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Remoteness, Urbanization, and India's Unbalanced Growth

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Summary. — The unbalanced nature of India's growth has caused considerable concern but little is known about its causes. We use a new data set of district-level income and socio-economic data to explore the determinants of transitional growth at the district level. We find that there is absolute divergence across districts but conditional convergence once we allow for district characteristics, particularly urbanization and the distance from a major urban agglomeration. State-level effects have also significantly contributed to India's unbalanced growth. The results suggest that while geography is important, policy differences may also account for much of India's uneven growth.

Key words — Convergence, unbalanced growth, India, gravity models, new economic geography, urbanization

1. INTRODUCTION

India's tentative economic miracle faces many hurdles, but one of the chief difficulties is the unbalanced nature of its growth (Pranab, 2010). The resulting income disparities have stimulated considerable debate over how the gains from growth in India are being shared, and may impede the political case for economic reform. [1]

Evidence of India's unbalanced growth is apparent from the numerous studies that find richer states are growing faster, so that state average incomes are diverging (Cashin & Sahay, 1996; Rao & Sen, 1997; Rao, Shand, & Kalirajan, 1999; Trivedi, 2003; Bandopadhyay, 2004; Ghate, 2008; Kar, Jha, & Kateja, 2011; Das, 2012; Ghate & Wright, 2012; Bandopadhyay, 2012). [2] This pattern of divergence might be regarded as unusual given that there are no political barriers to migration, approximately free trade, and a common set of federal institutions.

One possibility is that unbalanced growth reflects policy failures such as poor governance, different levels of public infrastructure across states, or the result of corruption. In particular India faces a severe shortage of public infrastructure which has been claimed to result in regional income disparities (Basu & Maertens, 2009; Cain, Hasan, & Mitra, 2012, Cha 4; Lall, Wang, & Deichmann, 2012; Lall *et al.*, 2010; Sachs, 2009). [3] Likewise India's states have had different market reform programs Cain *et al.*, 2012, Chap. 4. [4]

Nevertheless, as emphasized by the new economic geography (NEG) literature, unbalanced growth may also be a natural outcome in a growing economy, World Bank (2009). Differences in incomes can arise due to trade and migration costs, and economies of scale associated with agglomerations. Thus designing appropriate policy responses toward addressing India's unbalanced growth requires an understanding of the relative importance of these different possible causes. [5]

One way to gain a better sense of the sources of the imbalance is to look at the growth experience across India within states, that is, at the district level. The aim of this paper is, therefore, to use newly available data on India's 575 districts to gain a better understanding of the causes of India's unbalanced growth. In particular we wish to see whether the pattern of divergence across states is similar within states, and, if so, how geographical factors, infrastructure, and other possible factors affect these district-level differences.

We proceed, first, with a descriptive analysis of growth rates and income levels at the district level, between 2000–01 and 2007–08. This preliminary analysis shows a strong imbalance in growth rates across districts, suggesting that the growth in inequality across India runs much deeper than just differences across states.

Second we consider the causes of regional growth explicitly and, in particular, the role of geography, infrastructure, and literacy rates emphasized in the NEG literature. To achieve this we combine our data on per-capita incomes with district-level social and economic characteristics for each district including literacy, infrastructure, and spatial variables. Of particular interest is the role of the spatial distribution of markets faced by each district that captures the districts' remotest or access to markets in terms of trade, migration, and other linkages.

We find that urbanization, irrigation, electricity provision, and state dummy variables are all highly significant factors in explaining differences in transitional growth rates and income levels across Indian districts. Interestingly we find no evidence that literacy and road quality have any impact on these district growth rates or income levels.

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In terms of spatial factors we find very strong evidence that being close to a major city is a significant factor, but that being close to a large number of different markets is not important. We argue that this result is consistent with a setting where trade is largely in primary goods and there is relatively free mobility of labor and other factors across borders.

We also discuss the policy implications of these results. The results confirm that geography is important with significant benefits from urbanization and being close to cities. Nevertheless, even after controlling for these factors, the results suggest that there remains scope to promote more balanced growth through policy reform.

2. PRELIMINARY STATISTICAL ANALYSIS

(a) *District GDP data*

To investigate the pattern of growth across India we use two new data sets of district-level incomes and social and economic characteristics—respectively the *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.[6]

The availability of district-level income data provides the opportunity to observe regional disparities in India at a much finer level than previous studies based on Indian states. This is also advantageous insofar as there is likely to be a larger degree of heterogeneity in income levels, growth rates, and other characteristics such as urbanization or literacy, compared to state-level data.

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. First, Table 1 shows the wide disparity in income levels across states. There is a 9.8-fold difference in 2007–08 per-capita incomes 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.[7]

At the district level, however, that gap is much larger. The range in per-capita incomes in 2008 is from a minimum of Rs. (m) 3,858 in the *Sheohar* district (*Bihar*) to a maximum of Rs. (m) 139,868 in *Jamnagar* (*Gujarat*). This implies an income ratio of 36, which is equivalent, for example, to the ratio between the USA and Rwanda according to the Penn World Tables.

The district data are shown visually in Figure 1. It can be seen that there are generally lower incomes in central districts as well as in the eastern states. Likewise the wealthy western corridor running from the north of Delhi down the west coast of India through Western *Maharashtra*, *Karnataka*, *Goa* and *Kerala* is easily observed. Figure 1 is thus suggestive of a strong geographic pattern in the differences in per-capita district incomes across India.

The fact that the within-India differences are comparable to cross-country per-capita 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 convergence across regions.[8] In contrast, it points to the potential relevance of trade barriers, transport costs, and agglomeration effects as emphasized in the NEG literature.

(b) *Absolute convergence across districts*

A simple starting point from which to analyze differences in transitional growth rates across districts is to employ the standard concept of absolute β-convergence (Baumol, 1986; Durlauf *et al.*, 2005; Sala-i Martin, 1997). 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 per-capita income at time t in region i and $y_{i,0}$ is initial per-capita income.[9] The left hand side of (1) represents the transitional growth rate over the period $(0, t)$. 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 $\beta = 0.007$, which is statistically significant at the 1% level. 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)*.[10] Nevertheless for the vast majority of states 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 individual states.

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

Table 2 reports a simple variance decomposition using log per-capita incomes.[11] Here, *within-state* variance, v^W, refers to deviations of district log per-capita incomes, y_{ij}, from their state-level mean log per-capita income, $\bar{y}_j$, $y_{ij} - \bar{y}_j$, and *between-state* variance, v^B, refers to deviations of state-level mean log per-capita incomes $\bar{y}_i$ from the country-wide mean log per-capita income, $\bar{y}, \bar{y}_i - \bar{y}$. By definition, the total India-wide variance of per-capita incomes across all districts, v^T, is equal to the sum of the within-state variance and between state variance, $v^T = v^W + v^B$. This variance decomposition shows that there has been a similar increase in σ-divergence both within states and between states.

Further evidence on the pattern of Indian growth can be obtained by examining other aspects of the change in the distribution of district incomes. To that end Figure 2 plots the kernel density estimate of the probability density function (PDF) for district log incomes for 2001 and 2008.

It shows the shift in mean income; a fall in peakedness (kurtosis) with a slight increase in concentration on the left tail (skewness). Figure 3 similarly shows the cumulative distribution function (CDF). Together these visual images suggest while the income distribution has widened at the upper tail, incomes have increased at each point on the distribution. There is significant churning within the distribution, and only 16 districts (out of 575) remain in the same position on the distribution during 2001–08. Overall however Kendall's rank correlation *tau* statistic is 0.8, 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

Table 1. *State data and β–convergence coefficients*

State	Pop (millions)	Per-Capita GDP Rs 000's 2007–08	Share primary sector %	β	p-Value
All India	1,137.1	38	21	0.0107***	−0.0019
Andhra Pradesh	82.2	38	29	−0.0032	−0.0069
Arunachal Pradesh	1.2	34	26	−0.0134	−0.0345
Assam	29.3	24	35	−0.0332***	−0.0091
Bihar	95.6	11	25	−0.0068	−0.0138
Chhattisgarh	23.2	33	24	0.0188**	−0.008
Goa	1.5	108	14	na	na
Gujarat	55.9	52	19	0.0012	−0.0057
Haryana	23.8	62	21	0.0333*	−0.0114
Himachal Pradesh	6.5	49	22	0.0081	−0.0308
Jammu & Kashmir	11.0	29	27	0.0047	−0.0098
Jharkhand	30.2	23	22	0.0304	−0.0179
Karnataka	56.7	38	19	0.0102	−0.0091
Kerala	33.8	48	17	−0.0391*	−0.0206
Madhya Pradesh	69.0	20	33	−0.0005	−0.0096
Maharashtra	107.1	53	13	0.0119*	−0.0065
Manipur	2.4	24	26	−0.0009	−0.0184
Meghalaya	2.5	30	27	0.0102	−0.0164
Mizoram	1.0	34	15	0.0176	−0.013
Nagaland	2.2	33	34	−0.0157	−0.0305
Orissa	39.7	26	31	0.0492***	−0.0085
Punjab	26.4	52	31	−0.0054	−0.0298
Rajasthan	64.1	26	28	−0.0338***	−0.0123
Sikkim	0.6	40	18	na	na
Tamil Nadu	66.0	44	14	0.0089	−0.0092
Tripura	3.5	33	24	na	na
Uttar Pradesh	189.3	18	31	0.0133***	−0.0046
Uttaranchal	9.4	36	20	0.008	−0.0147
West Bengal	86.4	35	23	0.0033	−0.065

Note 1: *, **, *** denote 10%, 5% and 1% levels of significance respectively.
Note 2: Robust (White) standard errors are used.
Note 3: Union Territories are Excluded.
Note 4: n.a. indicates not enough observations available to estimate β.

initial income and growth. Examining the country as a whole, there is evidence of β and σ-divergence, reflecting faster growth in higher income districts with most districts experiencing growth across the entire distribution.[12]

3. TRANSITIONAL GROWTH ACROSS DISTRICTS

The preceding model of absolute β-convergence explicitly assumes that all regions within a country have the same steady-state income level (Barro & Sala-i Martin, 1991, 2005; Durlauf *et al.*, 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. Moreover, factor mobility will result in absolute convergence, even in the absence of identical technologies.

Nevertheless, even within a country, the assumptions that regions will converge to the same long-run per-capita income level seems fragile. In particular the NEG literature, following Krugman (1991) and Krugman and Venables (1995), has emphasized the importance of barriers to trade and factor migration and agglomeration effects due to external economies. Thus there may be significant obstacles to convergence and hence long-run differences in per-capita incomes.

There are two natural starting points for thinking about such barriers. The first is spatial or geographic barriers such as natural land barriers, trade costs, transport and migration costs, and agglomeration effects (Krugman, 1991). Head and Mayer (2004) however also point to the importance of human capital, knowledge externalities, and endowments.

The second broad set of explanation lies under the general heading of institutions and policy. State governments have considerable influence on market regulation (Acharya, Baghai, & Subramanian, 2010; Besley & Burgess, 2004). Also there are observable differences in the provision of public provision of infrastructure. Both infrastructure provision and policy differences have featured in existing discussions of India's unbalanced growth (Cain *et al.*, 2012, Chap. 4; Crost & Kambhampati, 2010; Desmet *et al.*, 2013; Ghate & Wright, 2012; Lall *et al.*, 2010).

(a) *Proximity to different markets*

The standard approach to allowing for spatial considerations is based on trade in varieties of manufactured goods, with Dixit–Stiglitz preferences, and iceberg transport costs (Fujita, Krugman, & Venables, 2001). Under these assumptions it is straightforward to show that the volume of trade will depend on a weighted average of all the trade costs to all markets. This is typically approximated in empirical work by *Market Access* defined as the GDP weighted average distance to all external markets: $MA = \sum_{j \in N} w_j \; d_{i,j}$ where: $d_{i,j}$ is the distance between district i and j; Y_j is income in region j and

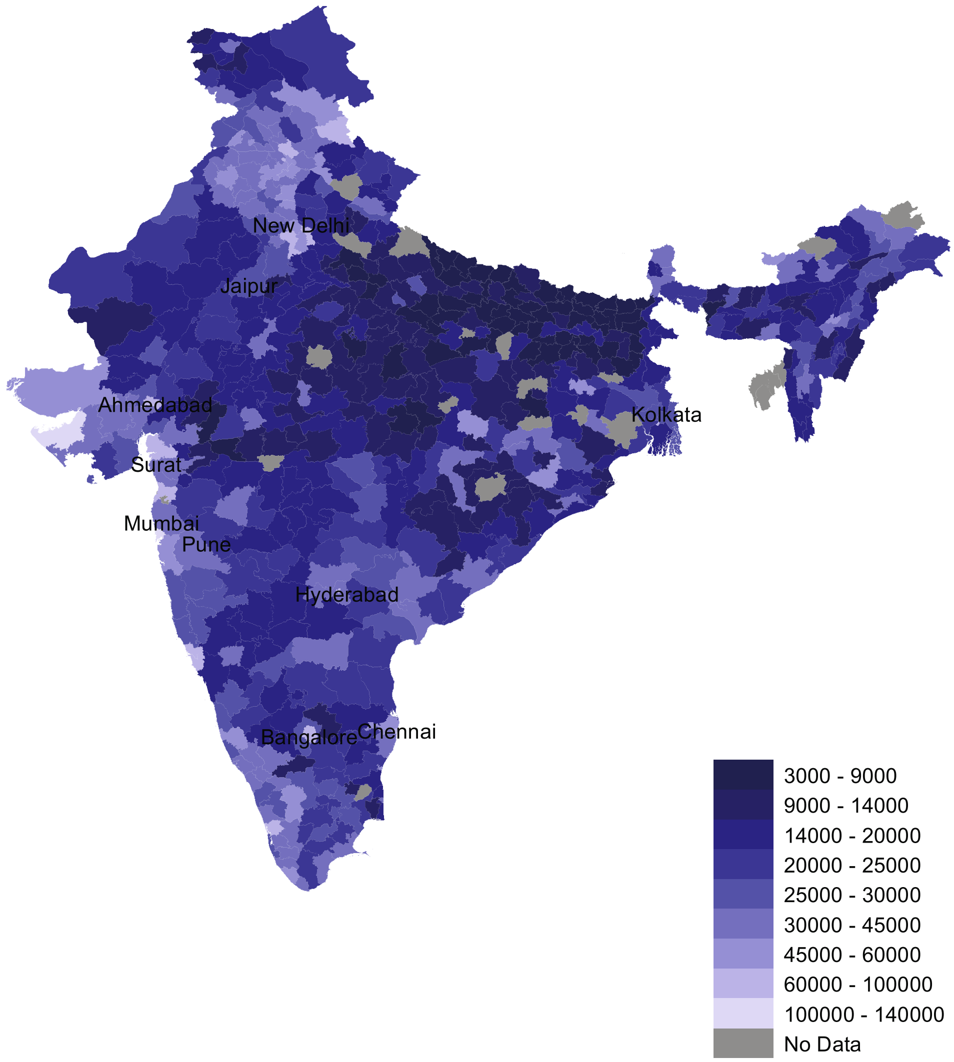

Figure 1. *Per-capita income by district.*

Table 2. *Decomposition of σ–convergence*

	Variance	Between state variance	Within state variance	Skewness	Kurtosis	Gini
2001	0.27	0.15	0.12	0.15	3.09	0.0307
2008	0.35	0.20	0.15	0.16	2.88	0.0322
Change	0.08	0.05	0.03			

Y is aggregate GDP (all-India), $Y = \sum_{j\in N} Y_j$; $w_j = Y_j/Y$; and N is the total number of districts.[13]

There are two limitations of the Dixit–Stiglitz setting for our purposes. The first is that it abstracts from factor mobility, particularly migration. Within India, migration from rural districts to cities is likely to be one of the main engines of convergence. As explained by Hering and Poncet (2010), in a Dixit–Stiglitz setting migration reduces the impact of trade on incomes so that market access becomes a less significant determinant of incomes.

A second limitation is that the bulk of the inter-state trade in India is in agricultural goods (Behera, 2006). Primary goods trade is typically characterized by homogeneity and competitive markets in the NEG and new trade theory, so that the importance of being close to a variety of different markets is typically assumed to apply only to non-primary goods trade (Head & Mayer, 2004; Redding & Venables, 2004).

Thus with trade in relatively homogeneous primary goods, various import and export markets become perfect substitutes. Likewise, since there are no legal barriers to migration, for alternative city designations, employment opportunities are perfect substitutes. In this setting trade, transport and migration costs will not necessarily depend on the accessibility of a number of different markets. Rather they will depend only on the accessability of markets with lowest transport trade and migration costs.

(b) *Urbanization and urban agglomerations (UAs)*

A key insight from the NEG literature is that the combination of increasing returns and factor mobility results

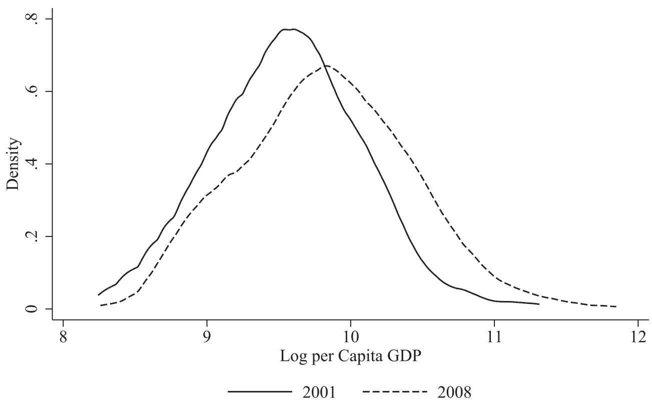

Figure 2. *Probability density function for indian district incomes.*

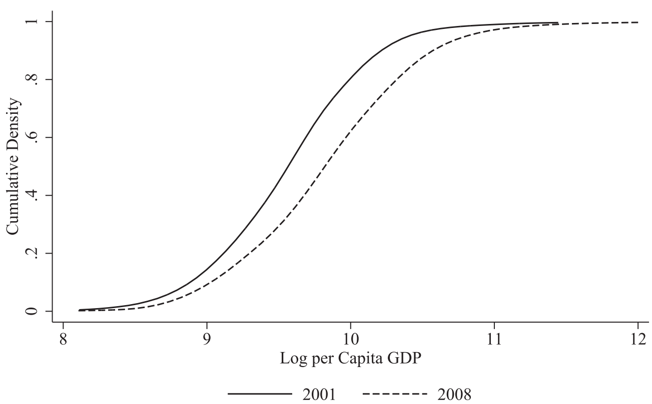

Figure 3. *Cumulative distribution function for indian district incomes.*

in a spatial concentration of economic activity, or agglomerations (Fujita *et al.*, 2001; Helpman & Krugman, 1985; Krugman, 1991; Krugman & Venables, 1995). It is argued that agglomerations reflect the existence of increasing returns combined with migration and factor movements. Consequently much of the growth process, such as technology adoption and capital accumulation, occurs in cities (Ciccone & Hall, 1996; Glaeser, Kallal, Scheinkman, & Shleifer, 1992).

Similarly there is a growing literature on the urbanization–growth nexus in India (Calı & Menon, 2012; Desmet *et al.*, 2013). For instance, (Desmet *et al.*, 2013) show that high density service clusters in India exhibit increasing concentration suggesting that they continue to benefit from agglomeration economies. They also provide evidence of the lack of agglomeration economies in medium-size locations in India. Finally, they suggest that a lack of infrastructure and poor policy choices have held back the growth of medium density locations.[14]

The likely role of urbanization, and UAs specifically, in explaining the growth of districts in India is therefore twofold. First, more urbanized districts will be able to benefit themselves from increasing returns and hence may be wealthier or experience faster growth. Second, however, UAs will be able to offer higher prices for exports and higher wages for migrants due to increasing returns. Hence UAs may also benefit neighboring districts through these forward linkages.

(c) *Proximity to urban agglomerations*

The importance of UAs along with: (i) the presence of internal migration, and; (ii) production and trade focused mainly of homogeneous primary goods, suggest that we should expect each district to generate most of its economic linkages with a nearby city and few linkages with other more distant districts or cities. A key hypothesis we wish to explore, therefore, is whether transport and migration costs between a district and the closest UA can influence a district's growth rate.

To consider this issue we define the variable *Minimum Distance*, D_i as the distance between district i and the closest UA. This definition is straightforward if we can succinctly define the UAs in India. In practice, however, a UA is not a well-defined empirical concept and requires some subjectivity. As shown in Table 3, India has three mega-cities with populations above 10 million, *Delhi*, *Mumbai*, and *Kolkata*. Of these, *Delhi* and *Mumbai* have extended urban agglomerations—defined as areas of unbroken urbanization—that exceed 20 million. Nevertheless even the smaller cities, *Bangalore*, *Hyderabad*, and *Ahmedabad*, have populations of over six million and overall, there are ten Indian cities with urban agglomerations over three million Table 3.

We begin therefore by initially defining the UAs as the seven largest Indian cities. This includes all cities that have populations over seven million. Hence we define $D_i = \min d_{i,j}, j \in M$, where $M = \{$*Delhi, Mumbai, Kolkata, Chennai, Bangalore, Hyderabad, Ahmedabad*$\}$. Then, as a robustness check, we also consider alternative definitions ranging from the six to 10 largest cities listed in Table 3.[15]

As a visual reference Figure 4 shows a map with the values of D_i for each district in India, based on the seven largest UAs. 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 be seen that there are clusters of less remote districts along the western corridor from *Delhi* to *Bangalore* and *Chennai*.[16]

4. THE EMPIRICAL MODEL

Our aim is to describe the association between the spatial factors discussed above, other socio-economic factors, and growth rates across districts. The proceeding discussion suggests the following descriptive model,

$$\ln y_i(t) - \ln y_i(0) = \alpha_0 + \alpha_1 \ln y_i(0) + \alpha_2 \ln D_i + \eta \mathbf{X}_i + \epsilon_i \qquad (2)$$

where D_i is *Minimum Distance*, $\mathbf{X}_i$ is a vector of other characteristics of region i including *Market Access* (*MA*), state dummy variables, and ϵ_i is a district-specific random shock reflecting, for example, institutions, climate, and endowments.

The inclusion of initial per-capita GDP, $\ln y_i(0)$, as an explanatory variable follows the growth literature (Durlauf & Quah, 1999). As shown in Appendix B, this specification can be derived from a partial adjustment model where it is assumed that the long-run steady-state income level of a region is influenced by the value of D_i, as well as all the conditioning variables in $\mathbf{X}_i$.[17] Thus the coefficient α_1 can be interpreted as the conditional convergence coefficient. It captures the notion that a larger income gap between the ith district and the UA in the initial time period will imply a faster growth

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).

rate for a given set of long-run conditioning variables, *Minimum Distance*, *Market Access* and other elements of $\mathbf{X}_i$.

Finally note that a larger *Minimum Distance* is expected to negatively affect district transitional growth rates. It can also be shown that α_2/α_1 can be interpreted as the elasticity of long-run income with respect to *Minimum Distance* (see Appendix B).

(a) *Data*

To construct *Market Access* and *Minimum Distance* we require data on the distance between various districts, $d_{i,j}$. For *Market Access* we obtain the $d_{i,j}$ from the latitude and longitude coordinates of each of district's headquarters. We then use these coordinates to construct a 575 $\times$575 matrix of district-to-district distances.[18] Likewise for *Minimum Distance* we use the minimum distance from one district headquarters to another.[19]

As noted above *Per-capita GDP* is the logarithm of district per-capita GDP in 2001. The other elements of the conditioning vector $\mathbf{X}_i$ are district and non-district socio-economic indicators. Specifically, the variables used are defined as follows: *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 in a given district, i.e. it is a measure of initial urban population; *Urbanization Squared* is the squared value of *Urbanization*; *Market Access*, as defined above, is the weighted average of trade costs to all markets; *Irrigated Land* is the logarithm of net irrigated land area (per million

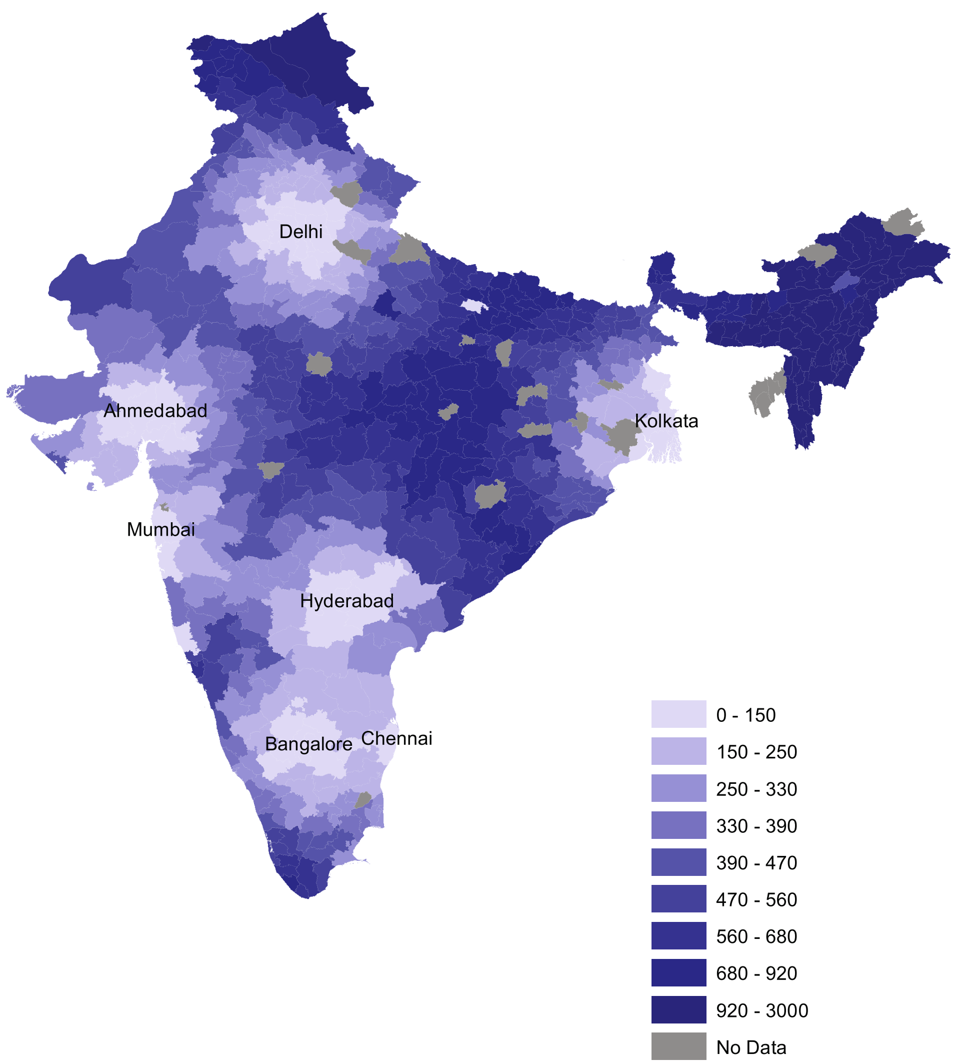

Figure 4. *Minimum distance to seven largest metropolitan centers.*

people) divided by the district population; *Pucca Road* is the logarithm of the percentage of households connected by pucca (hard) roads; *Metro Electricity* is the logarithm of the percentage of urban households with an electricity connection in the closest UA; *Metro Urbanization* is the logarithm of the percentage of urban households in the closest UA district; and *Metro Literacy* is the logarithm of the total literacy rate per hundred persons in the closest metropolitan districts. All variables refer to the initial (2000–01) level.

Finally we also include state dummy variables, given by *State*. Summary statistics for the key variables of interest are given in Table 4.

5. RESULTS

In what follows we estimate Eqn. (2) using our cross-section of Indian districts.[20] The results for our baseline model, Eqn. (2), are given in Table 5a. The regression results in columns (1)–(3), (6), and (7) include the variable *Minimum Distance*. In column (4) however we replace *Minimum Distance* by *Market Access*, and in column (5) we exclude both of these spatial variables. All regressions include the variable *Per-capita GDP*; otherwise the regressions differ by the number of additional explanatory variables included.

It can be seen that the sign of the convergence coefficient, β, is significant and negative across all models except in column (1). Specifically allowing for various observable characteristics across districts results in a finding of conditional convergence. For example in column (2) we find that once we control for differences in *Minimum Distance*, *Urbanization* and different states, districts that were initially poorer grew faster. This suggests that there is conditional convergence across districts where each district is converging to a particular level of long run wealth determined by *Minimum Distance*, *Urbanization*, and *State*. The significance of the convergence coefficient, β, thus provides strong support for our basic partial adjustment model.

As expected we find that an increase in *Minimum Distance* reduces the transitional growth rate. This result is robust across all the regressions and the coefficient is very stable with an elasticity of transitional growth with respect to D_i of -0.004. We discuss the implications of the size of this coefficient below.

Second, for a given initial income level, urban areas should also have faster transitional growth. This is verified in column (2) with *Urbanization* being positive and significant.

The final explanatory variable in column (2) is the vector of state dummy variables, *State*. It can be seen that the *F*-test of joint significance of the state dummy variables is highly significant across all of the various models. Since states have some autonomy with respect to laws and taxation, the *State* dummy variables reflect differences in institutions and governance. However state variables may also capture differences in climate, endowments, and geography.

In column (3) we introduce a range of other possible explanatory variables. It can be seen that *Electricity* and *Irrigated land* are significant at the 1% level. Since electricity supply is government controlled this result suggests that public infrastructure is also important in understanding differences across districts.

We find that *Irrigated land* is also a significant explanatory variable and has a negative sign. This suggests that more irrigated land per capita is associated with slower transitional growth. There are a number of possible explanations for this. One possibility is that irrigated land is associated with rural districts that have high levels of home production so that market income understates actual income.[21] The other explanatory variables, *Commercial banks* and *Pucca Roads* are found to be insignificant. It can be seen that with the addition of these variables *Minimum Distance* remains significant at the 5% level.

In column (4) we drop *Minimum Distance* and include *Market Access*. As described above *Market Access* is the standard spatial variable used to describe the impact of trade costs on international trade flows. It can be seen however that *Market Access* is not significant. As discussed above, because there is migration across district borders and most internal trade in India is in primary goods, this result is not unexpected.

Next in column (5) we consider the effect of excluding both spatial variables. There is little change in the coefficients of the remaining parameters suggesting that there is little bias associated with this omission.

In column (6) we consider whether there is evidence of nonlinear effects of urbanization (Bloom, Canning, & Fink, 2008; Calì & Menon, 2012; Desmet *et al.*, 2013; Glaeser, 2011; Krugman & Venables, 1995). Thus in column (6) we consider an interaction term between *Urbanization* (in 2001) and initial income as well as *Urbanization squared* (in 2001). It can be seen however that these additional terms are insignificant. The main effect of including these variables is to increase the point estimate of the coefficient on per–capita GDP, which is simply due to the inclusion of per-capita GDP in the interaction term with *Urbanization*.

Table 4. *Descriptive statistics*

	Mean	Variance	Minimum	Maximum	Skewness
Initial per-capita GDP	9.583	0.274	8.243	11.313	0.148
Minimum distance	6.004	0.671	2.067	8.018	−1.091
Market access	7.039	0.036	6.776	7.796	.7557
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	1.367
Metro urbanization	4.579	0.001	4.479	4.605	−1.638
Metro literacy	4.412	0.001	4.367	4.459	0.064

Note: See the text for a description of all variables.

Table 5a. *Transitional growth results*

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Initial per-capita GDP	0.0018	−0.0082**	−0.0129***	−0.0112***	−0.0112***	−0.0249**	−0.0238**
	(0.0030)	(0.0037)	(0.0042)	(0.0042)	(0.0042)	(0.0120)	(0.0119)
Minimum distance to UA	−0.0055***	−0.0047***	−0.0040**			−0.0039**	−0.0039**
	(0.0015)	(0.0015)	(0.0016)			(0.0016)	(0.0016)
Market access				0.0176			0.0160
				(0.0157)			(0.0156)
Urbanization		0.0103***	0.0067***	0.0069***	0.0066***	−0.0363	−0.0333
		(0.0021)	(0.0022)	(0.0022)	(0.0022)	(0.0313)	(0.0310)
Literacy			−0.0081	−0.0073	−0.0082	−0.0079	−0.0072
			(0.0087)	(0.0085)	(0.0086)	(0.0086)	(0.0086)
Electricity			0.0123***	0.0129***	0.0135***	0.0136***	0.0131***
			(0.0045)	(0.0045)	(0.0044)	(0.0047)	(0.0047)
Commercial banks			0.0053	0.0025	0.0032	0.0042	0.0035
			(0.0049)	(0.0050)	(0.0048)	(0.0049)	(0.0050)
Irrigated land			−0.0036***	−0.0037***	−0.0039***	−0.0030**	−0.0028**
			(0.0013)	(0.0012)	(0.0012)	(0.0013)	(0.0013)
Pucca road			0.0020	0.0019	0.0020	0.0017	0.0016
			(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)
Urban. × initial per-capita GDP						0.0040	0.0036
						(0.0038)	(0.0038)
Urbanization squared						0.0009	0.0011
						(0.0020)	(0.0020)
Metro electricity							
Metro literacy							
Metro urbanization							
Constant	0.0975***	0.1521***	0.1956**	−0.0001	0.1322*	0.3029**	0.1744
	(0.0358)	(0.0385)	(0.0861)	(0.1489)	(0.0820)	(0.1289)	(0.1785)
Gravity parameter	3.0196	−0.5696***	−0.3087***			−0.1585***	−0.1657***
	(20.6305)	(0.0188)	(0.0136)			(0.0206)	(0.0214)
F test *state*	24.23***	32.62***	10.30***	11.26***	11.28***	10.56***	10.44***
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
F test *per-capita GDP*						12.29***	12.35***
						0.0005	0.0004
BP test	0.47	2.40	6.00**	5.93**	6.79***	6.56**	5.85**
	0.4921	0.1210	0.0143	0.0149	0.0092	0.0104	0.0155
Observations	566	556	544	548	548	544	544
R-squared	0.3354	0.3841	0.4031	0.3994	0.3980	0.4066	0.4078

Note 1: *, **, *** denote 10%, 5% and 1% levels of significance respectively.
Note 2: Robust (White) standard errors are used.
Note 3: *F* test *state* are joint tests for State dummy variables.
Note 4: *F* test *per-capita GDP* are joint tests for significance of *per-capita GDP* + *per-capita GDP* * *Urbanization*.

Finally in column (7) we considers all of the variables including *Market Access*. It shows that the results are quite stable with little change in the sign or significance of any variables.

(a) *Characteristics of urban agglomerations*

The results suggest that we can attribute some of the regional disparities in growth rates to differences in district characteristics, including the *Minimum Distance* to a UA. But in our discussion of *Minimum Distance* we implicitly assumed that all UAs are equivalent. Nevertheless UAs may differ in important ways and this may affect the potential growth of neighboring districts.

In Table 5b we therefore consider additional explanatory variables that relate to each district's closest UA. One way to interpret this is that the different UAs may have different long-run incomes (see Appendix B for an analytical discussion of this point).

It can be seen that the additional explanatory variables are all insignificant with the exception of the literacy rate in the UA (*Metro Literacy)*. This is positive and significant across all models suggesting that districts are advantaged by being closer to cities where literacy is higher. This result is consistent with arguments in the NEG literature that emphasize the role of external economies that give rise to UAs and the possibility of complementarities between these external economies and human capital, (Head & Mayer, 2004).

Including the additional UA district characteristics however has little effect on the estimated coefficients of the other variables which again tend to be very stable across all specifications in Tables 5a and 5b. Hence the conclusions on the low rate of convergence are robust to the inclusion of the UA district characteristics. Likewise *Minimum Distance* continues to be statistically significant in all specifications of the models.

(b) *Convergence*

We have found that while there is absolute divergence across districts, there is also conditional convergence once we control for a few characteristics including *Minimum Distance*. Nevertheless though we have found strong evidence of conditional convergence, the estimated value of $\beta = -0.85\%$ to -1.3% is much slower than the values found in the growth literature across a wide array of counties.[22] The estimate of -1.3% (Column 3, Table 5b), for example, implies that the gap between each district's current income level, and its long-run or steady-state income level, is halved only every 62 years. At this rate, at the end of a decade, a per-capita income gap between two districts would still be 90% of the gap that existed at the start of the decade. Thus the forces of convergence, or "trickle down", appear to be very weak across Indian districts.

For models where we include the interaction term, *Initial per-capita Income* × *Urbanization*, the joint significance test for per-capita income evaluated at the mean level of *Urbanization* is highly significant. This suggests that the strength of convergence is smaller in more urbanized districts.[23] The low convergence rate in more urbanized districts is consistent with increasing returns (or a lower rate of diminishing returns) in more urbanized areas. It suggests that the pattern of absolute divergence and weak conditional convergence is mainly driven by growth in the more urbanized districts.

(c) *The impact of proximity to urban agglomerations*

To what extent does *Minimum Distance* matter for understanding differences in growth and incomes across India? The coefficient α_2 gives the impact on the transitional growth rate and ranges from approximately -0.003 to -0.005. The negative effect of distance on transitional growth is supported by other papers in the literature, such as Calı and Menon (2012), who highlight the positive spill-overs from urban

Table 5b. *Transitional growth results including metro variables*

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Initial per-capita GDP	0.0014	−0.0085**	−0.0130***	−0.0116***	−0.0116***	−0.0250**	−0.0248**
	(0.0030)	(0.0037)	(0.0042)	(0.0042)	(0.0042)	(0.0122)	(0.0121)
Minimum distance to UA	−0.0049***	−0.0039***	−0.0033**			−0.0032**	−0.0033**
	(0.0016)	(0.0015)	(0.0016)			(0.0016)	(0.0016)
Market access				0.0016			0.0026
				(0.0168)			(0.0167)
Urbanization		0.0103***	0.0067***	0.0068***	0.0067***	−0.0356	−0.0351
		(0.0020)	(0.0022)	(0.0022)	(0.0021)	(0.0317)	(0.0315)
Literacy			−0.0057	−0.0057	−0.0058	−0.0056	−0.0055
			(0.0093)	(0.0092)	(0.0092)	(0.0093)	(0.0093)
Electricity			0.0121***	0.0130***	0.0130***	0.0135***	0.0134***
			(0.0045)	(0.0046)	(0.0045)	(0.0047)	(0.0048)
Commercial banks			0.0038	0.0019	0.0019	0.0028	0.0027
			(0.0049)	(0.0049)	(0.0048)	(0.0049)	(0.0051)
Irrigated land			−0.0036***	−0.0039***	−0.0039***	−0.0030**	−0.0030**
			(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Pucca Road			0.0019	0.0019	0.0019	0.0016	0.0016
			(0.0025)	(0.0024)	(0.0024)	(0.0024)	(0.0024)
Urban. × initial per-capita GDP						0.0040	0.0039
						(0.0039)	(0.0039)
Urbanization squared						0.0008	0.0008
						(0.0020)	(0.0020)
Metro electricity	0.2349	0.2586	0.2537	0.2505	0.2510	0.2397	0.2388
	(0.1602)	(0.1600)	(0.1731)	(0.1750)	(0.1742)	(0.1729)	(0.1738)
Metro literacy	0.0966*	0.1084**	0.0998*	0.1226**	0.1242**	0.0990*	0.0964*
	(0.0500)	(0.500)	(0.0517)	(0.0529)	(0.0505)	(0.0517)	(0.0542)
Metro urbanization	−0.0837*	−0.0704	−0.0730	−0.0740	−0.0750	−0.0722	−0.0706
	(0.0485)	(0.0473)	(0.0485)	(0.0497)	(0.0492)	(0.0483)	(0.0489)
Constant	−1.0146	−1.1826	−1.0914	−1.2384	−1.2384	−0.9202	−0.9326
	(0.7672)	(0.7711)	(0.8416)	(0.8402)	(0.7571)	(0.8576)	(0.8540)
Gravity parameter	3.4018	−0.4596***	−0.2509***			−0.1294***	−0.1311***
	(0.2078)	(0.0180)	(0.0137)			(0.0208)	(0.0209)
F test *state*	58.98***	27.04***	10.29***	11.54***	11.66***	10.70***	10.26***
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
F test *per-capita GDP*						12.48***	12.46***
						0.0005	0.0004
BP test	0.62	2.58	6.07**	6.26**	6.32**	6.55**	6.46**
	0.4297	0.1081	0.0137	0.0123	0.0119	0.0105	0.0110
Observations	566	556	544	548	548	544	544
R-squared	0.3436	0.3928	0.4109	0.4084	0.4084	0.4142	0.4142

Note 1: *, **, *** denote 10%, 5% and 1% levels of significance respectively.
Note 2: Robust (white) standard errors are used.
Note 3: F test *state* are joint tests for State dummy variables.
Note 4: F test *per-capita GDP* are joint tests for significance of *per-capita GDP* + *per-capita GDP* * *Urbanization*.

growth to nearby rural areas. However we also wish to explore the quantitative implications of this estimate.

Specifically the coefficient represents the partial effect of a one-percentage point change in the minimum distance to one of the seven UAs, on the growth rate. That is, $\alpha_2 \equiv \partial \ln(y(t)/y(0))/\partial \ln D$. The estimate of α_2 implies that a district that is twice as remote will have a transitional growth rate that is 0.20–0.35 percentage points lower than the closer district.[24]

The most remote district in our data is *Tamenglong*, in Manipur, which is near the Burmese border and 2531 km from *Kolkata*. At the other end of the spectrum the district *South 24 Parganas* is only 7.9 km from *Kolkata*. For this maximum distance the more remote district would have a transitional growth rate that is 1.7–2.9 percentage points lower. Thus *Minimum Distance* variable has an economically important effect on observed transitional growth rates for the very remote regions.

It is also useful to think of the impact of *Minimum Distance* in terms of income levels. That is, given these differences in transitional growth rates, what would be the implication in the long term for inequality across regions? As discussed in Appendix B, the empirical model (2) has the form of a standard partial adjustment model. This allows us to interpret the ratio of coefficients as the elasticity of *Minimum Distance* with respect to long-run equilibrium differences in per-capita incomes, $\gamma = -\alpha_2/\alpha_1$.

The value of γ is reported for each model in Tables 5a and 5b, along with a joint significance test. It can be seen that the estimates of γ are significant at the 1% level across all models with a value ranging from approximately -0.25 to -0.57.

Suppose we consider the most conservative estimate of the gravity parameter of $\gamma = -0.25$ This means, for example, that if a more isolated district, i, is twice the distance from the UA than a closer district, $j, D_i/D_j = 2$, then the more remote district will have a steady-state income level that is approximately 84% of the closer district.[25]

However at the maximum difference in remoteness, of 320:1, we would expect the more remote district to have a per-capita income level of only 24% of the closer district. Thus the distance coefficient suggests quite a large impact on income levels for very remote districts but relatively modest effects for districts that are within a range of twice or half the average distance.

(d) *Policy implications*

We have found that per-capita incomes across India's districts are diverging rather than converging, which is the opposite of most within-country experiences. Once we control for several conditioning factors, however, we find a standard pattern of regional conditional convergence of 1–2% per annum. Differences in urbanization play an important role in explaining divergence in growth rates across districts, along with electricity provision, state characteristics, literacy levels in the closest city, and distance to the closest urban agglomeration.

First we note that despite the fact that we have data for 575 districts, the state dummy variables are still jointly significant. This supports the view that differences in policies across India's states are important for understanding growth. Typically discussions on these issues focus on state differences in infrastructure, education, transport polices, and labor laws.[26] Nevertheless interstate migration flows in India are very small relative to inter-district migration flows, World Bank (2009). Thus the significance of the state dummy variables may also indicate that border policies and other barriers, such as language and cultural barriers, may be restricting migration.

With respect to the impact of government policy on growth our results also show that differences in growth rates within states are also associated with differences in electricity supply and literacy in the closest city. Thus the results suggest that more balanced growth, in part, requires improving the delivery and distribution of public infrastructure investments within states.

The results also suggest that divergence across districts results from urbanization. Urban areas grow faster and also converge to their long-run growth rates at a slower rate. This high and more persistent growth pattern is consistent with NEG theory that shows how increasing returns and factor mobility result in agglomerations with high incomes and high growth.

As emphasized by Ottaviano (2003) and Breinlich, Ottaviano, and Temple (2013), the link between policy and NEG models is not well developed. Nevertheless increasing returns, as well as being a key source of economic growth, will tend to cause a divergence of regional per-capita incomes. Growth with minimal regional divergence, however, can be facilitated by ensuring that factor mobility is as free as possible so that labor and capital can relocate and receive the higher factor returns in urban centers, (World Bank, 2009).

With respect to factor mobility, however, our results also suggest that transport and migration costs are significant since more remote districts have significantly lower growth. Munshi and Rosenzweig (2009) and Ghani *et al.* (2012) likewise note that India lags behind other countries at a similar stage of development in terms of geographical mobility. Thus there may be considerable scope to mitigate growing inter-district inequality by facilitating factor mobility in remote regions.

Specifically it is important to ensure that migration and firm location decisions are not artificially restricted by state border policies. Policy needs to encourage the expansion of urban centers through appropriate complementary public infrastructure, such as electricity and schooling, and removing barriers to land ownership. Likewise it also needs to encourage migration and factor flows through, for example adequate transportation infrastructure and laws and welfare policies that do not discriminate against migrants.[27]

Finally note that we have not attempted to explain the growth of the large metropolitan centers themselves. Rather we have focused on the differing experiences of districts outside of these centers. Thus, though we have not discussed factors such as international trade, foreign investment, financial markets, governance, and corruption, these are still likely to be critical to understanding the rate of aggregate TFP growth.

6. ROBUSTNESS

(a) *Parameter stability*

As a robustness test we then extend our definition of a metropolitan district, or UA, to include the 10 largest UAs in India by population as in Table 3.[28] The overall conclusion is also robust to those UAs with very little change in significance of the key variables or the estimated size of the coefficients. Second we consider whether our distance variable is stable across different data sets. To do this we divide the whole data set into several subgroups, and then examine the stability of the model parameters. To this end, we re-estimate Eqn. (2) and (8) but drop several districts. Specifically, we first drop all north-east districts, then all districts from *Bihar* and *Maharashtra*. We also drop other observations; the various alternatives we consider are listed in Tables 6a and 6b.

A stability test is then conducted by using interaction dummy variables, where the dummy variable takes the value one for included districts and takes the value zero for excluded districts. Then we examine whether such interaction dummies are significant or not based on a *F*-test. The results are depicted in Tables 6a and 6b.

All the parameters, including the distance variable are found to be very stable across the data subsets, as shown in Tables 6a and 6b where the estimated *p*-values for the *F*-tests (given in parenthesis) are significantly larger than 0.05. Thus we do not reject the null hypothesis of constant coefficients. Hence we find no evidence that the parameters change across the subsets of the data districts.[29]

(b) *Endogeneity*

We also consider the potential for the explanatory variables to be endogenous, leading the OLS estimates to be biased and inconsistent. To investigate this, we first apply the Hausman test by comparing 2SLS and the OLS estimates.[30] The Hausman tests are negative for all these cases, which 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.[31] Tables 7a and 7b provide results of this endogeneity test for three variables: *District Literacy*, *District Pucca Roads*, and *District Urbanization*, which are included as controls in Tables 5a and 5b. We have also tested the exogeneity status of the Metro District variables included in Table 5b. The SUR based tests provide some support for exogeneity. Specifically they do not reject exogeneity. The validity of these instruments is examined using the standard *F*-test and Hansen's *J*-test of over-identifying restrictions. We find that the instruments generally satisfy our validity tests.[32]

Endogeneity can also occur through the variable *Market Access* because of the presence of the district GDP weights $w_j = Y_j/Y$ ($d_{i,j}$, which is the distance in kilometers in a straight line between district i and j is always exogenous). This is confirmed by the Hausman test.

We first note that the variable *Market Access* is always insignificant no matter what specification we use in the presence of the variable, *Minimum Distance*. Controlling for UA characteristics (in Table 5b), *Market Access* continues to be insignificant.

While these results suggest that endogeneity due to the introduction of *Market Access* may not be a problem, we

Table 6a. *Stability test for models excluding metro variables*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
North East	0.18	0.35	0.35	0.55	0.40	0.45	0.57
	(0.84)	(0.79)	(0.95)	(0.85)	(0.90)	(0.89)	(0.85)
Maharashtra	0.40	1.20	1.20	0.97	1.57	1.28	0.80
	(0.67)	(0.31)	(0.30)	(0.47)	(0.14)	(0.25)	(0.64)
Bihar	0.93	0.42	2.24**	1.75*	2.59**	2.19**	1.57
	(0.40)	(0.74)	(0.02)	(0.07)	(0.01)	(0.03)	(0.10)
North East and Bihar	1.07	0.72	0.72	0.56	0.82	0.68	0.51
	(0.35)	(0.54)	(0.68)	(0.85)	(0.57)	(0.71)	(0.90)
Maharashtra and Bihar	0.81	1.23	1.49	1.46	1.26	2.03**	1.49
	(0.44)	(0.30)	(0.16)	(0.15)	(0.27)	(0.04)	(0.13)
Karnataka	0.81	1.44	1.50	1.20	0.98	1.27	1.43
	(0.44)	(0.23)	(0.16)	(0.29)	(0.45)	(0.26)	(0.15)

Note 1: *p*-Values are given in the parenthesis.
Note 2: *F*-Tests are joint tests for sate dummy variables.

Table 6b. *Stability test for models including metro variables.*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
North East	0.51	0.75	0.51	0.59	0.44	0.46	0.74
	(0.73)	(0.56)	(0.87)	(0.84)	(0.90)	(0.90)	(0.71)
Maharashtra	0.15	0.64	0.74	0.61	0.85	0.82	0.57
	(0.93)	(0.63)	(0.68)	(0.82)	(0.56)	(0.59)	(0.87)
Bihar	0.94	0.43	2.24**	1.75*	2.58**	2.26**	1.60*
	(0.39)	(0.73)	(0.02)	(0.07)	(0.01)	(0.02)	(0.10)
North East and Bihar	0.69	0.70	0.71	0.56	0.83	0.75	0.54
	(0.60)	(0.59)	(0.70)	(0.86)	(0.58)	(0.66)	(0.89)
Maharashtra and Bihar	0.37	0.65	1.17	1.12	1.05	1.50	1.20
	(0.77)	(0.63)	(0.31)	(0.34)	(0.40)	(0.15)	(0.28)
Karnataka	1.54	1.60	1.53	1.25	1.29	1.43	1.34
	(0.19)	(0.16)	(0.12)	(0.24)	(0.24)	(0.16)	(0.18)

Note 1: *p*-Values are given in the parenthesis.
Note 2: *F*-Tests are joint tests for sate dummy variables.

Table 7a. *Results for endogeneity test for models excluding metro variables*

	(2)	(3)	(4)	(5)	(6)	(7)
Market access	NA	NA	7.006***	NA	NA	NA
			(0.0081)			
District literacy	619.547***	1.0245	1.0152	1.0557	0.9531	0.9577
	(0.0000)	(1.0000)	(1.0000)	(1.000)	(1.000)	(1.000)
District Pucca Road	856.3743***	120.0632***	68.3737***	119.4803***	91.4705***	65.7513***
	(0.0000)	(0.0000)	(0.0009)	(0.0000)	(0.000)	(0.0025)
District urbanization	490.4656***	21.8968	9.089	21.4989	22.107	8.4231
	(0.0000)	(0.9299)	(1.0000)	(0.9202)	(0.9252)	(1.0000)

Note 1: *, **, *** denote 10%, 5% and 1% 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 have heteroscedasticity.

Table 7b. *Results for endogeneity test for models including metro variables*

	(2)	(3)	(4)	(5)	(6)	(7)
Market access	NA	NA	4.394**	NA	NA	NA
			(0.0361)			
District literacy	301.7376***	0.5442	0.5591	0.5399	0.5445	0.569
	(0.0000)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)
District Pucca Road	297.4828***	24.7409	64.2781***	23.4085	20.3217	59.8895**
	(0.0000)	(0.9385)	(0.0066)	(0.9477)	(0.9882)	(0.0224)
District urbanization	283.7623***	20.43	6.807	20.1736	20.7042	7.0247
	(0.0000)	(0.9828)	(1.0000)	(0.9787)	(0.9806)	(1.0000)

Note 1: *, **, *** denote 10%, 5% and 1% 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 have heteroscedasticity.

re-run the model proxying for district GDP weights $w_j = Y_j/Y$ by 2001 district population weights. We find that *Market Access* continues to be insignificant when included along with *Minimum Distance* and the other variables (i.e., irrespective of whether we control just for district characteristics, or district and metro characteristics).

We also try using IV to check whether endogeneity is an issue using average (un-weighted) log distance to instrument for *Market Access*. We find with this IV estimate, *Market Access* is still always insignificant in the presence of the variable *Minimum Distance*.[33] Thus we find no evidence that *Market Access* is significant which is consistent with our expectations as explained in Section (a).

7. CONCLUSION

Though India's growth has been unbalanced, the causes of this pattern of divergence are not well understood. We therefore examine the evidence for convergence of per-capita incomes at the district level using a new data set of district per-capita incomes and socio-economic characteristics. We find little evidence of convergence either within states or across all districts as a whole. Rather there is absolute divergence of income levels across districts.

We therefore attempt to explain differences in transitional growth across districts with reference to district characteristics and initial district per-capita incomes. We argue that an important spatial variable to consider in the case of India, is the district's proximity to a major urban agglomeration. This follows from the NEG literature which emphasizes the importance of urban agglomerations and increasing returns, and the fact that, for migrants, the largest cities are likely to be close substitutes in terms of employment opportunities.

We find that urbanization and electrification are significantly associated with higher transitional growth rates across all our models. Thus the results support Desmet *et al.* (2013) who argue that frictions, policies, and a general lack of infrastructure in medium-density cities is preventing the spread of growth in India. Likewise we find that the state dummy variables are jointly significant. This supports studies that have emphasized the role of different degrees of regulation across states (Acharya *et al.*, 2010; Besley & Burgess, 2004), but may also reflect the impact state border policies that restrict trade and factor movements.

We also find that the proximity of a district to major UA is also a significant explanatory variable across our various models. Thus the model is a capable of explaining much lower growth rates in very remote districts. Notably, however, we also find that the more conventional market access variable used in the NEG literature—which gives more weight to the number of different markets—is not significant in any of our models. This makes sense in the Indian regional context where manufactured goods trade that depends on varieties, is very small.

Thus geographical factors, particularly urbanization and proximity to a large urban agglomeration, are found to be very important. Nevertheless we also find evidence that some factors associated with the policy setting, such as electrification and differences across states, are also important in understanding the differences in growth across India's districts.

NOTES

1. See for example (Bhagwati & Panagariya, 2013; Dreze & Sen, 2013).

2. Complementing these state-level studies is the literature on rising inequality at the individual or household level, and differences in wages across skill levels (Cain, Hasan, Magsombol, & Tandon, 2010; Chamarbagwala, 2008; Chaudhuri & Ravallion, 2007; Datt & Ravallion, 2002; Dev & Ravi, 2007; Mishra & Kumar, 2005).

3. According to Crost and Kambhampati (2010), this differential supply of public infrastructure also applies to schooling infrastructure. This may be important if, as suggested by some, that there has been a sharp increase in the returns to schooling following reforms Cain *et al.*, 2010; Mehtabul, 2012.

4. Krishna and Sethupathy (2012, Chap. 6) however argue that the evidence of links between inequality and reforms in India are fairly weak.

5. See for example World Bank (2009) for a general summary of this literature. With respect to India specifically, Desmet, Ghani, O'Connell, and Rossi-Hansberg (2013) find that India's spatial pattern of growth displays a much higher than usual difference in growth rates across different sized urban areas.

6. These data have attracted some debate. See Himanshu (2009) but also, importantly, the reply by Bhandari (2009).

7. 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.

8. For example the hypothesis of absolute β-convergence has found widespread support in other countries (Durlauf, Johnson, & Temple, 2005; Sala-i Martin, 1996).

9. We report β for all states except *Goa*, *Pondicherry* and *Chandigarh* where the number of districts is 2 or 1.

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

11. Details of this simple decomposition are given in the appendix.

12. This is consistent with evidence such as Dev and Ravi (2007) and Cain *et al.* (2010) who use household expenditure survey data to show that inequality rose over the sub-period 1993–2004, though absolute income levels were generally also rising. Hence the pattern across households, states, and districts since 2000 appears to be similar, with growth occurring in all districts but greater gains for districts in the upper end of the distribution.

13. This definition is used in gravity models of trade as well as "wage equation" models that attempt to explain differences in incomes across regions as a result of trade barriers (Head & Mayer, 2004; Redding & Venables, 2004).

14. This pattern also suggests a higher than normal congestion in such places, (Desmet *et al.*, 2013). Likewise the (World Bank, 2009) argues that the general pattern of growth across the world is one of increasing urbanization but eventual stability of relative spatial concentration.

15. As we shall see, the results are very robust to these alternative definitions.

16. This picture of a western corridor of relative urbanization is even stronger if we consider the ten largest UAs.

17. This characterizes differences in short-run growth rates as observations along a transition path between an initial income level and a target long-run steady-state level or long-run equilibrium "target". It is used for example by Krugman (1993) in a regional context but is commonly used as a motivation for cross-country empirical studies (Durlauf & Quah, 1999). Though it is not assumed that each region has reached its long-run or steady-state income level, it is nevertheless shown that these long-run values, in conjunction with initial income, $y_i(0)$, will determine the regions speed of convergence along its transitional growth path.

18. The coordinates are obtained from http://www.gps-coordinates.net/ and converted to radians. The distances in kilometers are then calculated using the Haversine formula. The 575×575 matrix of district to district distances is available from the authors on request.

19. We obtain data from *Google Maps* and a variety of other sources including Indian state tourism data.

20. 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.

21. It is also possible that irrigated land simply captures more rural agricultural districts thus having the opposite sign to *Urbanization*.

22. For example it is roughly half of Barro's "iron law of convergence", (Barro, 2012; Sala-i Martin, 1996, 1997). Nevertheless it should be noted that the conditional convergence model used here is quite different from the standard cross-country model.

23. For the most rural area (least urbanized) the convergence coefficient estimate is -2.4%. For the most urbanized district, the convergence coefficient is very small (0.6%). The convergence effect estimated at the mean value *Urbanization* is -1.3%, similar to the preceding results.

24. This follows since $\ln 2 = 0.69$. The distance to a UA in the sample is 532 km with a standard deviation of just under 400 km. So doubling the distance is approximately equal to increasing the distance by one standard deviation from the mean.

25. That is $y_i^*/y_j^* = (D_i/D_j)^\gamma = 0.84$. Alternatively if a more remote district had a long-run equilibrium income level that is approximately 50% of the closer districts, it would be 16 times further from the center.

26. For example see Besley and Burgess (2004), Acharya *et al.* (2010), Panagariya (2008), Lall (2007), Ghate (2008), Bhagwati and Panagariya (2013) and Ghani, Goswami, and Kerr (2012). Several studies have also drawn particular attention to the problem of electricity supply. Currently, electricity supply in India is significantly constrained by adequate supplies of coal, even though approximately 90% of India's 650,000 villages now have power lines. Ghate and Wright (2012), for instance, show that faster growing states in India are those states that have been better at progressively releasing themselves from this constraint. See also Wolak (2008).

27. Similarly World Bank (2009) also argue that rural employment programs may restrict growth by discouraging migration. Our results can be interpreted as offering support for this view.

28. Because of space constraints, we do not include these results, but they are available from the authors on request.

29. 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.

30. 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

31. Stata provides an indirect test for endogeneity in a seeming unrelated regression (SUR) framework. The *Suest* command in Stata compares the equality of two parameter vectors (OLS and 2SLS) in a SUR setting. The test statistic follows a χ^2 distribution with the number of model parameters as the degrees of freedom.

32. The F-test shows that the instruments for the "total literacy rate" and the "percent urbanization" are not weak. The instruments for "Pucca road" are found to be weak though, as noted previously, the variable Pucca Road is found to be insignificant under a variety of specifications and also under IV estimation. Hansen's J-test indicates that the instruments used for "percent urbanization" and "Pucca road" are significant and are valid instruments. However, the findings corresponding to "total literacy rate" are mixed in nature. At the 1% level the findings suggest that the instruments are valid and they are also valid at 5% level for most models. Detailed results of these tests are available upon request.

33. We also we find that (un-weighted) average distance is not a weak instrument based on standard F tests.

34. 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.

35. This also requires the restriction that $D_i \geqslant 1$, which will be true in our data.

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APPENDIX A. VARIANCE DECOMPOSITION

This appendix briefly describes our variance decomposition. Let y_{ij} be the underlying variable (say, per-capita logged income) of j^{th} district in i^{th} state, $j = 1, 2\ldots, n_i, i = 1, 2\ldots K$. 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

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

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

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

Then

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

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

APPENDIX B. DERIVATION OF EQN. (2)

The purpose of this appendix is to use a standard partial adjustment model to assist with interpreting the inefficiencies in the empirical model in Eqn. (2). First consider a standard partial adjustment model given by

$$\ln \hat{y}_i(t) - \ln \hat{y}_i(0) = \beta\left(\ln \hat{y}_i^* - \ln \hat{y}_i(0)\right), \tag{3}$$

where $\hat{y}_i$ is district income per effective worker, $\hat{y}_i \equiv (y_i/A_i), A_i$ is a labor productivity term and y_i is income per worker in district i. The left hand side of (3) is the transitional growth rate of output per effective worker in region i. On the right hand side is the gap between current income per effective worker and the long-run steady-state value of output per effective worker $\hat{y}_i^*$. Thus the transitional growth rate of district i is assumed to depend on the gap between the current income initial levels of output per effective worker. In what follows the speed of adjustment, β will be a parameter to be estimated.

Next let y_i denote district i per-capita income and y^* denote the steady-state income per worker in a nearby UA. Then for district i consider a variable θ_i such that, in a steady-state equilibrium,

$$y_i^* = \theta_i\, y^* \tag{4}$$

The variable $\theta_i \leqslant 1$ thus measures the extent of all barriers to complete convergence, such as trade and transport costs, communications costs, road quality, and other geographic barriers. If $\theta_i < 1$ district i will only achieve partial convergence to the metropolitan center or UA.

In terms of effective workers (4) implies $\hat{y}_i^* = \theta_i\, \hat{y}^*$.[34] Then using (3) the transitional growth process for some non-metropolitan district i, can be derived as

$$\ln y_i(t) - \ln y_i(0) = gt - \beta \ln y_i(0) + \ln A_i(0)$$
$$+ \beta(\ln \hat{y}^* + \ln \theta_i). \tag{5}$$

In Eqn. (5) the transitional growth rate of district i depends on: (i) the initial per-capita income of district i, $y_i(0)$; (ii) the level of labor productivity of district i, $A_i(0)$; (iii) the steady-state value of income per effective worker in the relevant UA, $\hat{y}^*$ and; (iv) the distance between district i and the UA, θ_i.

To operationalize (5) we need to specify an empirical counterpart to (4). The gravity literature suggests a simple inverse relationship such as $\theta_{i,j} = \theta\ D_i^{\gamma}$. Hence, using logarithms we have

$$\ln \theta_{i,j} = \ln \theta + \gamma \ln D_i + \eta\ \mathbf{X}_i \tag{6}$$

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. [35]

From (5) and (6) we obtain an empirical model, which is (2) in the text.

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

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.

This shows that $\alpha_2/\alpha_1 = \gamma$ recovers the elasticity of long run income with respect to *Minimum Distance*, as claimed in the text. Specifically from (4) and (6) we have

$$\gamma = \frac{\partial \ln \left(y_i^*/y_j^* \right)}{\partial \ln(D_i/D_j)}$$

Thus if we consider two districts i and j with identical characteristics, except for their distance from the metropolitan district k, *Minimum Distance*, then the value of γ determines the difference in long run incomes in the long run equilibrium. As can also be seen from (2), the coefficient $\alpha_2 = \beta\gamma$ gives the impact on the transitional growth rate.

Finally, a further simple extension of (2) allows for the possibility that the UAs 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 UA district j. Then, assuming $f(\mathbf{Z})$ is log linear gives

$$\ln y_i(t) - \ln y_i(0) = \alpha_0 - \alpha_1 \ln y_i(0) + \alpha_2 \ln D_i + \eta \mathbf{X}_i + \delta \mathbf{Z}_j + \epsilon_i. \tag{8}$$

This then provides a basis for including the additional UA characteristics as discussed in Section (c) and Table 5b.