Regional Inequality in India in the 1990s:

A District-Level View*

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Abstract

This paper examines changes in regional inequality in India in the 1990s, using data for 210 of India's districts, spread across nine states. It provides a finer-grained quantitative analysis of growth patterns than has hitherto been attempted for India. The methodology is that of cross-section growth regressions, which seek to explain longer-run growth rates in terms of initial conditions of development. By identifying these connections, the study seeks to illuminate the role of aspects of physical infrastructure, financial development and human capital in influencing regional patterns of growth. In turn, this may have implications for government policies at the national and state levels. We find no evidence for divergence, but evidence for growth convergence in some cases, dependent on initial conditions. The district level results are supportive of the importance of literacy, and access to finance and roads. The methodology can be used to identify districts which may require additional policy intervention along these dimensions, as well as districts where the performance is worse than the average, even after conditioning on development measures, suggesting other causes of backwardness.

Keywords: regional inequality, growth convergence, economic reform, inclusive growth
JEL Codes: O18, O47, O53, R12

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1. Introduction

Regional inequality in India is an important concern: since the country is large and heterogeneous, even state-level comparisons may miss significant patterns or trends in this dimension of inequality. Most of the many studies of trends in regional inequality[1] use a variant of the neoclassical growth model to specify a regression equation to be estimated,[2] and seek to establish if growth rates across states are such that per capita state domestic products are converging (mitigating regional inequality) or diverging (worsening it). Almost always, statistical analysis of this issue is conducted with state level data, albeit sometimes disaggregated by sectors.[3] This makes sense given the availability of data and political salience of the states. But India's states are large (as populous as typical countries), and heterogeneous in size. Working with data in per capita terms helps address purely econometric issues created by size heterogeneity, but it remains the case that observations of entities of very different sizes receive equal contributory weight in estimating "average" effects.[4]

Singh et al. (2003) did implement a growth convergence exercise using data from the National Sample Survey (NSS), which is at the level of agro-climatic regions. There are 78 such regions in India, but complete data for 59 regions was available. Regions do not cut across state boundaries. The advantages of using data at this level are greater homogeneity in size and internal characteristics, a larger cross-section, and a sense of variation in performance within states. In the absence of per capita product or income data, they used five alternative measures of economic activity, following an earlier analysis of Bhandari and Khare (2002):[5] petrol sales, diesel sales, bank credit, bank deposits and cereal production. Singh et al. (2013) extend this analysis to consider economic performance as measured by per capita consumption expenditure.

In a major study of economic performance at the district level, Debroy and Bhandari (2003) identified 69 "backward" districts based on six indicators, viz., poverty ratios, hunger, infant mortality rate, immunization, literacy rate and enrollment ratios. Each indicator reveals a particular set of worst-performing districts. For example, based on poverty ratios, they found that the districts with the highest poverty ratios were present, apart from the BIMARU states (Bihar, Madhya Pradesh, Rajasthan and Uttar Pradesh),[6]

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[1] For brief surveys of this literature, see, for example, Singh et al. (2010) and Kar et al. (2011).

[2] In an alternative approach, Ahluwalia (2002) used the Gini coefficient and finds that interstate inequality, after being stable for most of the 1980s, increased, starting from the late 1980s, and even more in the 1990s. He added some simple regressions but these do not change the conclusions: these were effectively restricted versions of convergence regressions, with the parameter of initial income level set to zero.

[3] See Kar and Sakthivel (2007) for an example of a sectoral analysis.

[4] Most state-level studies mitigate this problem by focusing on the major states, excluding smaller, typically special category states. However, this reduces an already small cross-section sample size.

[5] Those authors constructed an economic performance index based on the five variables listed, and used the index to compare performance across two years, rather than estimating growth convergence.

[6] This acronym was coined because of its similarity to the Hindi word *bimar*, meaning 'ill.' There are two points to note. First, the coinage was meant to apply to the undivided states, including, therefore, what are now the new states of Chhattisgarh, Jharkhand and Uttarakhand. Second, it excluded Odisha, which is in many ways in the same category of most backward or poorest states. Recently, Government of India (2013)

in Gujarat, Maharashtra, Karnataka, Tamil Nadu, Andhra Pradesh, Orissa, West Bengal and the North-East.[7] Given that each indicator selected a different set of districts, a backward district was defined by them as one which was worst-performing in four out of the above six indicators. The 69 districts so identified were distributed as follows: 26 in Bihar, 13 in UP, 10 each in Jharkhand[8] and Odisha, 6 in Madhya Pradesh, 3 in Arunachal Pradesh, and 1 in Karnataka.[9]

Debroy and Bhandari (2003) observed that connections between 69 backward districts and the rest of the economy are grossly inadequate, with poor national highways, state highways and railway networks. Poor infrastructure deters the private sector, making development dependent on public funds. Flood problems in Bihar, UP and Orissa are also considered as the cause for their backwardness. Thus, addressing these two issues among others is crucial for uplift of these backward districts. As we shall see in subsequent sections, our district-level analysis provides a quantitative analysis of the linkages informally explored by Debroy and Bhandari.

Debroy and Bhandari did not examine changes in performance over time, and such studies are scarce at the district level. In one recent example, Dubey (2009) used data for 47 districts spread across 5 states[10] to examine intra-state inequality trends. Using the Gini coefficient of per capita total consumption expenditure and the coefficient of variation of the headcount ratio of poverty, he found some evidence of increasing intra-state inequality from 1993-94 to 2004-05. In another example, Raman and Kumari (2012) examined district level data for 13 indicators of agricultural development in India's largest state by population, Uttar Pradesh. They found increasing intra-state disparities in some indicators, though not in an overall index of agricultural development, between 1990-91 and 2008-09. They identified the worst-performing districts for each indicator, and argued that intra-state disparities were "high and alarming."

This paper provides a broader perspective on regional inequality at the district level. We constructed a unique data set for 210 districts covering 9 states, and this allows for a relatively comprehensive view of trends in regional inequality in the 1990s. Hence, our study presents a significant advance in understanding regional inequality at a much more fine-grained level than studies of inequality across states. Accordingly, in the next section, we describe the data, theoretical framework and empirical methodology. Section

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has provided a new attempt to measure the degree of underdevelopment in each state. In any case, the purpose of the current study is to go below these state-level characterizations, because seemingly better-off states such as Maharashtra, Karnataka and Andhra Pradesh may also have portions that are quite backward in terms of human and economic development.

[7] Hunger had a similar spatial distribution with less universality and more concentration in the East and the North-East. Backward districts based on infant mortality rates were concentrated in the BIMARU states and Odisha with some presence in Karnataka and Andhra Pradesh. Lack of immunization was found to be prevalent in the BIMARU states. Districts with low literacy rates and enrollment ratios were found to be spread all over the country.

[8] Given that Jharkhand was part of the undivided Bihar state (and therefore part of the BIMARU group), this count yields the remarkable fact that over half of the most backward districts of India were in that specific region.

[9] A subsequent study that identified the 100 most backward districts in India was that of Barooah and Dubey (2007).

[10] The states were Gujarat, Haryana, Kerala, Odisha and Punjab.

3 presents our results, and Section 4 offers conclusions and suggestions for further research.

2. Data, Theoretical Framework and Empirical Methodology

We use data on district level domestic product (DDP), along with data on population, road kilometers, literacy rates, and credit and deposit levels. DDP data was obtained from individual state governments, credit and deposit levels from RBI regional offices, and the other variables from the Indian Census. The main data constraint was in availability of DDP data, and this restricted us to nine states. The nine states covered were Andhra Pradesh, Karnataka, Kerala, Maharashtra, Punjab, Rajasthan, Tamil Nadu, Uttar Pradesh and West Bengal, together accounting for over 60 percent of the country's population and domestic product.[11] The sample states were on average slightly above the national average per capita NSDP. There is also some regional variation in the sample, although with relatively greater coverage of the southern states (4), followed by northern states (3) and one each from the west and east. The data used are for 1991 and 2001, allowing a ten-year snapshot of growth across the districts in our sample. Changes in district boundaries, typically through bifurcations, were dealt with by combining district data for later years.

There are issues of DDP data comparability across states (e.g., Indira et al., 2002), but we believe that the analysis still has validity. In particular, individual-state regressions can avoid issues of comparability across states. To some extent, comparability can also be handled by including state dummies in pooled regressions, and by assuming clustered error terms. Overall, we would argue that even imperfect measurement is better than none at all, and to the extent that biases in data can be identified, one can also point out potential biases in the results. Methodologically, it is also worth noting that measurement error in the dependent variable (here, DDP, which is most subject to data problems) does not lead to biased coefficients, only to greater imprecision – though its lagged value does also appear on the right hand side of the regressions. The omission of relevant explanatory variables in the regressions may therefore be a greater practical source of bias.

The theoretical framework for the empirical analysis comes from neoclassical economic growth theory, which explains growth in terms of factor accumulation. In the absence of continual technical progress, diminishing returns to factor accumulation imply that there is a long run steady state with constant per capita output, i.e., asymptotically, there is no growth in per capita output. Thus, economies starting with different factor endowments will converge to the same steady state, as long as there are no differences in technologies or other productive opportunities. If, instead, there is exogenous technological progress, then economies will grow at the rate dictated by this technological change. Typical neoclassical growth models yield a log-linearization around the steady state of the form:

[11] Missing data for some districts within Uttar Pradesh and West Bengal also slightly reduce the coverage of our sample. In particular, all the districts now in Uttarakhand are excluded from our sample.

$$ln\ y(t) - ln\ y(0) = -\ (1 - e^{-\lambda t})ln\ y(0) + (1 - e^{-\lambda t})ln\ y^*$$

Here y is the measure of income or output per capita, and the parameter λ is the rate of convergence to the common steady state of the system, y^*.

If there are persistent differences in technologies or other determinants of production, then long run convergence to a steady state still takes place, but these steady states can differ, their characteristics being conditional on the differences in productive potentials. Where faster growth is also affected by other variables besides initial income levels, the convergence is said to be conditional: in other words, a country or region with worse initial conditions (e.g., infrastructure) may converge to a steady state that is different from that of a country or region with better initial conditions. Thus, one can identify three possible scenarios: absolute convergence, where different entities are moving toward the same steady state, conditional convergence, where they are converging to (possibly very) different steady states, and divergence, where there is no evidence of convergence. The last case is inconsistent with neoclassical growth models, but conceivably fits some endogenous growth models, which typically assume some externality that overcomes diminishing returns. Conditional convergence is quite consistent with increasing disparities across entities. Variables such as literacy, health and physical infrastructure, as well as measures of the economic policies followed, can be used as conditioning variables. The conditioning variables themselves may be endogenous, but if one uses these variables at their initial values, they are predetermined over the growth period being studied, and one can posit a causal relationship. The empirical implementation of a convergence regression, allowing for the impact of different initial conditions, then takes the following form:

$$ln(y_{i,t}) - ln\ (y_{i,t-\tau}) = \gamma\ ln\ (y_{i,t-\tau}) + \Sigma^{k}_{j=1}\pi^{j}\ x^{j}_{\ it-\tau} + \mu_i + \varepsilon_{it}$$

Here, i denotes the cross-sectional units (countries, states, regions), τ the initial time period, t the final time period, the x^j are the various conditioning factors, and μ_i are possible additional fixed effects not captured by those factors. The parameter γ is approximately equal to the theoretical parameter λ, and therefore measures the rate of convergence if negative, or divergence if positive. The final term is an error component, reflecting unobservable factors. All our empirical estimations are of this form, using per capita DDP as the output measure.

Two additional methodological points are in order. In addition to the conceptual benefit of a disaggregated analysis, there is some econometric advantage to working with district level data. Districts are much more homogeneous in size than are the states themselves. Hence, a cross-sectional analysis with district level data avoids the problem of unevenness in the underlying size of the units represented by different observations.[12] We can also deal with non-classical error terms by using some variant of generalized least squares (GLS). To mitigate various forms of heteroskedasticity, we employ Huber-White

[12] This problem also exists in cross-country convergence regressions, where countries as disparate in size as India and Nepal will each be treated as equally influential observations in a regression.

(robust) estimates of error variances. A likelihood ratio test rejects the null hypothesis that all the states in the sample have the same error variances. Hence we employ clustered, robust error estimators, where the error variances are clustered at state level, as a special case of GLS.

3. Results

We begin with basic absolute convergence regressions, presented in columns 1 and 2 of Table 1. Column 1 features estimates using robust standard errors, while column 2 uses clustered, robust errors. In particular, the estimates in the second method are robust to any type of correlation within the observations of each cluster (i.e., state). There is no statistically significant indication of absolute convergence or divergence. The coefficients across the two estimation methods are not qualitatively different in sign and statistical significance. However, the explanatory power of the absolute convergence regressions is extremely low: clearly, initial conditions beyond initial income levels matter for predicting future growth.

Table 1: Absolute Convergence Regressions

LHS = Growth	**Robust Errors** (1)	**Clustered Errors** (2)	**State Dummies** (3)
ln(DDP/Pop.)91	-0.11	-0.11	-0.36**
	(0.1)	(0.2)	(0.2)
Kerala			0.054
			(0.04)
Karnataka			0.15***
			(0.05)
Maharashtra			-0.051
			(0.04)
Punjab			0.072
			(0.10)
Rajasthan			-0.21***
			(0.03)
Tamil Nadu			0.15***
			(0.04)
Uttar Pradesh			-0.41***
			(0.06)
West Bengal			0.054
			(0.05)
Constant	1.24	1.24	3.52**
	(1.2)	(1.7)	(1.4)
Observations	210	210	210
R-squared	0.02	0.02	0.52

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1 (column 3) also presents results for absolute convergence, allowing for differences across the states. Including state level dummies captures differences in base growth rates. The dummy for Andhra Pradesh is omitted, so it serves as the benchmark state. The results indicate significantly higher base growth for Karnataka and Tamil Nadu, and lower base growth for Rajasthan and Uttar Pradesh, relative to the benchmark state. Allowing for state dummies, even though it imposes the restriction that all states have the same convergence rate, increases the estimated convergence rate substantially, as well as dramatically increasing the explanatory power of the regression. The results in Table 1 illustrate the value of the disaggregated approach pursued in this analysis, since state-level regressions impose the restriction that the base growth rate is the same for all the states.[13] Allowing for state-level dummies also partly addresses data definition differences across the states. Hence, the low estimated base growth rate for Uttar Pradesh may be due to data issues. However, without further data collection and analysis, it is impossible to isolate this possible effect.

Table 2: Absolute Convergence Regressions with State Dummies and Interaction Terms

State	N	Convergence parameter	Constant
Andhra Pradesh	22	-0.11	1.38*
		(0.09)	(0.8)
Kerala	14	0.067	-0.55
		(0.3)	(2.5)
Karnataka	20	-0.20	1.91
		(0.2)	(1.5)
Maharashtra	29	-0.59*	5.25*
		(0.3)	(3.0)
Punjab	12	-0.51**	4.66**
		(0.2)	(1.8)
Rajasthan	27	-0.28**	2.22*
		(0.1)	(1.2)
Tamil Nadu	20	0.17*	-1.41
		(0.1)	(0.9)
Uttar Pradesh	50	-0.033	-0.052
		(0.1)	(1.2)
West Bengal	16	0.26	-2.13
		(0.3)	(2.2)
	N = 210		R-squared = 0.61

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[13] At most, one can include something like zonal dummies (e.g., for north, south, east and west), but unless a panel is used, the degrees of freedom are very limited in state-level regressions.

Table 3: Conditional Convergence Regressions

	(1)	(2)	(3)	(4)
Ln(DDP/Pop.) '91	-0.37	-0.36**	-0.51**	-0.49**
	(0.2)	(0.2)	(0.2)	(0.2)
Ln(Road Km.)	0.11**	0.086*	0.068**	0.069***
	(0.04)	(0.04)	(0.03)	(0.02)
Literacy '91	0.0061**	0.0065**	0.0073*	0.0099**
	(0.002)	(0.003)	(0.003)	(0.004)
Credit/Pop. '91	4.68**		2.59	
	(1.6)		(1.5)	
Deposits/Pop. '91	-1.72		-0.40	
	(1.2)		(1.0)	
Cred./Dep. '91		0.33**		0.22**
		(0.1)		(0.08)
Kerala			-0.19	-0.31
			(0.1)	(0.2)
Karnataka			0.25***	0.24***
			(0.04)	(0.03)
Maharashtra			-0.13**	-0.16***
			(0.04)	(0.04)
Punjab			0.056	0.067
			(0.08)	(0.05)
Rajasthan			-0.086*	-0.050
			(0.04)	(0.04)
Tamil Nadu			0.061	-0.0070
			(0.05)	(0.07)
Uttar Pradesh			-0.31***	-0.25***
			(0.04)	(0.04)
West Bengal			0.058	0.10**
			(0.04)	(0.05)
Constant	2.41	2.26	3.91**	3.50**
	(1.8)	(1.4)	(1.4)	(1.1)
Observations	210	210	210	210
R-squared	0.27	0.31	0.64	0.64

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

It is also possible to extend the assumed differentiation across states further, by including interaction terms as well as state dummies. Table 2 presents results for absolute convergence, with state level dummies, and interacting these dummies with initial year DDP per capita (in logarithms), to capture differences in convergence speeds. In this case, rather than omitting Andhra Pradesh, we omit the overall constant term for symmetry, so that the dummy coefficients are the respective baseline growth rates for individual states. Allowing for differing convergence rates across states changes the earlier results quite a bit. The results in Table 2 indicate higher base growth for Punjab, and to some extent Andhra Pradesh, Maharashtra and Rajasthan. The interaction terms indicate faster convergence for Punjab and Rajasthan, and to some extent Maharashtra, but also suggest weak evidence for divergence of districts within Tamil Nadu.[14] The results in Table 2 further illustrate the value of the disaggregated approach pursued in this analysis, since state-level regressions impose the restriction that the convergence rate is the same for all the states.

Next, we examine possibilities of conditional convergence, returning in his case to the assumption of identical parameters across the states in the sample, but allowing for the growth impact of different initial conditions. We use three categories of conditioning variables. First, we include district road kilometers as a measure of physical infrastructure.[15] Second, we include literacy rates as a measure of human capital. Third, we include either credit per capita and deposits per capita, or a single credit-deposit ratio, in either case attempting to measure district-level availability of financial capital or financial development. Another way to think about our conditioning variables is in terms of access to key aspects of economic activity. The road variable potentially measures access to markets, the literacy rate can be thought of as measuring access to jobs, and the financial variables capture access to credit. We would expect all the conditioning variables to have positive impacts on the level of economic growth.

Table 3 presents the basic conditional convergence regressions. We allow for clustered error terms, and allow for two possible specifications of the financial access effect: in the first, we include per capita credit and deposit values, while in the second, we use the credit-deposit ratio. The results are presented without and with state-level dummies, with Andhra Pradesh again being the baseline state for the dummies. The measures of access to markets, access to jobs and access to credit all have coefficients with the expected positive signs. In the case of the financial variables, financial development per se, as measured by deposits per capita, does not have a significant positive effect on growth, but the credit variable matters as expected in either specification. The other variables are similar in magnitude and significance across the specifications. The state level dummies in columns (3) and (4) are also not too different from those in Table 1. The convergence coefficients all indicate fairly rapid convergence, though the sample excludes Madhya Pradesh (still including Chhatisgarh in this period), Odisha and Bihar (still including Jharkhand in this period), so it does not encompass some of the most underdeveloped parts of the country in the 1990s.

One aspect of the impact of financial depth or financial access on growth is the presence of large credit-deposit ratio outliers in the data, which are cities that are financial centers. These outliers may also be biased measures, because credit is obtained through corporate headquarters based in major cities, and counted there in the data, while investments are made in wider geographic areas. In that case, the impact of the credit variable might be understated in the previous estimates. On the other hand, if these outliers represent a true, strong effect of credit on local growth, then the strong positive coefficient of credit may

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[14] This regression is similar in effect to running separate regressions for the individual states, which can be found in Singh et al. (2010), but it imposes additional restrictions on the error structure, as compared to single-state regressions.

[15] In Singh et al. (2010), we also present results for road kilometers normalized by district area – however, those results are weaker. The reason for this bears further investigation.

be driven by these few observations, and therefore higher than if the outliers are omitted. However, omitting the seven most extreme outliers as measured by the credit-deposit ratio does not qualitatively change the results of Table 3.[16]

We also explored other robustness checks and extensions, reported in detail in Singh et al. (2010). Allowing convergence rates to be different across the states in the sample did not qualitatively affect the estimated impacts of the three conditioning variables. Restricting the analysis to the four southern states, it was found that the literacy variable was no longer positive and significant. This implies that variation in literacy rates across districts in these four states did not affect growth in the 1990s. Combined with the result for the sample as a whole, the possible implication is that literacy rates matter for growth until some rough literacy threshold is crossed, something the southern states have done better at. Allowing for interaction terms (e.g., road kilometers and literacy rates with initial per capita DDP) in the whole sample, it seemed that roads mattered more for growth in initially poorer districts, and literacy mattered more for initially richer districts. The latter result is not necessarily at odds with the result for the southern states, which posited diminishing returns to literacy, since there was no formal interaction with per capita output in that comparison. However, the possibilities of mechanisms and interactions are quite diverse, and the main conclusion is that they bear further investigation.

Table 4: Ten Worst Districts Relative to Regression Line

Table 3, col. (1) regression	
State	**District**
MH	Gadchiroli
UP	Pratapgarh
UP	Deoria
UP	Basti
UP	Ghazipur
UP	Rae Bareilly
UP	Fatehpur
UP	Azamgarh
UP	Faizabad
UP	Bahraich

It is also instructive to examine the residuals from regressions such as we have reported. Negative residuals relative to an estimated regression line indicate possible factors that are not captured by the included explanatory variables. For example, in Table 4, we report the ten districts with the largest negative residuals relative to the estimated relationship reported in Table 3, column (1). In this case, it is assumed that baseline and convergence parameters are the same across the 210 districts. The worst district relative to the estimated regression line is Gadchiroli, at the eastern tip of Maharashtra, and as far as one can get from the wealth and infrastructure of Mumbai within that state. The contrast illustrates again the limitations of analyzing data just at the state level for India. The other nine districts in Table 4 are all in eastern Uttar Pradesh, illustrating a regional

[16] Details may be found in Singh et al. (2010).

concentration of underdevelopment and slow growth. Since these districts are picked out relative to an estimated relationship that allows for differences in literacy, roads and credit, the implication is that other factors also matter for growth. In fact, as shown in Singh et al. (2010), the list of worst districts as measured by the size of negative residuals varies quite a bit with specifications that include additional conditioning variables.

4. Conclusions

This paper extends previous growth analyses for India by examining the growth mechanisms at the district level, allowing a more refined understanding of the country's regional disparities. Most previous analyses for regional inequality in India have used state-level data: while the states are important political and policy-making entities, they are also large enough that focusing on state-level trends can miss out on more localized problems of relative or even absolute economic stagnation. In many ways, the district is the most significant economic and administrative unit in the country, and mapping growth performance and determinants as we have done provides additional guidance for policy makers in terms of where to focus policy attention. The paper provides evidence that access to credit, literacy and access to roads all mattered to some degree for district-level growth in the 1990s. The results are quite robust across a variety of specifications.

There are two sorts of policy implications that can be drawn from the analysis. The first looks at, and derives policy recommendations from the estimated average impacts captured in the regression coefficients of the convergence regressions. Thus, the district level results presented in the paper are supportive of the view that improving literacy rates and road connectivity can be important factors in accelerating local growth.[17] Similarly, there is evidence that credit access can have a positive impact on growth.

The second policy implication comes from identifying districts that are well below the estimated average relationships between growth and initial conditions. These districts may be suffering from other deficits, or particular obstacles to growth that can potentially be identified and focused on through appropriate policy measures. At the least, further data can be collected and analyzed for districts that do worse than would be predicted based on initial conditions of access to credit, road connectivity or literacy. For example, land tenure systems or social fragmentation may matter for growth, as they do for agricultural productivity or expenditures on public goods (e.g., Banerjee and Iyer, 2005; Banerjee and Somanathan, 2007).

We must also make clear the limitations of this study for policy-making. First, as just noted, the set of variables used is not comprehensive, and additional broad data collection may lead to a more encompassing set of conditioning variables, which could change the policy conclusions. Social fragmentation, land systems and governance quality are all examples of factors that are likely to be important as growth determinants. Second, the analysis provides no guidance on the specific design of policies, or of institutions for policy implementation. Much of the criticism of Indian policies with respect to promoting

[17] For a recent, very detailed analysis of the significant economic impacts of India's rural road program, see Aggarwal (2013).

inclusive growth has focused on issues of detailed policy design, and effectiveness of implementation. Our analysis cannot provide any lessons on how to improve literacy or improve access to credit: it merely confirms that these issues are important for understanding growth performance at a fine-grained level. Clearly, further research on mechanisms of growth at a disaggregated level is needed, to complement a considerable amount of research being done on the effectiveness of institutions and policies through efforts such as randomized controlled trials.

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