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Growth, Geography, and the Iron Law: Understanding Divergence Across Indian Districts.

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Abstract

The existing literature on Indian growth finds no evidence of β convergence across states. This represents a puzzle given the relatively free flows of capital, labour and commodities across state borders. We use a new data set to estimate convergence rates across 575 Indian districts and find that the pattern of absolute β-divergence remains. To explain this we develop a model of conditional convergence that includes a gravity indicator of trade and migration costs – specifically the distance from a major metropolitan center – as a conditioning variable. We find strong evidence of conditional convergence with an elasticity close to Barro's "iron law". We also find that geography and public infrastructure variables are important conditioning variables.

Keywords: Convergence, Divergence, Indian Economic Growth, Gravity Models.

JEL: O4, O5.

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1 Introduction

India's tentative economic miracle faces many hurdles, but one of the chief difficulties is sustaining the political impetus for reform. This is rendered more difficult by the fact that growth has been unbalanced – both across states and between urban and rural areas, (Bardhan 2010). The growing regional disparities appear to have dampened political resolve for further economic reforms that might further amplify regional inequalities.

Understanding the cause of this unbalanced growth, and the factors that hasten or impede the benefits of economic reform, is therefore important. The existing literature on regional convergence, however, has been largely constrained to the analysis of inter-state differences. In this study we use a new data set of per capita incomes for 575 districts across India to describe the pattern of regional growth and try to identify factors than can explain the pattern of regional divergence.

We find that the pattern identified in the literature so far – of absolute β divergence across Indian states – remains when we analyze growth patterns at the district level. We also find that the variance of incomes within and between states have both been increasing.

Since trade and transport costs may be significant and hence be able to explain a lack of absolute convergence, we then consider a model of conditional convergence. Specifically we consider whether the distance, or remoteness, of each district from a major metropolitan center can explain differences in district income levels and transitional growth rates.

We find strong evidence of conditional convergence across Indian districts, with an estimated rate of conditional β–convergence of approximately -2.7%, which corresponds very closely to Barro's "iron law of convergence" (Barro 2012). We also find that the distance of a district, from a major metropolitan center, is an important explanatory variable along with indicators of public infrastructure.

1.1 Literature Review

Many previous studies have considered the evidence for convergence across Indian States but find little evidence of β–convergence (Rao, Shand and Kalirajan 1999, Trivedi 2003, Bandopadhyay 2004, Das 2012, Ghate 2008, Das 2012, Ghate and Wright 2012). Rather, the pattern is one of divergence or, convergence to a bimodal distribution (Bandopadhyay

2004, Kar, Jha and Kateja 2011, Bandopadhyay 2012).[1] As noted above these findings for Indian States are curious since the hypothesis of absolute β–convergence has found widespread support in other countries (Sala-i Martin 1996, Durlauf, Johnson and Temple 2005). There is also no consensus on what the sources of this divergence might be. For example Cain, Hasan and Mitra (2012) find that states that are more open, with more roads and less labour market regulation, fared better. However Krishna and Sethupathy (2012) argue that the evidence of links between inequality and reforms in India are fairly weak.

2 The Dataset

The availability of district level income data, however, provides the opportunity to observe these regional disparities at a much finer level, with a larger degree of heterogeneity in income levels, growth rates and other characteristics such as urbanization or literacy, across the units of observation, than is possible with state level data. To that end we assess the pattern of growth and convergence across India using district level data. These district level data on incomes and social and economic characteristics, are taken from *Indicus* "Development Landscape" and "District GDP" data-sets. The data consist of 575 district level observations of district income for two years, 2001 and 2008.[2]

We begin with a preliminary exploration of the data by considering different indicators of convergence and how the shape of the distribution of district incomes has changed over time.

Table 1 shows the wide disparity in income levels across states. There is a 9.8 fold difference between the richest state *Goa*, and the poorest state *Bihar*. This is larger than the real income gap between the GDP per capita of the USA and Angola, and only slightly smaller than the real income gap between the USA and India.[3]

At the district level, however, that gap is much larger. The district data are shown visually in Figure 1. The range is from a minimum of RS. (m) 3858 in the Sheohar district (Bihar) to a maximum of RS. (m) 139868 in Jamnagar (Gujarat). This is an income ratio of 36 which is equivalent, for example, to the ratio between the USA and

[1] Likewise there is evidence of growing inequality across India, such as Mishra and Kumar (2005), Chamarbagwala (2008) and Chaudhuri and Ravallion (2007).

[2] This data has attracted some debate. See Himanshu (2009) but also, importantly, the reply by Bhandari (2009).

[3] This comparison is based on the Penn World Tables PPP values, that report Angola with a relative per capita GDP of 11.51 and India 7.21 in 2008.

Rwanda according to the Penn World Tables.

It can also be seen that there are generally lower incomes in central districts, particularly in the eastern states. Likewise the wealthy western corridor running from north of Delhi down the west coast through Western *Maharashtra* and *Karnataka*, *Goa* and *Kerala* is easily observed. Figure 1 is thus suggestive of some strong geographic pattern in the differences in incomes across India.

The fact that the within-India differences are comparable to cross-country differences is remarkable given that there are no political barriers to migration, approximately free trade, and a common set of federal institutions, policies and governance. That such differences could persist over time is in stark contradiction to the standard competitive model that motivates the extensive literature on absolute β–convergence across regions. In contrast, it points to the potential relevance of trade barriers, transport costs and conglomeration effects as emphasized in the economic geography literature.

2.1 Absolute β and σ convergence

The standard concept of convergence in cross sectional regional data is absolute β–convergence (Baumol 1986, Sala-i Martin 1997, Durlauf et al. 2005). This is given by the coefficient β from (1)

$$y_{i,t} - y_{i,0} = \beta \, y_{i,0} \; + \; \varepsilon_i \tag{1}$$

where $y_{i,t}$ is the natural log of income at time t in region i and $y_{i,0}$ is initial income.[4] The results of estimating (1) across Indian districts are given in Table 1. It can be seen that across India there is strong evidence of a small rate of divergence with $\beta = 0.007$. Hence, on average, richer districts have been growing slightly faster than poorer districts.

Table 1 also shows the results of estimating (1) for each state separately. Thus we ask whether there is convergence across districts within each state. In four states, *Assam*, *Chhattisgarh*, *Kerala* and *Rajasthan* there is significant absolute β–convergence of district level incomes. However there is also significant within-state divergence in three states – *Haryana*, *Orissa* and *Uttar Pradesh (UP)*.[5] For the vast majority of states however the estimated β – convergence coefficient is insignificantly different from zero. Thus there is little evidence of strong convergence, either across the country as a whole or within

[4] We report β for all states except *Goa*, *Pondichery* and *Chandigarh* where the number of districts is 2 or 1.

[5] Moreover both *UP* and *Orissa* are among the poorest states with the largest primary sector income shares, above 30%.

individual states.

Next we consider σ convergence, which is defined as a decline in the variance of district level per capita incomes across time. Table 2 shows the variance of district incomes in the two periods, 2001 and 2008. It can be seen that there was a 30.7% increase in the variance of incomes across districts – from 0.27 to 0.35. Thus there has also been σ divergence.

Table 2 reports a simple variance decomposition.[6] Here, *within-state* variance, ν^W refers to deviations of district incomes y_{ij} from their state level mean income, $\bar{y}_j$, $y_{ij} - \bar{y}_j$, and *between-state* variance, ν^B, refers to deviations of state level mean incomes $\bar{y}_i$ from the country-wide mean income, $\bar{y}$, $y_j - \bar{y}$. By definition the total India-wide variance of incomes across all districts, ν^T, is equal to the sum of the within-state variance and between state variance, $\nu^T = \nu^W + \nu^B$. This variance decomposition shows that there has been a similar increases in σ–divergence both within states and between states.

Further evidence on the pattern of Indian growth can be obtained by examining other aspects in the change in the distribution of district incomes. To that end Figure 4 plots the kernel density estimate of the probability density function (PDF) for district incomes for 2001 and 2008. It shows the shift in mean income and also a fall in peakedness (kurtosis) with a slight increase in concentration on the left tail (skewness). Likewise Figure 5 shows the Cumulative Distribution Function (CDF). Together these visual images suggest the income distribution has widened at the upper tail, but income has increased at each point on the distribution.

Nevertheless there is significant churning within the distribution. Only six districts remain in the same position on the distribution between 2001 and 2008. Some notable cases include *Baster* in *Chhattisgarh*, which is the best performing district and improved from 418th position (in 2001) to 5th position (2008). Conversely *Korba* district also in *Chhattisgarh* is the worst performing district falling from 23nd position (in 2001) to 480th position (2008). Overall, however, Kendall's rank correlation *tau* statistic is 0.78, suggesting a high correlation of rankings between the two periods.

Thus, though there is some evidence of convergence within a few states, among most states there is no correlation between initial income and growth, and across the country as a whole, there is evidence of β and σ divergence. The pattern of divergence reflects faster growth in higher income districts, with most districts experiencing growth across the entire distribution.

[6]Details of this simple decomposition are given in the appendix.

3 Conditional Convergence and Geography

The preceding model of absolute β–convergence explicitly assumes that all regions within a country have the same steady state income level, (Barro and Sala-i Martin 1991, Durlauf et al. 2005, Barro and Sala-i Martin 2005). This can be justified, for example, by the factor price equalization theorem, which states that free-trade and identical technologies will result in a convergence of incomes across regions. More generally factor mobility will result in absolute convergence, even in the absence of identical technologies.

In the presence of barriers to trade, information or factor migration, however, persistent income differences may exist, Krugman (1991). Likewise, as emphasized by Lucas (1988), regional externalities and conglomeration effects may also create divergence of incomes. Thus, even in a regional context, there may be significant obstacles to convergence and hence long run differences in per capita incomes.[7] With respect to India, specifically, Desmet, Ghani, O'Connell and Rossi-Hansberg (2012) have argued that high density cities are India's engines of growth.

In view of this, the concept of conditional convergence may be appropriate. Specifically consider a long run equilibrium where all districts are growing at rate g. Denote productivity at time t, measured in effective labour units, as $A_i(t)$ and assume that $A_i(t) = A_i(0)^{gt}$. Then on a balanced growth path, district income per effective worker $\hat{y}_i^* \equiv (y_i^*/A_i^*)$ will be a constant.

Next suppose that the convergence path to the steady state, or balanced path equilibrium is given by a standard partial adjustment model

$$\ln \hat{y}_i(t) - \ln \hat{y}_i(0) = \beta(\ln \hat{y}_i^* - \ln \hat{y}_i(0)), \tag{2}$$

which says that the current growth rate of district i depends on the gap between the current income level and the long run balanced path level, both measured in terms of output per effective worker. Though the form of this expression is familiar from the cross country literature, in our regional context we also need a theory of how differences in regional steady state incomes, y_i arise.

[7] In a less formal way these characteristics also featured in earlier development literature such as Lewis (1955).

3.1 Quantifying Remoteness

It is well understood that cities have a special role in the growth process, (Glaeser, Kallal, Scheinkman and Shleifer 1992). Likewise, as discussed above, the strength of the impact of growth in cities on surrounding districts will depend on trade costs and other geographic factors. Thus a district that is very remote might have a low long-run per capita income level, relative to one that is very close to a major city.

As in the trade costs literature we can capture the degree of trade, transport and migration costs by using measures of distance (Anderson and Wincoop 2004). Specifically suppose there is a single metropolitan center. Then the distance between a district i and this center would be a simple indicator of the remoteness of district i.

Thus letting y^* denote the steady state income per worker in the metropolitan center, then for some district i we may consider a variable θ_i such that in a steady-state equilibrium,

$$y_i^* = \theta_i \; y^* \tag{3}$$

where y_i^* is the steady state income per person for district i and θ_i measures extent of all barriers to complete convergence, such as trade and transport costs, communications costs, road quality and other geographic barriers. The variable θ_i thus determines the maximum degree of convergence, or catch-up, that can be obtained. Specifically if $\theta_i < 1$ district i will only achieve partial convergence to the metropolitan center.

In terms of effective workers (3) implies $\hat{y}_i^* = \theta_i \; \hat{y}^*$.[8] Then using (2) the transitional growth process for some non-metropolitan district i, can be derived as

$$\ln y_i(t) - \ln y_i(0) = gt - \beta \ln y_i(0) + \ln A_i(0) + \beta \left(\ln \hat{y}^* + \ln \theta_i \;\right) \tag{4}$$

In equation (4) the growth rate of district i depends on: (i) the initial per capita income of district i, $y_i(0)$; (ii) the level of labour productivity of district i, $A_i(0)$; the steady-state value of income per effective worker in the relevant metropolitan center, $\hat{y}^*$; and, the distance between district i and the metropolitan center, θ_i.

Thus (4) says that the growth rate of per capita income for some district i, depends on its current level of per capita income relative to its long run balanced growth path level, which in turn, depends in part on the remoteness of the district from the metropolis and

[8]We assume long run technology convergence so that $A_i^* = A^*$. Alternatively one could assume that technological gaps exist in the long run and that this difference is absorbed as an argument in the function θ_i.

its steady-state per capita income level.

4 An Empirical Model

To implement equation (4) empirically we first need to define what we mean by a "metropolitan center". Moreover there will be more than one metropolis, so we also need to obtain some way of measuring θ_i, given that there may be several large cities close by.

As shown in Table 3, India has three mega-cities with populations above 10 million, *Delhi*, *Mumbai*, and *Kolkata*. Of these Delhi and Mubai have extended urban agglomerations - defined as areas of unbroken urbanization - that exceed 20 million. Nevertheless even the smaller cities, Banglaore, Hyderabad and Ahmedabad, have populations of over 6 million and there are ten Indian cities with urban agglomerations over 3 million. We begin therefore by initially defining a "metropolitan center" as the seven largest Indian cities which includes all cities that had populations over 6 million. As a robustness check we also consider alternative definitions up to the ten largest cities listed in Table 3. As we shall see, the results, are very robust to these alternative definitions.

Next we define the variable *Distance*, D_i, as the minimum distance, by road, between district i and the closest metropolitan center.[9] Figure 2 shows D_i for each district in India. Given the location of the seven largest cities the map shows a band of relatively remote districts between *Delhi* and *Hyderabad* through *Madhya Pradesh* and *Chhattisgarh*. The remaining remote districts are located in the geographic extremities, especially the far north of *Jammu and Kashmir*, the eastern most districts of *Gujarat* and the far western districts. It can also been seen that there are clusters of less remote districts along the western corridor from Delhi to Bangalore and Chennai. This picture of a western corridor of relative urbanization is even stronger if we move to consider the ten largest metropolitan centers, as shown in Figure 3.

The final step needed to operationalize (4) is to specify an empirical counterpart to (3), which is a function of the minimum distance from a district to a metropolitan center. The gravity literature in international trade suggests a simple inverse relationship such

[9] The data on distance between districts from *Google Maps* and a variety of other sources including Indian state tourism data. It denotes the minimum distance (by road) from one district headquarter to another.

as $\theta_{i,j} = \theta\ D_i^{\gamma}$. Hence, using logarithms we have

$$\ln \theta_{i,j} = \ln \theta\ + \gamma\ \ln D_i + \eta\ \mathbf{X}_i \tag{5}$$

where $\gamma < 0$, is the distance elasticity, $\mathbf{X}_i$ is a vector of characteristics of region i and η is a vector of coefficients. This follows the standard gravity model, familiar in the trade literature.[10]

From (4) and (8) we obtain an empirical model,

$$\ln y_i(t) - \ln y_i(0) = \alpha_0 + \alpha_1\ \ln y_i(0)\ +\ \alpha_2\ \ln D_i + \eta\ \mathbf{X}_i\ +\ \epsilon_i \tag{6}$$

where $\alpha_1 \equiv -\beta$, $\alpha_2 = \beta\gamma$, $\alpha_0 = g + \beta \ln A_i(0) + \beta \ln \hat{y}^* + \theta$, and $\ln A_i(0) = \ln A + \epsilon_i$, where ϵ_i is a district specific random shock reflecting, for example, institutions, climate and endowments.

Equation (6) is our base-line model. The convergence coefficient captures the notion that the larger the gap between the i^{th} district and the metropolitan center in the initial time period, the lower the growth rate. Distance is expected to negatively affect district incomes relative to the closest metropolitan center and hence reduces the transitional growth rate.

Finally a further simple extension of (6) is to allow for the possibility that the metropolitan districts have different balanced path income levels. Specifically suppose $\hat{y}_j^* = f(\mathbf{Z}_j)\ \hat{y}^*$, where $\mathbf{Z}_j$ is a vector of characteristics that affect the steady state income levels of metropolitan center j. Then, assuming $f(\mathbf{Z})$ is log linear gives

$$\ln y_i(t) - \ln y_i(0) = \alpha_0 - \alpha_1 \ln y_i(0)\ +\ \alpha_2\ \ln D_i + \eta\ \mathbf{X}_i + \delta\ \mathbf{Z}_j + \epsilon_i. \tag{7}$$

In what follows we estimate (6) and (7) using our cross-section of Indian districts.

5 Conditional Convergence Across Indian Districts

As discussed above, our data consists of using the district level GDP growth rates and district level characteristics from the *Indicus* data sets. Summary statistics for the key variables of interest are given in Table 4.

[10]This also requires the restriction that $D_i \geq 1$, which will be true in our data.

A visual inspection of the data suggests the presence of heteroscedasticity and the Breusch-Pagan (BP) test for heteroscedasticity on preliminary OLS results confirms this. As the form of heteroscedasticity is unknown, the application of GLS is not feasible. The implication of heteroscedasticity is that OLS will result in biased standard errors and tests based on these standard errors will be invalid. In what follows we therefore use White's (1982) robust standard errors to obtain valid inferences, even though efficiency is sacrificed.

We begin by reporting the results of a standard conditional convergence model without the *Distance* variable. This is shown in Column 1 of Table 5. The conditioning vector consists of the percentage of households with electricity, the number of *commercial banks*, *urbanization,* and the percentage of *irrigated land*. We also include state dummy variables and report the results of an F-test for the joint significance of these state dummy variables.

It can be seen that the sign of the convergence coefficient β, is negative as expected and all of these variables are statistically significant. The estimate value of β is -2.5% which is remarkably similar to the values found in the growth literature using quite different regional aggregations across a wide array of counties. This is also close to Barro's "iron law of convergence" (Sala-i Martin 1996, Sala-i Martin 1997, Barro 2012). Thus, though there was little evidence of absolute β–convergence, there is evidence of conditional convergence. The rate of 2.75% implies that the gap between each district's current income level, and its long run or steady state income level, is halved every 25 years. As discussed by Barro (2012) this slow rate is considered typical in the cross country literature, so might be considered very slow in this regional context.

In column (ii) we include our remoteness variable, *Distance*. It can be seen, first, that *Distance* is significant at the 5% level with a point estimate of -0.005. As expected, an increase in *Distance* reduces steady-state income level and hence also reduces the transitional growth rate for a given level of initial income, $y(0)$. It can be seen that the convergence coefficient remains significant and with a similar elasticity of -2.7%. In columns (iii) we include the percentage of good quality roads, *Pucca Roads*, as an explanatory variable. It is not significant however, and the results remain very similar.

In Column's (iv) and (v) we then include the vector of characteristics of the closest relevant metropolitan center (the $\mathbf{Z}_j$) as described in (7). This includes literacy rates, electricity use and urbanization rates. It can be seen that across these different models the key variables, initial income, $y_i(0)$, and *Distance*, D_i, are highly significant with the expected signs and have very similar point estimates. Finally across all models it can be seen that the variables *urbanization*, *electricity* and *commercial banks* are significant across all models.

The model thus sheds substantial light on the observed pattern of divergence across India. First it shows that the divergence of growth rates can be understood as resulting from differences in long run income levels. This is a useful starting point in formulating potential policy responses, as it suggests that absolute convergence will depend on increasing equality in these conditioning variables.

To that end the results also show that a significant fraction of the variance in growth rates can be understood as resulting from variables related to differences in the level of public infrastructure. This suggests that divergence in growth rate may be mitigated through improving economic policy, particularly infrastructure investment, in low growth regions. The potential policy role is underscored by the fact that the state dummy variables are highly significant, since previous literature has also pointed to significant policy differences at the state level, particularly with respect to labour laws, (Besley and Burgess 2004, Acharya, Baghai and Subramanian 2010)

In addition to these policy variables the results also show that geography is important. Specifically we find that urbanization rates are highly correlated with growth which could be interpreted as support for the idea that high density clusters are important sources of growth in India, as argued by Desmet et al. (2012). Finally we have also seen that remoteness is significant across all our models, which suggest that transport and information costs impose important regional constraints on development. The next section considers this last result in more detail.

6 The Impact of Remoteness

To what extent do different degrees of remoteness matter for understanding differences in growth and incomes across India. The elasticity of *Distance* with respect to steady state income is given by $\gamma = -\alpha_2/\alpha_1$. This value is reported for each model in Table 4, along with a joint significance test. It can be seen that the estimates of γ are significant at either the 5% or 10% level across each model with a value of approximately -0.2.

To interpret this consider two districts i and j with identical characteristics except their distance from the metropolitan center k. Then from (8) we have

$$\frac{y_i^*}{y_j^*} = \left(\frac{D_{i,k}}{D_{j,k}}\right)^{\gamma} \tag{8}$$

If, for example, the more isolated district, i, is twice the distance from the metropolitan center than the closer district, j, then from (8), we have $D_{i,k}/D_{j,k} = 2$. Assuming a value of $\gamma = -0.2$ this implies $y_i^*/y_j^* = 2^\gamma = 0.87$. Thus our estimates imply that the more remote district will have a steady state income level that is approximately 87% of the closer district. Likewise if the more remote district is four times further from the center, it will have a steady-state income that is approximately 76% of the closer district.

The most remote district in our data is "Tamenglong", in Manipur, which is a mountainous district near the Burmese border and is 2531 kilometers from Kolkata, the nearest metropolitan center.[11] At the other end of the spectrum the district "South 24 Parganas" is only 7.9 kilometers from Kolkata. This gives a ratio of approximately 320 which means, from (8), that other thing equal we would expect the more remote district to have an income level of only just under 1/3 of the closer district.

In terms of growth rates the coefficient on distance, $\alpha_2 = \beta$ and $\gamma = 0.005$ implies that, given the same current income level, a district that is twice as remote will have a growth rate that is 0.05 percentage points lower than the closer district, while one that is the maximum of 320 times more remote would have a growth rate that is 0.4 percentage points lower. Thus the results suggest that *Distance* may be very important for some Indian districts. Thus the results suggest that very remote districts may have significantly lower income levels, up to only a third of the metropolitan centers, and likewise, lower transitional growth rates up to nearly half a percentage point.

6.1 Robustness

As a robustness test we then extend our definition of a metropolitan center to include the 6 largest and 10 largest urban agglomerations by population as in Table 2. The overall conclusion is extremely robust to these alternative definitions of distance or remoteness with very little change in significance of the key variables or the estimated size of the coefficients.[12] Second we consider whether our distance variable is stable across different data sets. To do this we divided the whole data set into several subgroups, and then examine stability of model parameters. To this end, we re-estimate (6) and (7) but drop several districts from the data file. Specifically we first drop all north-east districts, then all district from Bihar and Maharashtra. Other alternatives are given in Table 6.

A stability test is then conducted by using interaction dummy variables, where dummy

[11] This excludes Dhaka in Bangladesh.

[12] These results are available upon request.

variable takes value 1 for included districts and takes value 0 for excluded districts. Then we examine whether such interaction dummies are significant or not based on an F-test. The results are depicted in Table 6.

All the parameters, including the distance variable, were found to be very stable across the data subsets, as shown in Table 6 where the estimated p-values for the F-tests are significantly larger than 0.05. Thus we do not reject the null hypothesis of constant coefficients. Hence this test indicates there is no evidence that the parameters change across the subsets of the data districts.[13]

6.2 Endogeneity

Aside from these robustness tests we also consider the potential for the explanatory variables to be endogenous, leading OLS estimates to be biased and inconsistent. To investigate this we first apply the Hausman test by comparing 2SLS and the OLS estimates.[14]. Unfortunately the Hausman tests are negative for all these cases. This is not unexpected since, as discussed above, there is evidence that our data are strongly heteroscedastic, invalidating the use of the Hausman test.

We therefore compare the equality of two parameter vectors (OLS and 2SLS) in a SUR setting. Table 7 provides results of this endogeneity test for three variables, viz., District Literacy, District Pucca Roads, District Urbanization as included in Table 5.[15] The test statistic follows a χ^2 distribution with the number of model parameters as the degrees of freedom [16] We find we cannot reject the null hypothesis of no endogeneity.

7 Conclusion

India's growth has been very unbalanced and there is a significant divergence of income levels across regions. The causes of this pattern of divergence - in this regional context with free trade and factor mobility - are not well understood. We therefore reexamine

[13] We examine parameter stability for the genuine regressors excluding the intercept and the state dummy variables. Note also that it is important that these subsets of the full data set are selected in a random fashion. For example creating subsets of the data based on different income groups would introduce a sample selection problem.

[14] For 2SLS the identifying variables we use are the percentage of household with telephones, percentage of people below the poverty line and female literacy rates

[15] We have also tested exogeneity status of the *Metro* variables included in Table 5. The SUR framework based tests strongly accept the null hypothesis of exogeneity.

[16] For example, Model (iii) has 38 parameters and Model (iv) has 39 parameters.

the evidence for absolute convergence at the district level, by using a new data set on district level incomes.

We show there is little evidence of absolute β–convergence either within states or across all districts as a whole. Rather there is β–divergence across all districts and also an increase in the variance of incomes across districts across time – $\sigma divergence$.

To better understand this divergence we consider a model of conditional β–convergence and include geographic remoteness as a conditioning variable. We find that there is indeed evidence of conditional convergence between Indian Districts, with a convergence rate of approximately -2.7%. This is close to Barro's "iron-law" of convergence and implies a half-life of 25 years. Thus the pattern of divergence can be understood as arising from poorer districts having lower steady-state income levels. A noted by Barro (2012) the convergence coefficient implies that convergence to these long run income levels is a relatively weak force.

To aim to better understand the causes of the differences in steady-state incomes across districts by considering the remoteness of each district. Specifically we include the distance between each district and the closest large metropolitan centers as a conditioning variable. This captures arguments from the economic-geography and trade literature that emphasizes the importance of transport costs and barriers to factor mobility in preventing absolute convergence. We find that distance has an important negative impact on a district's growth rate and steady state income levels, and can explain up to a three-fold difference in incomes.

Thus we have shown that the conditional convergence framework provides a useful framework for understanding India's uneven growth. Likewise we also provide some robust evidence on some of the important sources of the divergent growth experiences. In particular we show geographical remoteness, along with other factors related to public infrastructure, such as electrification and the availability of banks, can account for some of the variance in incomes and growth rates. Since many of these variables are related to public infrastructure investment, they are also suggestive of an important role for public policy in securing a more even distribution of the gains from economic growth.

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Table 1: Within State Convergence

State	Pop (Millions)	Per Capita GDP Rs 000's 2007-08	Share Primary Sector %	β	p-value
All India	1,137.1	38	21	0.0070***	(0.0069)
Andhra Pradesh	82.2	38	29	-0.0031	(0.7595)
Arunachal Pradesh	1.2	34	26	-0.0133	(0.6801)
Assam	29.3	24	35	-0.0332***	(0.0028)
Bihar	95.6	11	25	-0.0068	(0.6505)
Chhattisgarh	23.2	33	24	-0.1579**	(0.0125)
Gujarat	55.9	52	19	0.0012	(0.9054)
Haryana	23.8	62	21	0.0332*	(0.0596)
Himachal Pradesh	6.5	49	22	0.0082	(0.7635)
Jammu an Kashmir	11.0	29	27	0.0047	(0.7181)
Jharkhand	30.2	23	22	0.0304	(0.1031)
Karnataka	56.7	38	19	0.0102	(0.3941)
Kerala	33.8	48	17	-0.0391*	(0.0658)
Madhya Pradesh	69.0	20	33	-0.0005	(0.9665)
Maharashtra	107.1	53	13	0.0120	(0.1709)
Manipur	2.4	24	26	-0.0008	(0.9838)
Meghalaya	2.5	30	27	0.0101	(0.6059)
Mizoram	1.0	34	15	0.0175	(0.4883)
Nagaland	2.2	33	34	-0.0157	(0.5886)
Orissa	39.7	26	31	0.0492***	(0.0002)
Punjab	26.4	52	31	-0.0054	(0.8606)
Rajasthan	64.1	26	28	-0.0338***	(0.0059)
Tamil Nadu	66.0	44	14	0.0089	(0.4845)
Uttar Pradesh	189.3	18	31	0.0133**	(0.0214)
Uttaranchal	9.4	36	20	0.0079	(0.6176)
West Bengal	86.4	35	23	0.0033	(0.7685)

Note 1: *, **, *** denotes 10, 5 and 1 percent levels of significance respectively.

Note 2: Robust (White) standard errors are used.

Table 2: Decomposition of σ–Convergence

	Variance	Between State Variance	Within State Variance	Skewness	Kurtosis	Gini
2001	0.27	0.15	0.13	0.13	3.10	0.0306
2008	0.35	0.19	0.16	0.18	2.89	0.0342
Change	0.08	0.04	0.03			

Table 3: Metropolitan Districts

Extended Urban Agglomeration	Population 2011 (Millions)
Delhi	21,753,486
Greater Mumbai	20,748,395
Kolkata	14,617,882
Chennai	8,917,749
Bangalore	8,728,906
Hyderabad	7,749,334
Ahmedabad	6,352,254
Pune	5,049,968
Surat	4,585,367
Jaipur	3,073,350

Source: Government of India (2013)

Table 4: Descriptive Statistics

	Mean	Variance	Minimum	Maximum	Skewness
Per capita GDP	9.583	0.274	8.243	11.313	0.148
Distance	6.004	0.671	2.067	8.018	-1.091
Literacy	4.131	0.046	3.408	4.570	-0.750
Electricity (%)	3.776	0.578	1.131	4.588	-1.212
Commercial Banks	-9.698	0.175	-11.194	-8.227	0.500
Urbanization	2.870	0.565	0.279	4.605	-0.199
Irrigated Land	-3.253	1.163	-7.782	-1.139	-0.980
Pucca Road	3.968	0.617	-1.204	4.605	-3.063
Metro Electricity	4.557	0.000	4.543	4.583	1.376
Metro Urbanization	4.579	0.001	4.479	4.605	-1.635
Metro Literacy	4.412	0.001	4.367	4.459	0.065

Note: *Per capita GDP* is the logarithm of district per capita GDP in RS. Millions in 2001; *Distance* is the logarithm of the distance by road to the closest of the seven largest urban agglomerations as listed in Table 3; *Literacy* is the logarithm of the total literacy rate per hundred people; *Electricity* is the logarithm of the percentage of households with an electricity connection ; *Commercial Banks* is the logarithm of the number of commercial banks per thousand people; *Urbanization* is the logarithm of the percentage of urban households; *Irrigated land* is the logarithm of the net irrigated land area per million people; *Pucca Road* is the logarithm of the percentage of households connected by "Pucca Roads" ; *Metro Electricity* is the logarithm of the percentage of households with an electricity connection in closest metropolitan district; *Metro Urbanization* is the logarithm of the percentage of urban households in the closest metropolitan district; and *Metro Literacy* is the logarithm of the total literacy rate per hundred people in the closest metropolitan district.

Table 5: Conditional Convergence and Distance

	(i)	(ii)	(iii)	(iv)	(v)
Per capita GDP	-0.0249***	-0.0272***	-0.0272***	-0.0275***	-0.0275***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Distance		-0.0055***	-0.0055***	-0.0056***	-0.0050**
		(0.002)	(0.002)	(0.002)	(0.002)
Literacy	-0.011	-0.0109	-0.0112	-0.0063	-0.0063
	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)
Electricity (%)	0.0176***	0.0161***	0.0159***	0.0158***	0.0154***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Commercial Banks	0.0112*	0.0140**	0.0140**	0.0129*	0.0124*
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Urbanization	0.0069**	0.0068**	0.0069**	0.0067**	0.0069**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Irrigated Land	-0.0044*	-0.0038	-0.0038	-0.0037	-0.0038
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Pucca Road			0.0013		0.0013
			(0.003)		(0.003)
Metro Electricity				0.4521	0.4733
				(0.326)	(0.319)
Metro Urbanization				-0.1091*	-0.1065
				(0.064)	(0.065)
Metro Literacy					0.0691
					(0.062)
Constant	0.3432**	0.4305***	0.4260***	-1.1561	-1.5814
	(0.140)	(0.153)	(0.153)	(1.260)	(1.187)
Gravity Parameter		-0.2034**	-0.2030**	-0.2030*	-0.1840*
		(0.091)	(0.100)	(0.114)	(0.096)
R-squared	0.3036	0.3111	0.3095	0.318	0.3179
BP Test	111.57***	105.70***	102.66***	90.10***	89.87***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
F Test	24.74***	19.30***	8.79***	13.57***	8.96***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Observations	550	546	544	546	544

Note: *, **, *** denote 10, 5 and 1 percent levels of significance respectively using Robust (White) standard errors. F-tests are joint tests for state dummy variables. Numbers within brackets denote standard errors except for BP and F tests where they denote p - values.

Table 6: Stability Test

	(i)	(ii)	(iii)	(iv)	(v)
North East	1.29	1.03	1.12	0.89	0.97
	(0.26)	(0.41)	(0.35)	(0.54)	(0.47)
Maharastra	1.12	0.96	1.01	0.84	0.85
	(0.35)	(0.46)	(0.43)	(0.57)	(0.59)
Bihar	1.48	1.26	1.13	1.18	1.08
	(0.18)	(0.27)	(0.33)	(0.30)	(0.38)
North East and Bihar	1.54	1.38	1.17	1.15	1.01
	(0.16)	(0.21)	(0.31)	(0.32)	(0.43)
Maharastra and Bihar	1.21	1.16	1.04	1.12	1.05
	(0.29)	(0.32)	(0.40)	(0.34)	(0..40)
Degrees of Freedom of F-test	F(6,510)	F(7,504)	F(8,501)	F(9,501)	F(11,496)

Note 1 P-values are given in the parenthesis.

Note 2: F-tests are joint tests for sate dummy variables.

Note 3: As in table 1. Note 4: As in table 5.

Table 7: Results for Endogeneity Test

	(i)	(ii)	(iii)	(iv)	(v)
District Literacy	9.70 ***	9.34***	12.98***	10.17***	11.15***
	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)
District Pucca Road	NA	NA	5.61***	NA	5.59***
			(1.000)		(1.000)
District Urbanization	5.85***	7.33***	6.93***	7.51***	7.00***
	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)

Note 1: *, **, *** denotes 10, 5 and 1 percent levels of significance respectively.

Note 2: All tests follow χ^2 with appropriate degrees of freedom equal to the number of model parameters.

Note 3: Endogeneity tests are performed by comparing OLS and 2SLS parameter estimates. This comparison is done in SUR framework. The Hausman test is not appropriate as data has heteroscedasticity.

Appendix: Variance Decomposition

This appendix briefly describes our variance decomposition. Let y_{ij} be the underlying variable (say, per capita income) of j^{th} district in i^{th} state, $j = 1, 2 \ldots, n_i$, $\quad i = 1, 2 \ldots K$. Let $N = \sum_{i=1}^{n_i}$, the total number of observations. Define $\bar{\bar{y}} = \frac{1}{N} \sum_{i=1}^{K} \sum_{j=1}^{n_i} y_{ij}$, the Grand mean. Define $\bar{y}_i = \frac{1}{n_i} \sum_{j=1}^{n_i} y_{ij}, i = 1, 2 \ldots K$, the within mean. We define following three quantities...

Total sum of square (TSS)= $\sum_{i=1}^{K} \sum_{j=1}^{n_i} (y_{ij} - \bar{\bar{y}})^2$.

Within Sum of square (WSS)= $\sum_{i=1}^{K} \sum_{j=1}^{n_i} (y_{ij} - \bar{y}_i)^2$.

Between Sum of Square (BSS)= $\sum_{i=1}^{K} n_i (\bar{y}_i - \bar{\bar{y}})^2$.

Then

$$TSS = \sum_{i=1}^{K} \sum_{j=1}^{n_i} (y_{ij} - \bar{\bar{y}})^2 = \sum_{i=1}^{K} \sum_{j=1}^{n_i} (y_{ij} - \bar{y}_i + \bar{y}_i - \bar{\bar{y}})^2 = WSS + BSS.$$

Finally dividing each term by N gives the total, between and within-state variances, $\nu^T = TSS/N$, $\nu^W = WSS/N$ and $\nu^B = BSS/N$. Hence $\nu^T = \nu^W + \nu^B$.

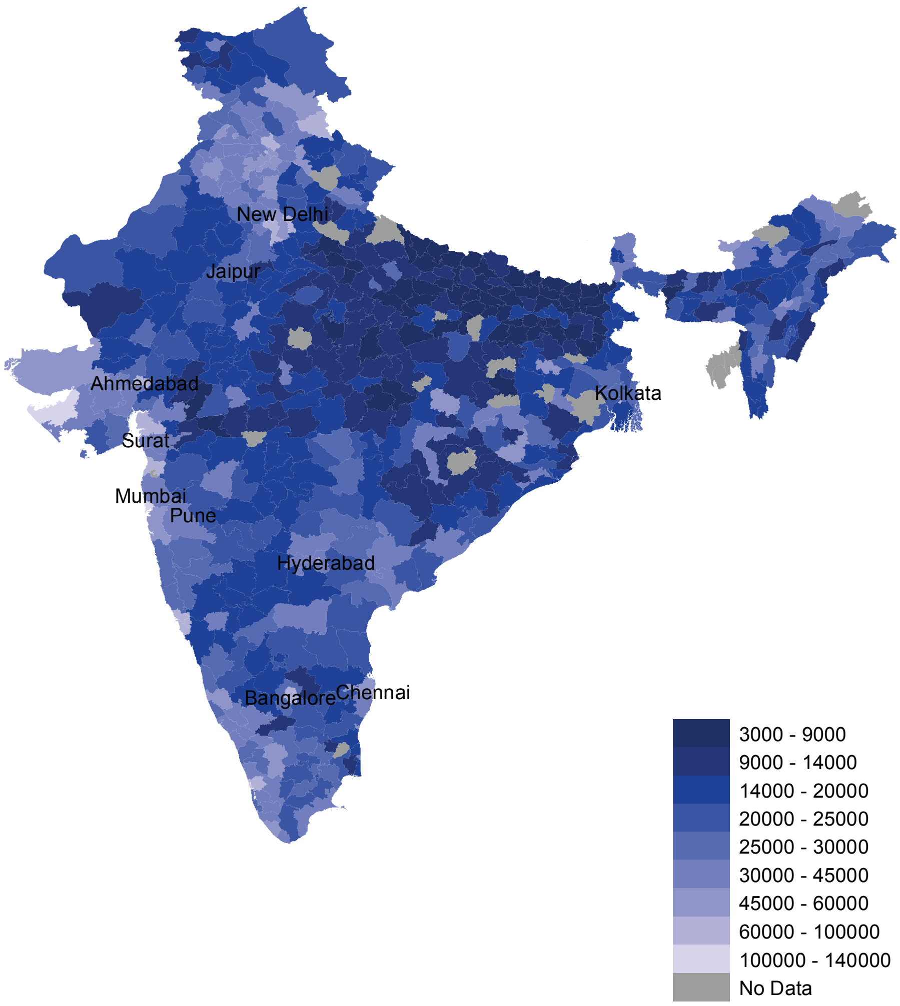

Figure 1: Per Capita Income by District

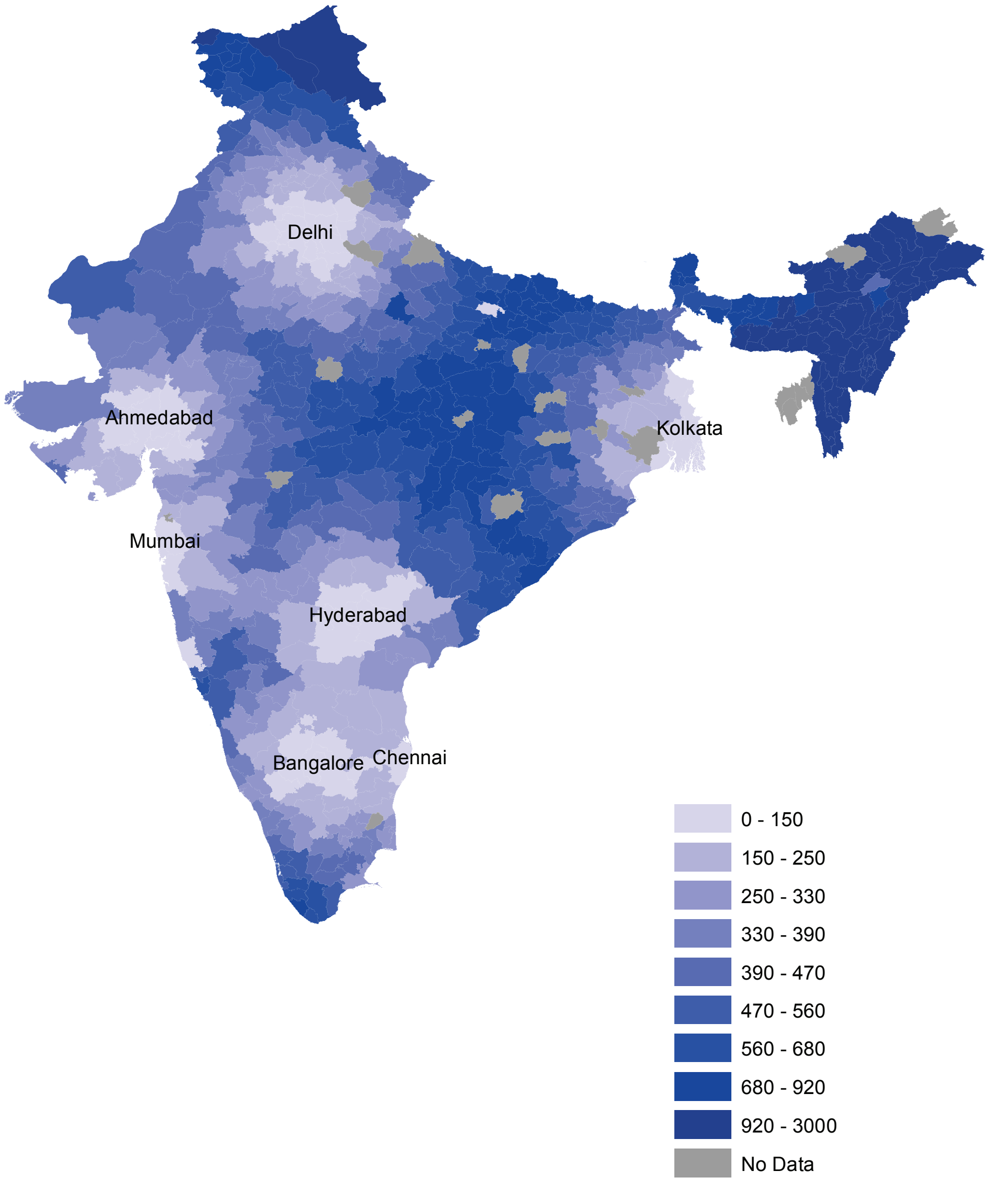

Figure 2: Minimum Distance to Seven Largest Metropolitan Centers

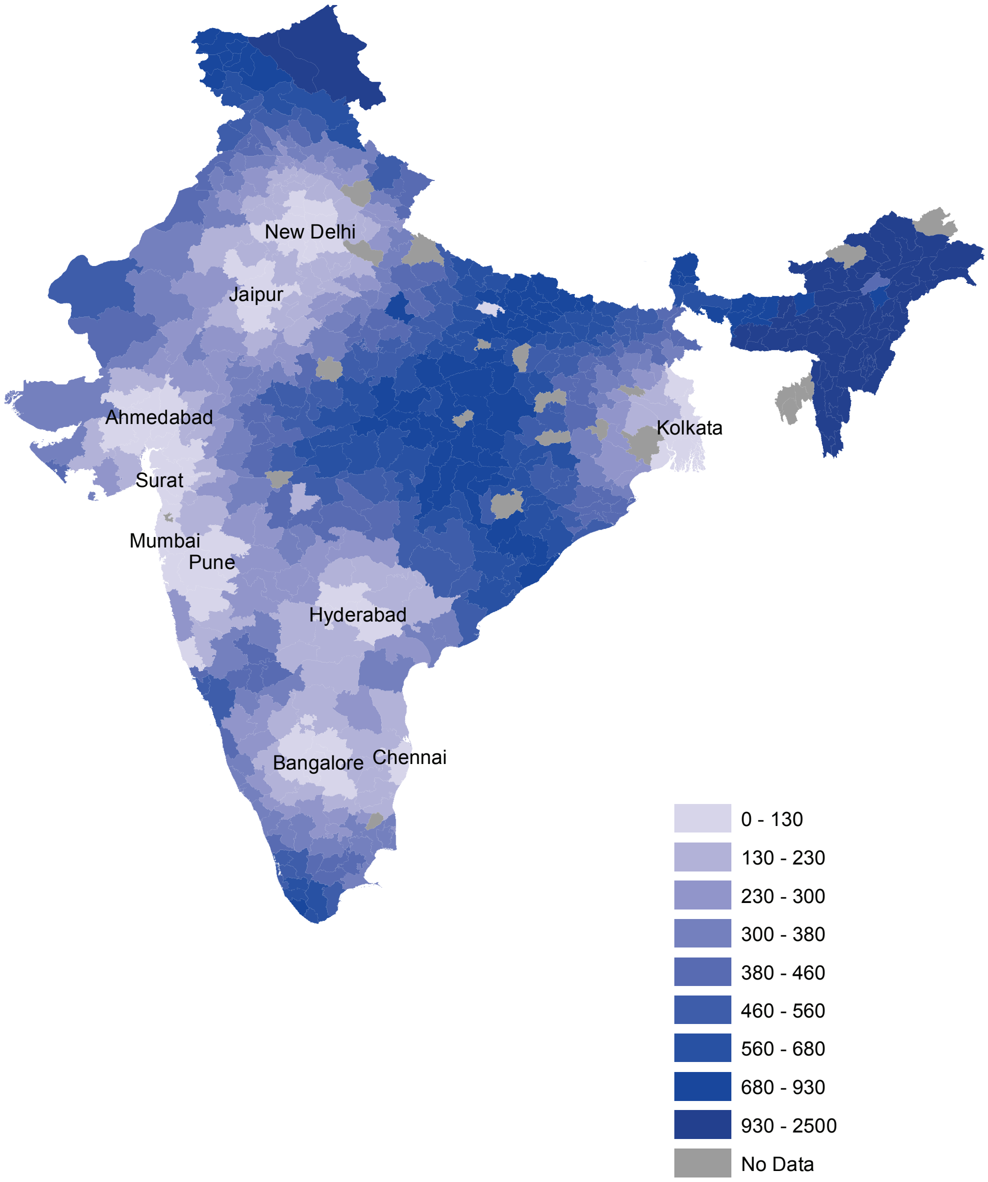

Figure 3: Minimum Distance to Ten Largest Metropolitan Centers

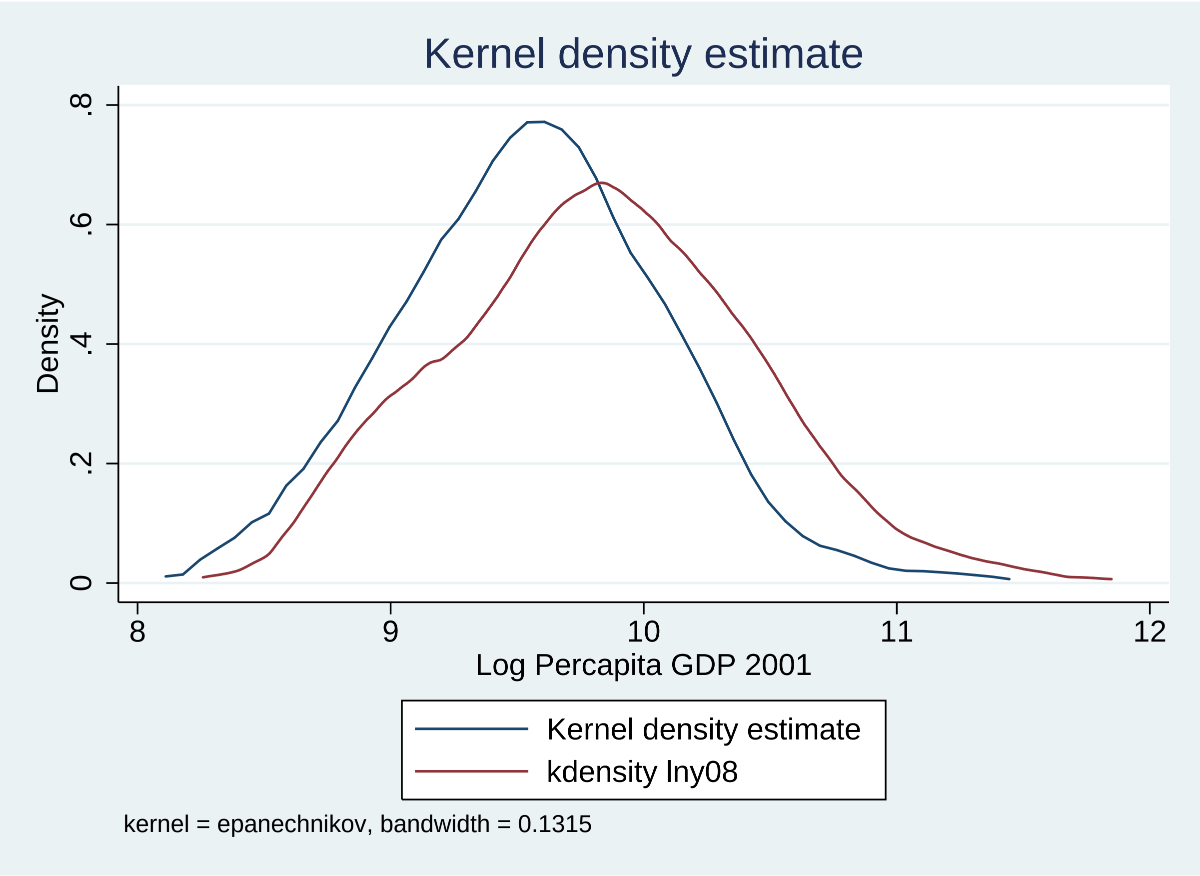

Figure 4: Probability Density Function for Indian District Incomes

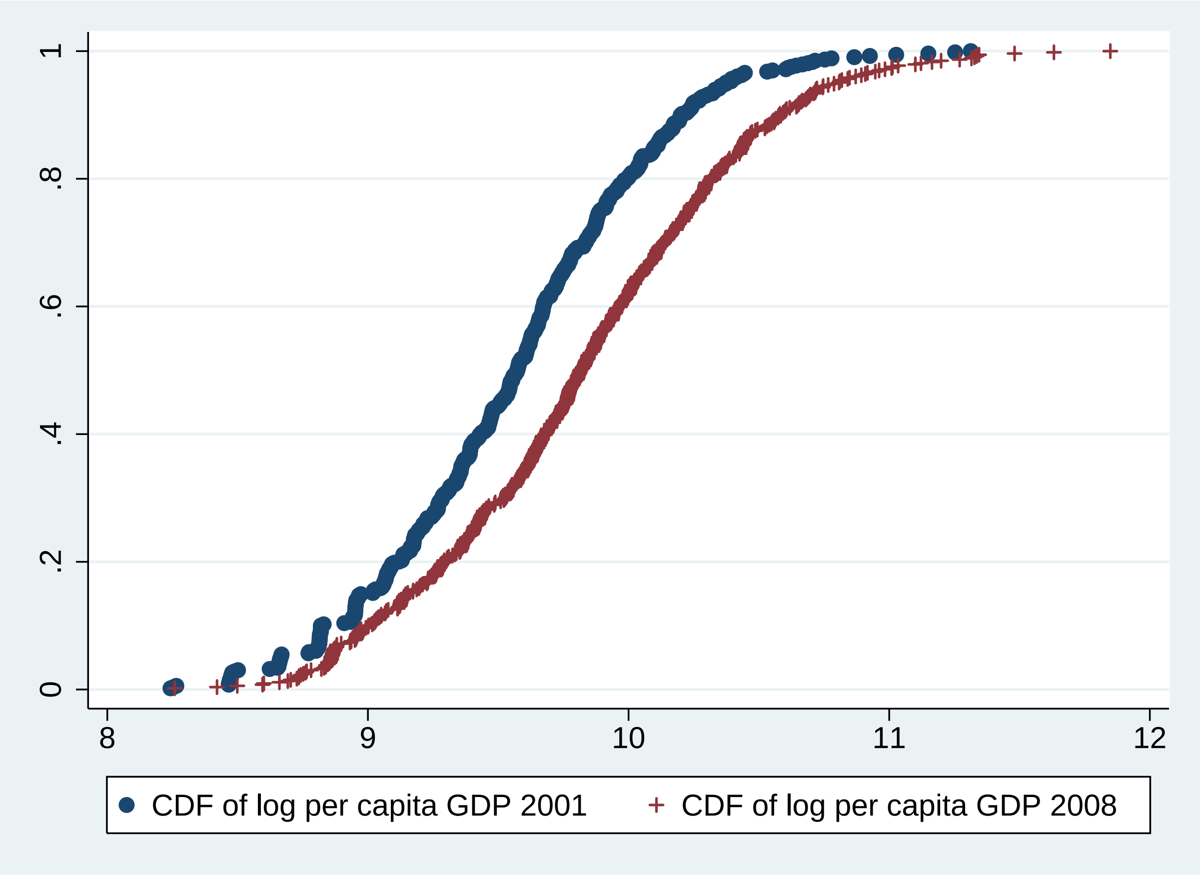

Figure 5: Cumulative Distribution Function for Indian District Incomes