income for the fiscal years, 1999/2000 and 2004/2005. To check for the robustness we repeat this exercise for the time period between 2001/2002 and 2004/2005. We ran Kolmogorov–Smirnov (KS) test to ascertain whether there is any statistically significant difference in the median adjusted per-capita income distribution between different fiscal years: from 1999/2000 to 2004/2005, and from 2001/2002 to 2004/2005.

The second part of our analysis is a follow-up from the first part. We ask the question: What are the factors that may 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:

$$Y_1 = X_0\beta_1 + WX_0\gamma_1 + \varepsilon_1 \tag{1}$$

$$\varepsilon_1 = \rho_1 W\varepsilon_1 + u_1$$

$$Y_2 = X_0\beta_2 + WX_0\gamma_2 + \varepsilon_2 \tag{2}$$

$$\varepsilon_2 = \rho_2 W \varepsilon_2 + u_2$$

$$\begin{pmatrix} u_1 \\ u_2 \end{pmatrix} \sim N\left(0, \sigma^2 \begin{pmatrix} 1 & \psi \\ \psi & 1 \end{pmatrix}\right)$$

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 2001/2002 and 2004/2005, respectively. X_0 is a matrix of development indicators data that are mostly obtained from the 2001 census (Census, 2001).[5] The coefficients βs measure the direct (own) effect. The coefficients γs capture the direct neighborhood effects and the coefficients ρs capture the indirect neighborhood effects. A negative γ implies spillover effects from the development indicators in neighboring district *j* have detrimental effect on the income of district *i*. A positive γ implies otherwise. For instance, it is expected that districts in the neighborhood of big cities will enjoy some positive externalities and hence will tend to have a higher income as compared with districts located further away. Gautam Budh Nagar (a district bordering Delhi) and Gurgaon (a district in Haryana in the neighborhood of Delhi) are 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 owing to moving away of productive resources to the more developed districts, therefore a negative γ.

To capture the neighborhood effect we take into account geographical location of each district and its neighboring districts, and build an adjacency matrix W. We define W such that $W_{ij} = 1$, if district *i* is adjacent to district *j*, and zero otherwise (for districts that are not adjacent). Spatial relations may exist because of the geographical proximity among the districts or because of the proximity evolving through economic/business relations. Geographical proximity is exogenous in nature whereas proximity arising out of economic relation is not. Because of endogenity problem that may arise from business relation, we use geographical proximity and not economic proximity, to construct our adjacency matrix.

Before performing our regression we do some pre-testing using Moran Index (I), to see whether this W matrix captures the spillover effect. We find that Moran I for 1999/2000 and 2001/2002 are significant at 1% level.[6] It shows that spatial correlation between incomes is statistically significant. Failing to capture such spatial correlations in a regression setting will result in biased estimates.

Thus we model the residual errors as spatially autocorrelated errors, i.e. any positive or negative shock in any specific district, is likely to affect the neighboring districts. The extent of spatial correlation is captured through ρ_1 and ρ_2. The total spatial multiplier at time period 1, i.e. for the year 2001/2002, can be derived from:

$$Y_1 = X_0 \beta_1 + W X_0 \gamma_1 + \varepsilon_1 \tag{3}$$

$$\varepsilon_1 = \rho_1 W \varepsilon_1 + u_1. \tag{4}$$

Plugging (4) in (3) yields:

$$Y_1 = X_0 \beta_1 + W X_0 \gamma_1 + u_1 [I - \rho_1 W]^{-1}$$

i.e. $Y_1 = X_0 \beta_1 + W X_0 \gamma_1 + u_1 \sum_{k=1}^{\infty} \rho_1^k W^k$.

Here, $[I - \rho_1 W]^{-1}$ is the spatial multiplier in period 1. $\rho_1 W$ is the spatial correlation between neighboring districts, say district i with its neighboring district h. $\rho_1^2 W^2$ is the spatial correlation with one degree of separation, i.e. spatial correlation between district h and district j, with district i lying between district h and district j. The cross equation correlation coefficient between income in 2001/2002 and 2004/2005 is given by ψ. 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).

In the third section, we do a policy exercise by analyzing the effects on the spatial income distribution because of changes in policy variables such as school enrollment (proxy for human capital); banks, electricity, closed drainage system, and drinking water (proxy for social and physical infrastructure); and factories (proxy for investment in productive capacity and opportunities to earn income).

4. Data, and the Results

The data on district-level per-capita income is taken from Planning Commission, Government of India (Planning Commission, 2010). We include districts from 29 states and six union territories in India. We consider the time period between 1999/2000 and 2004/2005, and between 2001/2002 and 2004/2005. Data for the years after 2004/2005 are not available for all the districts, resulting in significant drop in the number of observations.[7] Also, many districts are newly formed and information about per-capita income for them is not available for the earlier years.[8] 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 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 (2000/2001, 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.[9] 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 100,000 population, percentage of households using electricity as a source of light, percentage of households with closed drainage system in their neighborhood, school enrollment as a percentage of total population, number of hospitals and dispensaries per 100,000 population, percentage of households availing banking service and percentage of households with tap drinking water within the household premise. The data on number of murders by use of fire arms for the year 1999 in each district was collected from National Crime Record Bureau, Ministry of Home Affairs, Government of India (National Crime Record Bureau, 1999). We have calculated the gini coefficient data from the Lorenz ratio obtained from Chaudhuri and Gupta (2009). 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

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.

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, i.e. during 2004/2005, 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

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

Addendum statistics	*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	0.38	10.05

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)

Addendum table: test for difference in distribution function	*1999/00 and 2004/05 (without Gujarat and Delhi)*	*2001/02 and 2004/05*
Kolmogorov–Smirnov (KS) one sided test statistics (median adjusted log income)	0.042 (0.38)	0.036 (0.48)
Kolmogorov–Smirnov (KS) one sided test statistics (median adjusted income in level form)	0.084 (0.02)	0.061 (0.11)

[a] p-values are in the parenthesis.

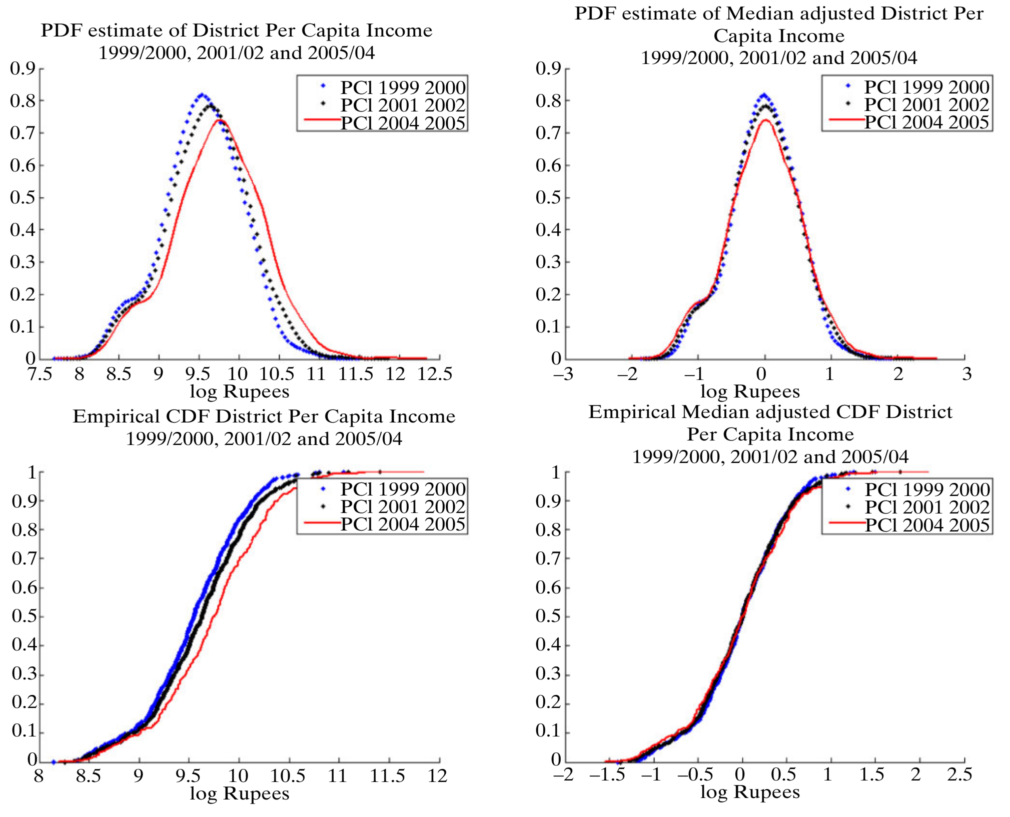

Figure 1. Median Adjusted Densities and Distribution of District-level Log-income in 1999/2000, 2001/02 and 2004/05

and 2004/2005, as well as between 2001/2002 and 2004/2005. 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.

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 through 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.

The income distribution functions also show evidence about first-order stochastic dominance: the income distribution function for 2004/05 lies everywhere below (i.e. to the right of) income distribution drawn for 2001/02.[10] 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.[11] What is more interesting is to examine whether among districts there is any significant change in the median adjusted per-capita (log) income distribution function between 1999/2000 and 2004/05, and between 2001/02 and 2004/05? This is relevant, especially, because we observe income density function for 2004/05 had become more platykurtic (with fewer extreme values) than it was during 1999/2000.[12] We ran the KS test to ascertain this (see, the addendum in Table 2).

Results suggest that between 2001/02 and 2004/05 there is no statistically significant difference in the median adjusted income distribution functions. This result is true whether we consider log of income, or income without log. Considering level income, we arrive at a similar conclusion, i.e. the income distribution function has not changed between 1999/2000 and 2004/05.[13] 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 poor districts have equally become well-off. There has been a reduction in absolute levels of income poverty among districts.

Next 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 (such as Solow growth model, endogenous growth models, or models dealing with micro-foundation of macroeconomics like rational expectation type models), 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), 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 the presence of more clinics per-capita, and in the presence of a better water and sanitation infrastructure (such as closed drainage system). As a proxy for access to finance, we choose bank branch, and as a proxy for governance and institution, we choose numbers of murders. Burgess and Pandey (2004) find that the rural bank branch expansion program in India has a significant effect in terms of reducing rural poverty and in increasing non-agricultural output. Kochhar et al. (2006), find that states with weaker institutions and poorer infrastructure have experienced lower GDP, and lower industrial growth. Menon and Sanyal (2007) find that labor unrest, credit constraints and indicator of state's economic health influence location decision of foreign firms investing in India. We take total murders as a proxy for governance.

Finally, Ahluwalia (2002) finds investment in productive capacity (especially, private sector investment) is an important factor explaining the variation in state-level income. We include the number of factories per 100,000 population as an explanatory variable as a proxy for productive capacity.

Therefore, the independent variables[14] 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)

Table 3. SUR Estimates of Income Distribution

	Equation (1) Dependent Variable		Equation (2) Dependent Variable	
	Log income 2004/05		Log income 2001/02	
System R^2		0.553		
Cross-equation correlations (ψ)		0.919		
$\bar{R}^2$	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[c]	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% and 1% level respectively. [a] On the basis of 61st round of the National Sample Survey conducted in 2004/05. [b] Figures for 1999. [c] W is the weighting matrix.

(Table 3). Our dependent variable is log of per-capita income for 2001/02 and 2004/05. All these data are at a district level.

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. The ongoing reform process cannot be blamed entirely for this occurrence. Reforms encourage more active market participation and hence will not guarantee equal returns to all. 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, or regional income inequality. Both the coefficients on factories and school enrollment are positive, and statistically significant, indicating that these factors positively affect income. Similarly, better physical and social infrastructure such as electricity, hospitals, closed drainage system, drinking water and banks, help business to grow in any particular region. The coefficient on murder rate is statistically not significant. This may be because of poor conviction rate in India.[15] Infrastructure, physical or social, is a key component that affects income, positively.

While analyzing the direct neighborhood effect we find the coefficients on factories and electricity are significantly positive, whereas, the coefficient on banks is significantly negative. This result is similar to that of Ahluwalia (2002), where he finds private sector investment in productive capacities such as factories, and in social (such as human capital) and physical infrastructure (such as ports, airports, national highways and telecommunication), positively affect state-level income. A negative neighborhood coefficient in the banking variable (captured as $W \times$ banking service) implies banks in the neighboring districts can lure away productive investment from district i and, hence, adversely affect its income. De and Vij (2012) find a negative neighborhood coefficient for the banking variable while examining response of commercial banks in giving loans to the drought prone districts in India.

The coefficients ρ_1 and ρ_2, capturing the indirect neighborhood effect, are significantly positive with values, 0.096 and 0.094, respectively. It means that the spillover effect of income is around 10%: if income in district i increases by 100%, income in the neighboring district j increases by 10%. In accordance to our expectation about persistence in income across time we find a high cross-equation income correlation (ψ). Income across both the time periods, 2001/02 and 2004/05, are highly correlated ($\psi = 0.91$). F-test statistics confirmed no change in structural coefficients. We accept the hypothesis: $\beta_1 = \beta_2$ and $\gamma_1 = \gamma_2$. A high cross-equation income correlation also implies that the districts with higher per-capita income will continue to perform better. 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 poorer districts. Although it might sound slightly presumptuous, we believe that the private sector (without depending too much on the government) is taking a lead in moving capital and labor to areas with lesser input costs (i.e. investing more in backward districts), thus contributing to uniform growth process in India.

Policy Analysis

We do a policy exercise to quantify percentage change in income variable resulting from one percentage change in policy covariates. This policy exercise is done for 2001/2002. Because the F-test of equality of structural parameters did not show any changes between 2001/2002 and 2004/05 we get a similar result when we undertake this policy exercise for 2004/2005 (Table 4).

For instance, for the district Bangalore Urban, every 1% increase in the number of factories will increase income in Bangalore Urban by 0.18%. Likewise, a 1% increase in electrification, closed drainage, school enrollment, banks and drinking water, increases per-capita income in Bangalore Urban by 0.30%, 0.41%, 0.25%, 0.17% and 0.27%, respectively. We also compute the spillover effect for the neighboring districts. A 1% increase in number of factories in Bangalore Urban increases per-capita income in the neighboring Dharmapuri district by 0.03 percentage points. Similarly, for the neigboring Bangalore Rural, Chamarajanagar and Kolar districts, a 1% increase in number of factories in Bangalore Urban raises income in these districts by 0.03%, 0.01% and 0.01%, respectively. Likewise, a 1% increase in electrification, closed drainage, school enrollment, banks and drinking water, in Bangalore Urban, increases income in the Dharmapuri district by 0.06%, 0.09%, –0.07%, –0.02% and

Table 4. Comparative Statics for Bangalore Urban

	Factories	*Electrification*	*Closed drainage*	*School enrollment*	*Banks*	*Drinking water*
Bangalore Urban	0.18	0.30	0.41	0.25	0.17	0.27
Dharmapuri	0.03	0.06	0.09	–0.07	–0.02	0.01
Bangalore Rural	0.03	0.06	0.08	–0.07	–0.02	0.01
Chamarajanagar	0.01	0.01	0.02	–0.02	0.00	0.00
Kolar	0.01	0.01	0.02	–0.02	0.00	0.00
Salem	0.01	0.01	0.01	–0.01	0.00	0.00
Erode	0.00	0.01	0.01	–0.01	0.00	0.00
Tumkur	0.00	0.01	0.01	–0.01	0.00	0.00
Mandya	0.00	0.01	0.01	–0.01	0.00	0.00
Viluppuram	0.00	0.01	0.01	–0.01	0.00	0.00
Tiruvanamala	0.00	0.01	0.01	–0.01	0.00	0.00
Vellore	0.00	0.01	0.01	–0.01	0.00	0.00

0.01%, respectively. Although having more schools and banks helps generate more income in Bangalore Urban, it also adversely affects income earning potential for the neighboring districts. This may happen because the bank lending money in Bangalore Urban may have less money to lend to the neighboring districts—something that we have stated earlier while analyzing our results from the SUR model. Likewise, more schools in Bangalore Urban may attract more talent from neighboring districts and therefore adversely affect supply of skilled labor in the neighboring districts.

We compare the spillover effects of these different policy variables at a pan-India level for the year 2001/02. Closed drainage systems have the maximum impact on income through own and spillover effects. For a 1% increase in closed drainage systems, income increases between 0.96% and 2.58%. The second biggest factor is the availability of potable water. A 1% increase in availability of tap water systems within households, increases income between 0.16% and 1.30%.

Given the positive impact of closed drainage (sanitation) and potable water on income, from the policy perspective it would be interesting to analyze the own effect, direct neighborhood effect and indirect neighborhood effect of these two important policy covariates. For the year 2001/02, we find that for every 1% increase in closed drainage systems, district-level median income increases by 1.39%. This is the own effect. The direct neighborhood effect is 0.59, i.e. for a 1% increase in closed drainage systems in the neighboring district (say j), median income of district i increases by 0.59%. Similarly, because of the increase in median income in the neighboring district j (made possible through better closed drainage systems), median income of district i increases by 0.79%—the indirect neighborhood effect. The own effect of closed drainage systems on the 95th percentile and 5th percentile income cohorts are 1.96 and 0.68, respectively. For the year 2001/02, the own, direct and indirect neighborhood effect, of potable water on median income are 0.21, 0.09 and 0.12, respectively. The own effect of potable water on the 95th percentile and 5th percentile income cohorts are 0.39 and 0.16, respectively. We get similar results for the fiscal 2004/05 (Table 5).

Many districts in India do not have a proper drainage system and lack drinking water. Poor drainage systems usually have stagnated water thereby becoming a breeding place for mosquitoes. This could result in an increase of malaria and water related disease in the vicinity, adversely affecting income. Similarly, proper potable drinking

Table 5. Impact of Closed Drainage and Drinking Water on Median Income

Log Income 2001/02	*Direct own effect*	*Direct neighborhood effect*	*Indirect neighborhood effect*
Closed drainage	1.39	0.59	0.79
Drinking water	0.21	0.09	0.12
Log Income 2004/05	*Direct own effect*	*Direct neighborhood effect*	*Indirect neighborhood effect*
Closed drainage	1.02	0.47	0.54
Drinking water	0.23	0.11	0.12

water systems have positive public health outcomes. If people are healthy, they can work harder and assimilate knowledge more efficiently which translates to higher productivity and income growth.

Among other policy variables investigated, banking services, school enrolment, factories and electrification, increases income by 0.01–0.25%, –0.57–0.14%, 0.24–0.60% and 0.10–0.75%, respectively.[16]

5. 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 citizens. Working with district-level data for the periods between 1999/2000 and 2004/2005, our 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 and poor income districts at a pan-India level. Income growth has been spatially correlated through social and physical infrastructures as well as indirectly though income spillovers. This analysis about dynamics of per-capita income shows development indicators such as infrastructure as an important component for income generation.

Consequently income generation and infrastructure development in one district aids in income generation in others in the neighborhood. This leads to a reduction in income disparity among districts.

Finally, a comparative static policy analysis shows that public expenditure in development in closed drainage systems has the most impact on income generation, possibly though greater public health outcomes.

References

Ahluwalia, Montek Singh, "State-Level Performance under Economic Reforms," in A. O. Krueger (ed.), *Economic Policy Reforms and the Indian Economy*. Chicago. IL: The University of Chicago Press (2002).

———, "Regional Balance in Indian Planning," in N. K. Singh and Nicholas Stern (ed.), *The New Bihar: Rekindling Governance and Development*. Noida, UP: HarperCollins India (2013).

Anselin, Luc, *Spatial Econometrics: Methods and Models.* Boston, MA: Kluwer Academic Publishers (1988).

Barua, Alokesh and Pavel Chakraborty, "Does Openness Affect Regional Inequality? A Case Study for India," *Review of Development Economics* 14 (2010):447–65.

Bhattacharya, B. B. and S. Sakthivel, "Regional Growth and Economic Disparity in India," *Economic and Political Weekly* 39 (2004):1071–77.

Burgess, Robin and Rohini Pandey, "Do Rural Banks Matter? Evidence from the Indian Social Banking Experiment," CEPR discussion paper 4211, Centre for Economic Policy Research, London (2004).

Census, *Office of the Register General and the Census Commissioner*, Ministry of Home Affairs, Government of India (2001).

Chaudhuri, S. and N. Gupta, "Levels of Living and Poverty Patterns: A District-wise Analysis for India," *Economic and Political Weekly* 44, no. 9 (2009):94–101.

De, Sankar and Siddharth Vij, "Are Banks Responsive to Exogenous Shocks in Credit Demand? District-level Evidence from India," India School of Business, Hyderabad, available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1964105 (2012).

Fields, Gary S., *Distribution and Development: A New Look at the Developing World*, Cambridge, MA: MIT Press (2001):102–104.

Jones, Charles I., "On the Evolution of World Income Distribution," *Journal of Economic Perspectives* 11, no.3 (1997):19–36.

Kelejian, Harry and R. Ingmar Prucha, "Estimation of Simultaneous Systems of Spatially Interrelated Cross Sectional Equations," *Journal of Econometrics* 118 (2004):27–50.

Kochhar Kalpana, Kumar Utsav, Rajan Raghuram, and Arvind Subramanian, "India's Patterns of Development: What Happened, What Follows," NBER working paper 12023, Cambridge, MA (2006).

Menon, Nidhiya and Paroma Sanyal, "Conflict and Foreign Investments: An Analysis of FDI in India," *Review of Development Economics* 11 (2007):629–44.

National Crime Record Bureau, "Crime in India—1999," Ministry of Home Affairs Report, Government of India (1999).

Planning Commission, "District Level Per-Capita Income," Government of India, available at http://districts.nic.in/dstats.aspx (2010).

Quah, Danny, "Empirical Cross Section Dynamics in Economic Growth," *European Economic Review* 37 (1993):426–34.

———, "Twin Peaks: Growth and Convergence in Models of Distribution Dynamics," *Economic Journal* 106 (1996):1045–55.

Rosenzweig, Mark R. and Kenneth I. Wolpin, "Government Interventions and Household Behavior in a Developing Country: Anticipating the Unanticipated Consequence of Social Programs," *Journal of Development Economics* 10 (1982):209–25.

Tendulkar, Suresh D., "Inequality and Equity during Rapid Growth Process," in S. Acharya and R. Mohan (ed.), *India's Economy Performance and Challenges*, New Delhi: Oxford University Press (2010).

Times of India, "Conviction Rates for Murder Abysmal," available at http://articles.timesofindia.indiatimes.com/2011-06-04/india/29620648_1_conviction-rates-murder-cases-rti-application (accessed 6 June 2011).

Notes

1. Quah (1993) consider log of per-capita income data for 118 countries between 1962 and 1985. Although our analysis contains data for a short span, we argue that given India's fast growth experience within this short span (an average annual growth rate exceeding 6% between 1999 and 2005) might make it possible to capture emergence of any cluster in the underlying income distribution function, especially, at a subregional level.

2. 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 owing to production, matching and other

market interaction involve movement of labors from one district to another; and even through network externalities of infrastructure.

3. The new 1993/94 base year SDP data series used for doing post-reform period analysis is different from the old 1980/81 base year SDP data series used for analyzing performance of states during the 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).

4. 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 districts 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 a district dummy for this region will fail to capture how elements of prosperity gradually spread from the core (say, Noida, the district headquarters of Gautam Budh Nagar) to the rest of Uttar Pradesh.

5. 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.

6. Moran I for 1999/2000 is 0.54 and for 2001/02 it is 0.53. It implies in 1999/2000, 54% of the income in district i is influenced by incomes in the neighboring districts (see Table 1).

7. The Planning Commission does not report data on district-level per-capita income data for the period after 2006/07.

8. In 2000 there were 585 districts and in 2011 there were 627 districts in India. Many of these districts are newly formed and for some of them information about the income variable is not available. A 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 2 April 2011).

9. 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. The 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.

10. An income distribution function stochastically dominates another if the percentage of people below any given income is higher in the first (1999/2000) than in the second (2004/05). The income distribution function that stochastically dominates the other also has higher poverty than the other.

11. For an excellent discussion on this topic, see, Fields (2001), pp.102–104.

12. We do not find evidence suggesting that there has been a statistical significant increase in standard deviation.

13. However, when we consider income without log we find a change in income distribution function at a 5% level, between 1999/2000 and 2004/05.

14. 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 experiments such as randomized controlled trial—something outside the scope of this paper.

15. Between 2005 and 2009 the average conviction rate for murder is only 36.2%. Out of nearly 127,000 murders only 44,601 people were convicted. See, *Times of India* News Service (available at http://timesofindia.indiatimes.com/india/Conviction-rates-for-murder-bysmal/articleshow/8720229.cms).

16. Figures for these results are available on from the authors at http://www.dur.ac.uk/a.n.banerjee/.