Regional Convergence and Catch-up in India between 1960 and 1992.

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Abstract

This paper examines the evidence for regional convergence or catch-up in levels and growth rates of per capita income among the 16 major states in India between 1960 and 1992. The results – estimated using OLS, the within-group LSDV estimator, Re-Weighted Least Squares, and Least Trimmed Squares – establish that unconditional convergence in growth rates does not obtain, but that there is clear and robust evidence of conditional convergence. This suggests that important differences between observed state incomes are likely to be caused by different steady-state incomes, to which convergence occurs. The cross-state income distribution is analyzed and the greater polarization between states in terms of levels of income is established using measures of dispersion and kernel density estimates. A tentative conclusion is that a small group of states are pulling away from the rest of the distribution, causing an incipient second peak.

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1 Introduction

One of the key questions that the study of economic growth tries to answer is whether initially disparate regions of the world converge to common steady state paths. This issue of *convergence* or *catch-up* – what it means or implies theoretically, and trying to find it within the data – has driven much of the resurgence in the study of economic growth at an aggregate level in the past decade and a half. This paper is part of that research: it is a comprehensive study of convergence in a panel of 16 states in India betweeen 1960 and 1992.

More specifically, this paper can also be considered a part of a growing agenda of exploring the ideas of growth theory within low-income countries. The first wave of empirical literature on growth was almost exclusively cross-country. Since then, as more data has become available, and as the limitations of cross-sectional and cross-country work have been better understood; more research has focussed on panel data and on within-country studies. In this respect, India is a rare and valuable example of a low-income country with long time series data for its constituent states. The data is by no means perfect.[2] However, even with all the required caveats, comparability across states in India is likely to be better than the average cross-country study.

There are, thus, good academic reasons for learning about convergence within India. But currently there is also considerable interest in the social, political, and economic implications of convergence (or divergence) among the states. A recent Financial Times survey on India mentions that,

> *"India seems to be diverging into almost two different countries: prosperous socially stable, rapidly modernizing southern and western regions and poor and politically volatile northern and eastern regions".*[3]

What kind of income convergence is occurring, in actual fact, between the different states, would shed much light on such conjectures, and on other popular and academic debates about economic growth within India.[4]

It should be mentioned at the outset that while many implications of existing theories of economic growth and convergence find empirical validation in the results reported here, none of the empirics were designed to explicitly test a particular theory versus another.

[2] To give just one example, the state of Jammu and Kashmir has several missing observations for the conditioning variables used in section 3. It is thus omitted from the conditional convergence regressions. More details are provided in the relevant sections of the paper and in the data appendix.

[3] *Amy Kazmin*, 'The North-South Divide', in the FINANCIAL TIMES, November 19th, 1999.

[4] For instance, critics of India's economic reforms programme launched in the 1990s have frequently remarked that the reforms are responsible for the greater disparity in incomes between states. While this paper does not directly address this debate, the results in section 4 do establish that the growth of income disparity between states is not, by any means, a phenomenon that started in the 1990s.

While that is an important objective of empirical research, it is deliberately not the objective of this paper. So for example, section 3 assesses the evidence on $\beta-$convergence without attempting to fit the theoretical straightjacket of the Solow (1956) model.[5] The main aim of this paper, to re-iterate, is on the issue of *convergence* or *catch-up* – whether initially disparate states in India display any tendency in the data to converge to common steady state paths between 1960 and 1992. In addition, since the sample only comprises 16 states, a subsidiary aim is to assess the robustness of results by using alternative estimation procedures. Apart from documenting convergence or the lack thereof, the analysis will also enable us to identify some of the key *influential* states which seem to be driving the empirical results.

The rest of this paper has the following structure. Section 2 clarifies the two main concepts of convergence which are prevalent in the literature and which are empirically examined in the paper, namely β and $\sigma-$convergence. The discussion is deliberately brief since the primary focus of this paper is the empirical evidence that follows. Sections 3 and 4 study the evidence on convergence, and comment on how the findings are related with experiences of specific states. In particular, section 3 documents the absence of unconditional $\beta-$convergence, but also strong and consistent evidence of conditional convergence. Section 4 is about $\sigma-$convergence. It analyses the cross-state income distribution using measures of dispersion and kernel density estimates, and finds evidence of increasing cross-state income disparities, or $\sigma-$divergence. Section 4 also comments on how cross-state income inequality might or might not be related to individual income inequality. Finally, Section 5 concludes.

2 What kind of convergence?

Even as a large and burgeoning literature has investigated whether there exist forces that lead to convergence, there remains some disagreement about its exact definition. Barro and Sala-i-Martin (1995) identify two notions of convergence. First, there is the concept of $\beta-$convergence, which also comes in two flavours. Loosely, it can be understood in terms of the following question: *do initially poorer states grow faster?* More precisely, it is the idea that a poor economy tends to grow faster than a rich one, so that the poor region possibly tends to catch up with the rich one in terms of the level of per capita income. The most popular formal model underlying the idea that initially poorer regions might grow faster is the neoclassical growth model of Solow (1956).[6] The key assumption that generates the convergence result in neoclassical models is diminishing returns to reproducible capital. The relatively less well off economy will have lower stocks of physical capital, and hence

[5] See Nosbusch (1999) for an attempt to test the Solow model using Indian data.

[6] Note that models with technology diffusion or factor mobility would also imply $\beta-$convergence. For a review of these models see chs. 3 and 8, Barro and Sala-i-Martin (1995).

higher marginal rates of return on capital. Therefore, for any given rate of investment, it will have faster growth in the transition phase. Note that such $\beta-$convergence implied by the Solow model is conditional; and perceptible only after other factors which may cause variation in steady states have been accounted for. Anything that drives apart investment rates in rich and poor regions will, *ceteris paribus*, drive their steady-state income levels apart, even as each region is converging to its diverging steady state.

In contrast to this, one can define a stronger kind of convergence that takes place unconditionally or absolutely, where initially poorer states grow faster, notwithstanding differences in initial conditions. In terms of the Solow (1956) model, if we postulate that all regions, in the long run, have no tendency to display variation in the rates of investment, capital depreciation, population growth, and so forth, then such a model would generate unconditional or absolute convergence to a common value of per-capita income.

The second concept of convergence, $\sigma-$convergence, concerns cross-sectional dispersion. $\sigma-$convergence occurs if the dispersion of say, per capita incomes across regions declines over time. More generally, it focusses on the evolution of the cross-sectional income distribution – its shape and the movement of the distribution over time. Other things being equal, $\beta-$convergence may eventually lead to $\sigma-$convergence.[7] However, if other things are not equal, perhaps because each region is subject to random disturbances, then $\beta-$convergence need not imply a reduction in the dispersion of income levels. Hence, conditional $\beta-$convergence as implied by the Solow model, is consistent with $\sigma-$divergence. For instance, anything that drives apart steady-state incomes in rich and poor regions will lead to $\sigma-$divergence, although each region might still be (conditionally) converging to a diverging steady-state.

The following section in this paper evaluates the evidence on $\beta-$convergence. It suggests the absence of unconditional $\beta-$ convergence, but strong and consistent evidence of conditional $\beta-$convergence once measures of human capital and physical infrastructure are controlled for. The reported speeds of conditional convergence are quite high, when compared to standard OLS estimates from cross-country studies. The overall implication is that there is no unconditional tendency for initially poorer states to grow faster.

Although the evidence in section 3 informs us about whether the poorer states are converging *on average*, it tells us very little about whether these states have actually caught up or are falling further behind other states in terms of levels of per capita incomes. In a series of influential papers, Danny Quah has argued that the most fruitful way of thinking about the question of whether poor states are catching up with rich states over time, is to focus on the changing distribution of state incomes over time – in other words, $\sigma-$convergence.[8] This is the subject of section 4. Analysis of the cross-state income distribution reveals no

[7] This is trivially true in the case of unconditional or absolute $\beta-$convergence. In such a world history, in the sense of different initial conditions, does not matter.

[8] See for example, Quah (1993,1997)

evidence of $\sigma-$convergence. In fact, there are many signs of $\sigma-$divergence, and instances of catch-up are few and far between.

3 Estimating $\beta-$ Convergence: Conditional or Absolute?

3.1 Preliminaries

In their landmark paper, Mankiw, Romer, and Weil (1992) suggest that an augmented Solow model – which expresses growth as an explicit function of the determinants of the ultimate steady state and the initial level of income – is a '*natural*' way to study convergence. If we run a regression which conditions for the determinants of steady states, like the investment rate in the Solow model, then we would expect a negative sign on the initial income coefficient. The idea is that within regions approaching the same steady state, the poorer ones will grow faster in the *transitional* period. In essence, we follow this approach. However, since our aim is to evaluate the evidence of $\beta-$convergence in states within India, rather than to explicitly test a particular growth model that predicts convergence, we use a more general specification in the empirics that follow – *a la* Barro (1991) and Caselli, Esquival, and Lefort (1996). The typical cross-country study of economic growth is built on an equation nested in the following specification, which is consistent with the Mankiw *et al* (1992) formulation as well,

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

where,

y_{it} is now real per capita income of country i at time t.

x_{it} are a set of conditioning variables, which capture differences in steady states

μ_i is the state specific fixed effect, which will pick up the influence of any omitted variable that does not vary over time in a panel

ε_{it} is the transitory error term that varies across countries and time periods, and has mean equal to zero

and, the coefficient γ identifies the convergence effect.

Equation (1) is consistent with a variety of neoclassical growth models that accept as a solution a log-linearization around the steady state of the form (see Barro and Sala-i-Martin, 1995),

$$\ln y(t) - \ln y(0) = -\left(1 - e^{-\lambda t}\right) \ln y(0) + \left(1 - e^{-\lambda t}\right) \ln y^* \tag{2}$$

where λ is the rate of convergence.[9]

[9] Note that the relation between γ and λ is only approximate. This is because the growth rate is observed as an average over an interval of τ years rather than at a point in time. The implied instantaneous rate of convergence λ will be slightly higher than the value indicated by the coefficient γ. λ will tend to γ as τ tends to zero. See Barro and Sala-i-Martin (1995, ch. 2) for more details.

The more general specification in equation (1) allows us to control for variables which might influence the steady-state level of income, but which are not included explicitly in Solow (1956). This approach is particularly useful, since state-level data on investment or capital – a key variable in the Solow model – is not available for most of the sample period. Instead, as described in section 3.3 we use proxies for physical and human capital in order to control for the different steady-state levels in most of the regressions.

3.2 Unconditional Convergence

Most evidence on unconditional convergence has come from within-country studies. Two well-known examples are US states (Barro and Sala-i-Martin, 1992) and Japanese Prefectures (Barro and Sala-i-Martin, 1995). In both cases the authors find evidence of unconditional $\beta-$convergence over long sample periods – 100 years for US states and 60 years for Japanese prefectures – and also over much shorter subperiods within the same sample. More recently, de la Fuente (2002) records evidence of unconditional $\beta-$convergence across Spanish regions in each of the three decades between 1965 and 1995 – a time period very similar to this study. By contrast, empirical evidence on unconditional convergence from developing countries has been much less encouraging. In the two studies that I have seen – on Mexico (Juan-Ramon and Rivera-Batiz, 1996) and on China (Jian, Sachs, and Warner, 1996) – unconditional convergence is a much less robust finding, and obtains only within limited time spans. Jian, Sachs, and Warner (1996) study the provinces of China between 1952 and 1993, and find evidence of divergence in real per capita incomes except in period 1978-1990. Similarly, Juan-Ramon and Rivera-Batiz (1996), investigate Mexico's states in the 23 year period from 1970 to 1993, and report convergence in incomes between 1970-85 and divergence thereafter.

Moving to India, two papers have focussed on the issue of convergence among states in India between 1960 and 1992. Cashin and Sahay (1996) use a cross-section regression and report evidence of unconditional $\beta-$convergence, although the convergence rate that they estimate is not statistically significant. They further sub-divide the 30 year period into three 10 year long time-spans, and find the strongest evidence of unconditional convergence in the decade 1961-71. On the other hand, even after controlling for shocks to the agricultural and manufacturing sector they find a conditional convergence rate of 1.5% per year, which is surprisingly low – lower even than the 2% reported from cross-country work. Their sample considers 20 states: the 16 major states considered in this paper plus 3 smaller states (Himachal Pradesh, Manipur, and Tripura), and the then Union Territory of Delhi. Bajpai and Sachs (1996) consider the same sample excluding Himachal Pradesh, and they also report evidence of statistically significant unconditional convergence in the decade of the 1960s, but not thereafter.[10] They suggest that this could be the result of

[10] Bajpai and Sachs (1996) report a peculiarly high unconditional convergence rate in the decade 1960-70

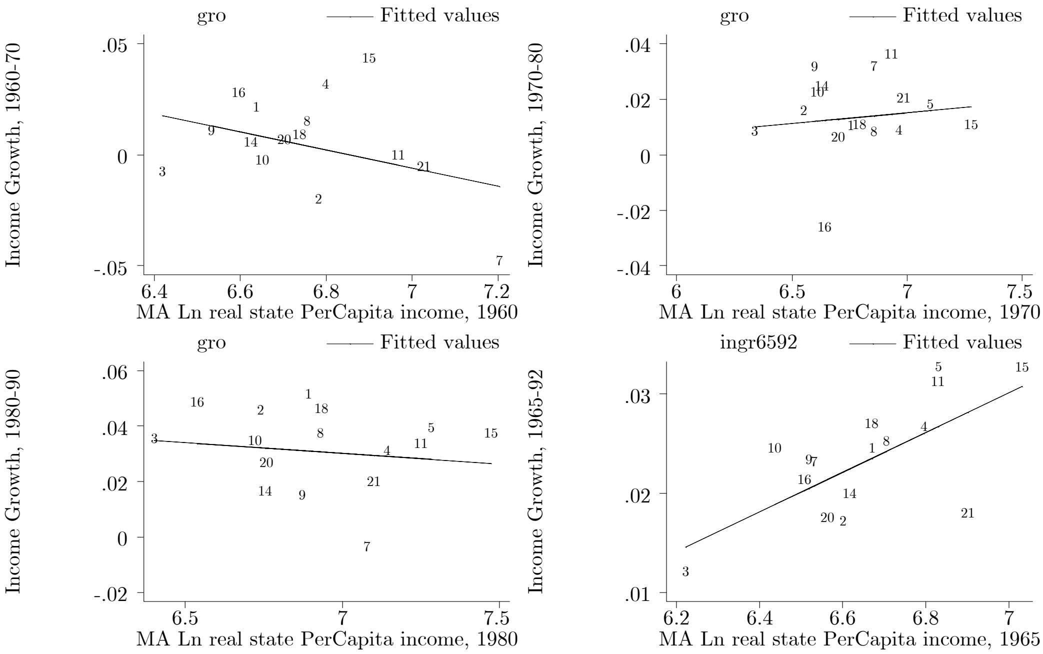

Figure 1: UNCONDITIONAL CONVERGENCE, 1960-92

high growth in the agricultural sector in India during the 60s.

There are a number of econometric concerns with both these studies. Most crucially, since their cross-sectional regression results are based on very few observations, sensitivity to outliers is likely to be a major problem. In fact, this possibility is never considered in either of the papers; and indeed, the econometric results of both papers often appear to be driven substantially by a few outlying states such as Delhi and Manipur.[11] In small sample cross-section or panel econometrics, it is especially important to ensure that a few influential but atypical observations don't distort parameter estimates, and that the results reflect trends in the majority of the sample. Temple (2000) suggests using robust estimation procedures alongside OLS estimates. A large difference between the results is a warning that conclusions drawn from standard estimating techniques such as OLS are being driven by a minority of observations. This estimation strategy is followed in the convergence regressions reported below.

of 99%.

[11] This is particularly problematic since Delhi and Manipur are very tiny states. Together both these states account for less than 1.5% of India's population, and approximately 2.5% of India's GDP. Delhi is really a city – it has been granted statehood only in the 90s. It has the highest per capita income – hardly surprisingly since it is the capital city; and one of the lowest growth rates during the period. Manipur, on the other hand, is a poor and economically backward state in the Northeast, and has had a high growth rate up until the 90s.

The first part of table I reports the cross-sectional regression estimates. Since both the papers cited above – Cashin and Sahay (1996) and Bajpai and Sachs (1996) – use 10 year spans, columns (1), (2) and (3) report regressions for the three decades 1960-70, 1970-80 and 1980-90. The estimated model is of the following form:

$$growth_{i,1960-70} = constant + \gamma(income)_{i,1960} + \varepsilon_i \tag{3}$$

and so on for another two points in time: 1970-80 and 1980-90.[12] In terms of equation (1), Δy_{it} is growth over a 10 year interval, and y_{it-1} is in fact the level of income lagged 10 years, and so on. The 10 year interval should clean out the growth rate from any short term fluctuations such as business cycles, a pre-election year spending boom, or simply a bad monsoon. It is equally important to control for measurement error and business cycle variation in the right-hand side variables, so in fact, we use a 3 period moving average of lagged income.[13] Note that equation (3), as written out, does not control for any determinants of steady state, and so a negative and significant value of γ would imply unconditional or absolute convergence to a common steady state.

Column (1) for the decade 1960-70 has only 15 observations since income data on Haryana is not available until 1965. The OLS coefficient on initial income is negative, suggesting unconditional convergence, but it is not statistically significant. The corresponding regression line is shown in panel 1 of figure 1. There appears no obvious negative relation between growth and initial income, but Jammu and Kashmir (state==7) looks like an outlier which might be influencing the regression estimate. To investigate this possiblility more formally, we compute a Re-Weighted Least Squares (RWLS) estimate, which is less sensitive to outliers than standard OLS.[14] We begin by estimating an OLS regression, and calculating Cook's distance, D – where D_i is a scaled measure of the distance between the coefficient estimates when the ith observation is omitted and when it is not.[15] Next, any gross outliers for which $D > 1$ are eliminated. After this initial screening a series of weighted regressions are performed iteratively. Iterations stop when the maximum change in weights drops below a certain predetermined level of *tolerance*. Weights derive from two weight functions used successively – *Huber* weights and biweights – wherein cases with larger residuals receive gradually smaller weights. The RWLS estimate of initial income

[12] The time periods over which growth rates are measured is varied in the exercises below; but for the sake of consistency, unless otherwise mentioned, all growth rates refer to average annual real per capita income growth rates over the period.

[13] However, using only the initial period income value – which is what most convergence studies do – makes no qualitative difference to the result.

[14] The RWLS estimate is computed using the *RREG* command in STATA 7.

[15] Cook's Distance, D, can be thought of as an index which is affected by the size of residuals – outliers – and the size of the leverage of each observation. Large residuals raise the value of D, as does high leverage. For the exact formulae, relation with other outlier diagnostics, and additional references see the Stata Reference Manual, Release 7.

is positive in contrast to the OLS estimate, suggesting that faint signs of unconditional convergence from the OLS estimates were in fact, *red herrings.* Given their small samples, similar problems with outliers and leverage points could well have plagued the findings of unconditional convergence cited above.[16]

Column (2) reports the unconditional convergence estimates for 1970-80. The OLS estimate on initial income is positive and insignificant. Panel 2 in figure 1 suggests that there is no discernible pattern amongst the states in this period. The RWLS estimate confirms this – the coefficient estimate is negative, but it is not statistically different from zero. Column (3) spans the decade 1980-90. Both the OLS and the RWLS estimates are negative, but in both cases they are estimated extremely imprecisely, and we cannot reject a t-test that the coefficients are in fact zero. Thus, there is no convincing evidence of unconditional convergence in any of the three decades between 1960 and 1990.

In column (4) we estimate the model for the entire period between 1965 and 1992. The OLS estimate is positive and statistically significant, suggesting unconditional divergence. Panel 4 of figure 1 shows the corresponding regression line. At first glance the relationship does not seem to be driven by outliers. The RWLS estimate confirms this. The positive coefficient is slightly bigger and estimated more precisely when the apparent outlier state, West Bengal (state==21) is downweighed. In fact West Bengal (state==21) appears to be one of the few "unconditionally convergent" states, as seen in panel 4 of figure 1. In 1965 it is one of the richest states in the sample, but over the 30 year period it has one of the lowest growth rates. On the other hand, the main examples of divergent states appear to be Punjab (state==15) at the top end, and Bihar (state==3) at the bottom end. Punjab (state==15) was the richest state in the 1960s, and has maintained one of the highest growth rates over the 30 year period on the back of strong agricultural performance. By contrast, Bihar (state==3) was the poorest state in the sample in the 1960s and it has barely grown over the 30 year period.

In columns (5) and (6) of table I, the panel versions of the unconditional convergence regressions specified in equation (3) are estimated. In column (5) we start with a 10 year panel, but following Islam (1995), we also rerun the regressions at 5 year intervals in column (6), to check if this makes any difference. The OLS estimate of initial income in the 10 year panel is positive but insignificant. The RWLS estimate is positive and more precisely estimated, but is still a long way away from statistical significance. For the 5 year panel in column (6), the OLS estimate is negative, but again estimated too imprecisely to be taken seriously. The RWLS estimate is positive, and estimated somewhat more precisely, but is nevertheless statistically insignificant.

The panel estimates afford a larger number of observations than the cross-sectional

[16] Looking closely at the weights from RWLS reveals that Jammu and Kashmir (state==7) is down-weighted severely in the iterations, and is zero in the final estimate.

regressions. This allows us to use the Least Trimmed Squares (LTS) estimator, due to Rousseeuw and Leroy (1987), to check if there is any negative relationship between growth and initial income in the majority of the data, rather than in the entire sample. LTS minimizes the sum of squares over a fraction – say 70% – of the observations, the chosen fraction being the combination which gives the smallest residual sum of squares. Temple (2000) points out that LTS estimators are "*particularly well suited to an exercise such as a growth regression, where the idea is to learn about possible generalizations in the context of many disparate countries, some of which may be exceptions to the general pattern.*" The LTS estimator can be thought of as a robustness check as well. Since diagnostics like Cook's distance (used in RWLS) evaluate each observation separately, they might not be sufficient if pairs or groups of outliers exert undue influence but mask the influence of each other when testing for a single one. The LTS estimator is therefore particularly useful in the presence of multiple outliers or leverage points.

There are, however, drawbacks in throwing away 30% of one's sample. It is possible that LTS would omit 'good' leverage points – those which affect the precision of the estimated coefficients rather than the point estimates. Note that standard errors for the LTS estimates are obtained by bootstrapping the data, and should be interpreted accordingly. In addition, Temple (2000) mentions that in confining oneself to a part of the data which the model describes well, there is a danger that even a poor model would fit relatively well in the restricted sample. Keeping these drawbacks in mind, we will focus primarily on the sign of LTS point estimates, as a supplementary check on the results from the other estimation methods.

The LTS estimates of initial income are reported in columns (5) and (6). In both cases they are positive, and in terms of magnitude, they are similar to the cross-sectional estimates for the entire period in column (4). This is evidence that the majority of the data exhibit no trend towards unconditional $\beta-$convergence.

To sum up: the regression estimates provide no evidence of absolute $\beta-$convergence amongst the major Indian states between 1960 and 1992, regardless of the length of time-span examined. If anything there is slight evidence of absolute $\beta-$divergence, albeit based on a small sample of 16 states.[17] This conclusion is robust and contradicts previous work on unconditional convergence across Indian states cited above. A more tentative conclusion also seems to emerge from this evidence: unconditional convergence for regions within low-income countries – China (Jian *et al*,1996), Mexico (Juan-Ramon and Rivera-Batiz, 1996), and this study – seems at best, non-robust, and at worst, non-existent. This

[17] In Trivedi (2000), I have also checked for unconditional convergence in an expanded sample of 24 states based on an alternative dataset which contains comparable incomes data between 1980 and 1995. This sample includes the 4 of the smaller North-Eastern states, Himachal Pradesh, and the former Union Territories of Delhi, Goa, and Pondicherry. For the sake of brevity the results are not reported here, but even in this expanded sample there is no evidence of absolute $\beta-$convergence.

is unlike the case of US states (Barro and Sala-i-Martin, 1992), Japanese prefectures, or European regions, (Barro and Sala-i-Martin, 1995), or indeed regions withing Spain (de la Fuente, 2002), for which there is clear evidence of unconditional convergence.[18] However, this should not be pushed too far, because the studies on the US, Japan, and Europe, (but not Spain), use longer spans of data than the studies on Mexico, China, and this current work on India.

TABLE I: UNCONDITIONAL CONVERGENCE (1960-90)

Dependent Variable: Growth Rate of Real State PerCapita Income

	Cross-Section				Panel	
	(1)	(2)	(3)	(4)	(5)	(6)
	1960-70	1970-80	1980-90	1965-92	10 year	5 year
Initial income (OLS)	-0.041	0.008	-0.008	0.020	0.004	-0.005
	(-1.11)	(0.66)	(-0.80)	(3.18)	(0.33)	(-0.33)
Initial income (RWLS)	0.002	-0.001	-0.005	0.024	0.014	0.009
	(0.07)	(-0.07)	(-0.38)	(4.30)	(1.24)	(0.65)
Initial income (LTS)					0.018	0.029
					(0.86)	(1.61)
Number of Observations (NT)	15	16	16	16	47	95
RMSE (OLS)	0.021	0.015	0.015	0.004	0.021	0.040
RMSE (RWLS)	0.019	0.012	0.015	0.004	0.019	0.036
Minimum Weight in RWLS	0	0	0.48	0.30	0.001	0
Number of Observations (70%) that determine LTS estimates	na	na	na	na	33	66

Notes: t-statistics are reported in parentheses. For OLS estimates, t-statistics are computed using heteroscedasticity corrected (Huber/White/Sandwich) estimates of standard errors. For LTS estimates, t-statisics are based on Bootstrapped standard errors (using 1000 replications).
RMSE is the Root Mean Square Error. Constants not reported.

3.3 Conditional Convergence

Much cross-country work has documented the presence of conditional convergence, i.e. poorer countries growing faster only after variables that determine the steady state level of output have been controlled for. Based on early cross-sectional work a convergence rate of 2% was given much credence (Barro and Sala-i-Martin, 1995). Later panel data studies

[18] One explanation for this could be that greater diversity in economic, social and political characteristics and institutions obtains within regions of large developing countries such as Indian states, in comparison to developed countries. The assumptions that generate unconditional convergence in models like Solow (1956) – such as similar preferences and technologies, as well as basic institutions – are more likely to be true in more developed countries.

have reported convergence rates well in excess of 10%.[19] In the Indian context Nosbusch (1999) and Nagaraj, Varoudakis and Veganzones (1998) report evidence of conditional convergence across states. Nosbusch (1999) is an attempt at fitting the textbook Solow model to state-level data in India, with the savings rate, population growth, and depreciation as the right-hand side variables. It reports high rates of conditional convergence – ranging from 7% in a regression without human capital, to 36% in a regression with human capital. Nagaraj *et al* (1998) study the period betwen 1970 and 1994 and find systematic evidence of conditional convergence, with rates varying from 18% to 48%. Their study emphasizes inter-state differences in various types of social, economic and physical infrastructure, and on whether these can explain differences in inter-state growth rates.[20]

Testing for conditional convergence involves introducing variables which might determine the steady state to the right hand side of the previous regressions. What variables a particular researcher chooses to include in the vector x depends on economic theory, *a priori* beliefs about the growth process, and data availability. The data availability constraint is especially binding when working on a panel of states within a low income developing country. Missing values occur quite often, in particular, in the case of Jammu and Kashmir. Hence in the conditional convergence regressions reported in table 2, the state of Jammu and Kashmir is dropped from the sample under estimation.

Since the aim of this paper is to look for forces of convergence in the data, and not to test a particular model of convergence, a good place to start thinking about the conditioning variables is a robustness study. In the baseline specification used to test robustness of the many different variables found in the empirical growth literature, Levine and Renelt (1992) choose the initial level of income, the investment rate, the secondary school enrollment rate, and the rate of population growth. In his study, Sala-i-Martin (1997) chooses the initial level of income, life expectancy and primary school enrollment rate at the start of the period. Life expectancy is used to proxy for non-educational human capital, while school enrollment is used to proxy educational human capital. Initial income captures the conditional convergence effect. According to Sala-i-Martin (1997), these variables have certain properties that make them the appropriate benchmark to test against: *"...they have to be widely used in the literature, they have to be...evaluated at the beginning of the period...to avoid endogeneity, and they have to be...somewhat 'robust' in the sense that they systematically seem to matter in all regressions run in the previous literature."*

Following from this, we use the infant mortality rate and the high school school enrollment rate to proxy for non-educational and educational human capital.[21] The other

[19] For example, Caselli, Esquival, and Lefort (1996).

[20] A key difference between Nagaraj *et al* (1998) on the one hand, and Nosbusch (1999) and this paper on the other, is in our use of price deflators which vary across states as well as over time. This is important in view of the subcontinental dimensions of India.

[21] The reasons for the choice of these particular proxies are explained in detail in Trivedi (2002). In

obvious variable to include in order to control for study of steady-state incomes is physical capital. Unfortunately, there is no good capital formation data available at the state-level in India, until very recently. Hence, we use a principal components measure of physical infrastructure based on two series on energy production (installed capacity and generation), one series on energy consumption (high voltage electricity consumption by industry), and one series on the length of state highways.[22] More details on the sources and construction of all these variables can be found in the data appendix.

A methodological concern which needs to be addressed at this stage relates to the possible endogeneity (or reverse causality) of the right-hand side variables in the conditional convergence regressions. Simultaneity is pervasive given the nature of most of the regressors utilized. For example, it is not *a priori* obvious whether school enrollment affects growth by increasing human capital in an economy, or if economic growth affects school enrollment by improving schooling resources. This may happen because better economic growth increases the amount of resources that can potentially be diverted to schooling.[23] Instrumental Variable estimation is an option if good instruments are available. In practise, however, it is notoriously difficult to find variables that are both highly correlated with the endogenous variables, and which could plausibly have been left out of the regression on growth in the first place. One solution lies within the panel set-up of the data, and involves using lags of the right-hand side variables, so that they are pre-determined with respect to the dependant variable. Many of the variables employed as determinants of either growth or the steady state income level, are likely to have their effect after a lag anyway. Given the dimensions of the panel and its reduced form, it seems sensible to use 5 year lags of the control variables. In the estimates reported below, an average of the value of the variable over the previous 5 years is computed and used as a regressor. This avoids randomness in the value of a given variable in any one of the previous 5 years from overwhelmingly influencing the estimated coefficients, and retains valuable information contained in the annual data.[24] So for a panel based on equation (1) for example, the first

brief, apart from census based literacy rates, which are measured across 10 year intervals, the high school enrollment is one of the most reliable measures of education available annually at the state level. The infant mortality rate is used because estimates of the commonly used measure – life expectancy at birth – are not available for states in India until after the 1970s.

[22] The statistical technique of Principal Components analysis is fairly standard, and explained in Dunteman (1989). It enables the combination of an original set of variables into a single variable which represents most of the variation in the original set.

[23] Note however, that this does not appear to be the case with Indian states. Richer states do not always spend more on education and social services in per capita terms than poorer states.

[24] It might be argued that even 5 years is too short a time span to fully partial out the effect of short term cycles and shocks. However, longer intervals will reduce T and therefore accentuate the familiar 'Nickell (1981) bias' in dynamic panel data models with fixed effects. In an ideal world, ($T \rightarrow \infty$), I believe, between 10 and 20 years might be an appropriate span.

two cross-sections in time with fixed effects will look like,

$$growth_{i,1960-65} = \gamma(income)_{i,1965} + \Sigma_{j=1}^{k}\pi_j \overline{x_{i,1955-60}^{j}} + \mu_i + \varepsilon_{it} \qquad (4)$$

$$growth_{i,1965-70} = \gamma(income)_{i,1965} + \Sigma_{j=1}^{k}\pi_j \overline{x_{i,1960-65}^{j}} + \mu_i + \varepsilon_{it} \qquad (5)$$

and so on. Such a specification rules out contemporaneous correlation between the right-hand side variables and the error term.

Column (1) of table II reports the OLS estimates of a regression of growth on initial income and the three control variables without the fixed effects, μ_i. The key result is that lagged income is now negative and statistically significant – evidence of conditional convergence. The speed of the convergence is approximately 5.3% a year. At this rate, it would take a state close to 13 years to get half way towards its steady state output.[25] Figure 2 shows the partial relation between growth and initial level of income, as implied by the regression in column (1).[26] In contrast to the lack of a clear pattern between growth and initial income in figure 1, it clearly depicts the conditional convergence effect. The graph also seems to indicate that the relation is not being driven by a few outliers. More rigorous confirmation of this fact is provided by the robust estimation procedures in columns (2) and (3) in the same table.

Of the other conditioning variables, the infant mortality rate has a statistically significant negative effect and physical infrastructure has a statistically significant positive effect on the steady state level, and hence on transitional growth. The education variable has a negative coefficient, but it is too poorly estimated to be taken seriously.

Column (2) provides the RWLS estimates of the same regression. There is very little difference in the OLS and RWLS coefficient estimates, and the standard errors are also roughly the same. The LTS estimates in column (3) are more instructive. They also confirm the presence of conditional convergence – in fact the bigger value of the coefficient on initial income suggests that when attention is restricted to the chosen 70% of the sample, the tendency towards conditional convergence is even more clearly apparent. However, the notable change from columns (1) and (2) is that the LTS estimate of high school enrollment is positive (but still estimated very imprecisely). Closer inspection of the

[25] This can be calculated by noting that the half-life, say t^*, of a variable growing at a constant negative growth rate (in this case λ), is the solution to $e^{-\lambda t^*} = 0.5$. Taking logs, $t^* \simeq \frac{0.69}{\lambda}$. Recall from equation (2) that in the vicinity of a balanced growth path, $\ln y(t) - \ln y^*$ evolves as

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

[26] The vertical axis on the graph plots the residual growth rate after filtering out the parts explained by all the explanatory variables other than initial income. The horizontal axis plots the corresponding residual element of initial income. The fitted line is from an OLS regression, and has the same slope and standard error (up to a degree of freedom adjustment) as the estimated coefficient and standard error from the regression in column (1) of table II.

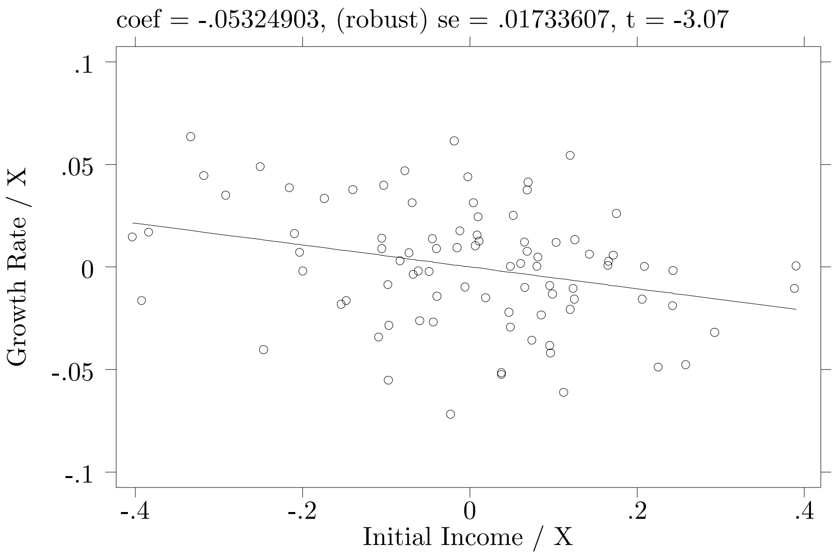

Figure 2: GROWTH RATE VERSUS INITIAL INCOME: PARTIAL RELATION FROM COLUMN (1), TABLE II

residuals from the LTS estimates reveals that all observations from Kerala (state==9) except one, had the highest residuals. Kerala is an atypical state, with exceptionally high levels of education, but with only an average level of income.[27] Re-estimating the OLS regression in column (1) without Kerala produces a positive and significant coefficient on high school enrollment (estimate=0.001, *t*-statistic=2.17), and leaves the sign and significance of the other estimates unchanged.[28]

Table II column (4) adds fixed effects to the previous specification. In the growth literature Islam (1995) was the first paper to clarify the use of the fixed effect in panel data estimation. It will capture the influence of any omitted variable that causes persistent differences in state-specific production functions. It can thus be thought of as controlling for initial conditions – resource endowments, climate, institutions and so forth. In principle, one could use Instrumental Variable estimation, but given the nature and scope of initial conditions and given that so many variables can be thought of as affecting economic growth, suitable instruments are unlikely to be easy to come by. Temple (1999) explains that the chief alternative is to use a fixed effects panel data specification:

[27] Between 1960 and 1992, Kerala had an average high school enrollment rate of 80.8% against an average of 41.3% for the entire sample. For the same period, its real per capita income was marginally below the sample average. For a more detailed analysis of Kerala's unique developmental achievements, see Drèze and Sen (1995).

[28] It is interesting – but not entirely unexpected – that since all Kerala observations were, in a sense, 'outliers' or 'influential', RWLS estimates, which evaluate each observation separately, were unable to correct for this.

"In the absence of a suitable proxy..., the only way to obtain consistent estimates of a conditional convergence regression is to use panel data methods. Since initial efficiency is an omitted variable that is constant over time, it can be treated as a fixed effect, and the time dimension of a panel used to eliminate its influence."

Controlling for state-specific initial conditions raises the speed of convergence quite substantially in column (4). The negative coefficient on initial income goes up by a factor of three (compared to the corresponding OLS estimate without fixed effects in column (1)), and it is very significant. This increase is in line with previously reported results in the panel data literature – both cross-country and from India.[29] The coefficient on infant mortality is unchanged but is statistically significant only at the 10% level. On the other hand, the coefficients on physical infrastructure and high school enrollment increase in value, and they are both statistically significant. Figure 3 depicts the relation between growth and initial income from column (4), constructed analogously to figure 2. The bigger conditional convergence effect is apparent, and it does not seem to be driven by influential outliers. The fixed effects are not reported separately, but they are collectively significant. An F-test that all the fixed effects are equal to zero is rejected with a p-value of 0.003. This suggests that the process of $\beta-$convergence is impeded by persistent differences in initial conditions across states.

Columns (5) and (6) provide the robust regression estimates for the conditional convergence regression with fixed effects. Once again, the RWLS coefficient estimates are very similar to the OLS estimates, except that the standard error for the coefficient on the infant mortality rate is bigger. The LTS estimates emphasize the conditional convergence effect and the impact of physical infrastructure relative to the OLS and RWLS estimates.[30] Overall, conditional $\beta-$convergence is a robust characteristic of per capita income across states in India between 1960 and 1992.

To summarize this section, we have examined the twin hypotheses of conditional and unconditional $\beta-$convergence which flow from Neoclassical growth models like Solow (1956). By so doing, we have in large part answered an extememly important question about whether poorer states in India grow faster, on average. The empirical results presented here suggest that unconditional $\beta-$convergence does not obtain, and that this is a robust feature of the data. This reverses the findings and implications of some of the previous studies on regional convergence in India cited above. On the other hand, there is strong and consistent evidence of convergence once factors that affect steady-state levels

[29] See Islam (1995), Caselli *et al* (1996), and Nagaraj *et al* (1998) among others.

[30] Note that the bootstrapped standard errors calculated for the LTS estimates in column (6), table II, are much less reliable than those calculated elsewhere in tables I and II. This is because the bootstrapping algorithm in S-Plus encounters singularity problems on account of the fixed effects in this particular specification. Nevertheless, the resultant t-statistics are reported for the sake of consistency.

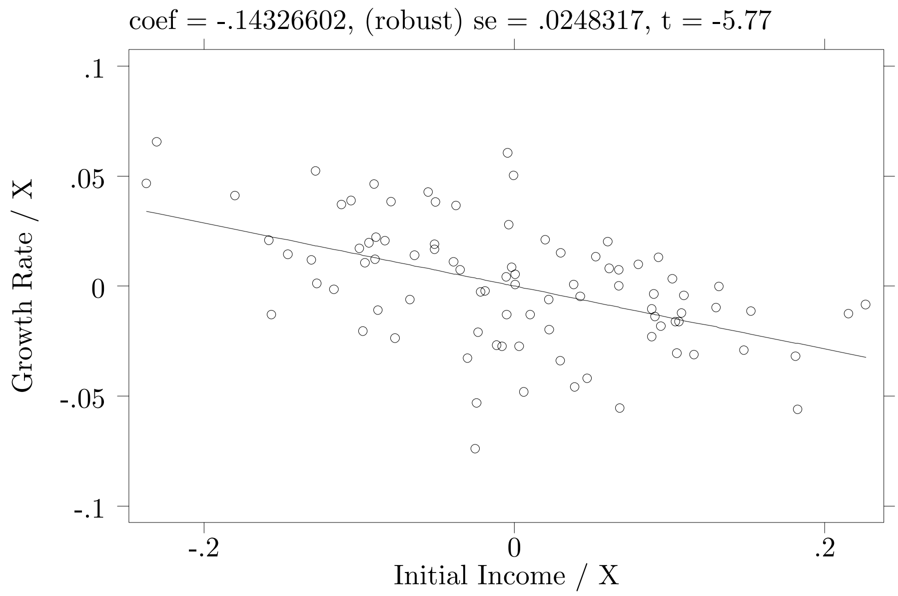

Figure 3: GROWTH RATE VERSUS INITIAL INCOME: PARTIAL RELATION FROM COLUMN (4), TABLE II

of income are controlled for. These include proxies for educational and non-educational human capital, physical capital, and initial conditions. Poorer states do indeed grow faster than richer states in their transition phases, but they are growing towards differing steady states. Another key result is the high rates of conditional convergence – between 5 and 15 percent with different specifications.[31] This implies that the average time an economy spends to cover half of the distance between its initial position and its steady state ranges from 5 to 15 years. Given these relatively high speeds of convergence, many economies will usually be close to their steady states, and important differences in per capita income levels across states will mainly be explained by differences in their steady state values. Consequently, studying movements of income levels becomes especially significant to understand whether states are, in fact, catching up with each other or falling behind. In other words, one needs to understand how the cross-state income distribution is evolving over time.

[31] These estimates lie at the lower end of the range of estimates for conditional $\beta-$convergence recorded in previous work on India. In related work, Trivedi (2000) has reported higher rates of convergence – up to 25% – with a bigger set of variables controlling for steady-state levels.

TABLE II: CONDITIONAL CONVERGENCE

Dependent Variable: Growth Rate of Real State PerCapita Income

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	RWLS	LTS	OLS	RWLS	LTS
Lagged (t-5) income	-0.0532	-0.0551	-0.0754	-0.1433	-0.1442	-0.1642
	(-3.07)	(-2.77)	(-1.89)	(-5.77)	(-4.73)	(-2.54)
lagged (t-5) average infant mortality rate	-0.0001	-0.0001	-0.0002	-0.0001	-0.0001	-0.0002
	(-2.14)	(-2.25)	(-1.82)	(-1.81)	(-1.44)	(-1.34)
lagged (t-5) average high school enrollment	-0.0001	-0.0001	0.0003	0.0015	0.0015	0.0007
	(-0.29)	(-0.23)	(0.38)	(2.78)	(2.18)	(0.57)
lagged (t-5) average physical infrastructure	0.0138	0.0137	0.0103	0.0168	0.0173	0.0245
	(3.82)	(3.07)	(1.63)	(3.62)	(2.84)	(1.91)
constant	0.41	0.42	0.57	0.98	0.99	1.17
	(3.34)	(3.02)	(2.11)	(5.73)	(4.72)	(2.54)
fixed effects	No	No	No	Yes	Yes	Yes
Number of Observations (NT)	88	88	88	88	88	88
RMSE	0.029	0.030	na	0.027	0.028	na
Number of Observations (70%) that determine LTS estimates	na	na	62	na	na	62
Minimum Weight in RWLS	na	0.37	na	na	0.03	na

Notes: t-statistics are reported in parentheses. For OLS estimates, t-statistics are computed using heteroscedasticity corrected (Huber/White/Sandwich) estimates of standard errors. For LTS estimates, t-statistics are based on Bootstrapped standard errors (using 1000 replications).
RMSE is the Root Mean Square Error.

4 Looking for $\sigma-$Convergence

4.1 Preliminaries

As noted above, conditional $\beta-$convergence does not necessarily imply that states are actually coming closer together in terms of levels of income. In fact, even if we had found unconditional $\beta-$convergence between states in India, this would imply convergence in levels of income only in the complete absence of any random shocks which might push states away from each other. Hence, a sensible way of thinking about the question of whether poor states are catching up with rich states over time, is to focus on the changing distribution of state incomes over time. This is the idea behind the notion of $\sigma-$convergence. So, in this chapter we examine the issue of catch-up and convergence by directly studying the cross-state distribution of levels of income.[32] In section 4.2, we start by examining

[32] The term '*distribution*' is used somewhat loosely here, and in what follows. With only 16 points at any given time, scepticism about the robustness of such a *distribution* would not be unwarranted. Surprisingly

Figure 4: STANDARD DEVIATION OF THE CROSS-STATE INCOME DISTRIBUTION, 1965-92

the dispersion of the cross-state income distribution over time. This gives us the first clear evidence of $\sigma-$divergence in the data. Evidence from kernel density estimates is also presented; and it is shown that in fact, the cross-state income distribution is characterized by persistence, catching-up, and falling behind, all at once, even as the distribution as a whole spreads out over time. In section 4.3, an important qualifications to these findings of increased income disparity is provided. By weighing state incomes by their respective populations, it is shown that an upward trend in individual income inequality is most clearly evident only after the mid-1980s.

4.2 How is the Cross-State Income Distribution Evolving over Time?

A straightforward way to check for $\sigma-$convergence is to look at the standard deviation of the cross-state income distribution over time. Figure 4 plots the standard deviations from 1965 to 1992 of the log of real state per capita incomes across all the 16 states. Apart from a brief period in the late 1960s and in the first half of the 1980s, there is a discernible increase in the cross-state income dispersion, which looks set to continue into the 1990s. This is a sign of $\sigma-$divergence. However, from figure 4 it is not clear what states are driving this increase in dispersion – are these states at the core or the periphery of the cross-state distribution?

however, studying the cross-state income spread yields some interesting and consistent insights even for this small sample.

Figure 5 depicts a series of Tukey Box Plots for the sample of 16 states.[33] In constructing these box plots a *normalized* measure of income is used in order to facilitate comparison.[34] The figure shows that the upper and lower adjacent values in 1991 are much further apart relative to say, 1966, indicating the increased disparity between the richest and poorest states. The key insight from this figure is that the inter-quartile range (the middle 50% of the cross-state distribution) has only moderately widened between the 1960s and the 1990s. This suggests that most of the work – in terms of the increasing standard deviation over time shown in figure 4 – is being done by states at the extremities of the income distribution. States such as Punjab (state==15) at the top end, whose outlier-ness is evident in the figure, and Bihar (state==3) at the bottom of the income distribution are responsible for much of the increased cross-state income inequality.

In figure 6 we move from analyzing the moments of the cross-state income distribution over time, to looking directly at the distribution itself. Using the semi-parametric Epanechnikov kernel, we estimate the cross-state income distribution in 1966, 1976, 1981 and 1991.[35] Following the convention in the literature, the bandwidth is calculated 'optimally'.[36] For the kernel density estimates we do not use the normalized income measure because it is interesting to visualize if the country-wide income distribution shifts to the right over time. In fact, this is the first thing we notice – that, on average, incomes in all states have increased over time. The second striking feature is the spreading out of the distribution – although this is not unexpected given the evidence in figure 4. In figure

[33] The box in the middle of each box plot describes the central tendencies of a distribution. The thin line inside the box is the median; the top and bottom lines of the box are the 75th and 25th percentile respectively. The rays emanating from the box reach the upper and lower adjacent values. If the inter-quartile range is r, then the upper adjacent value is the largest income value observed no greater than the 75th percentile plus $1.5 \times r$. The lower adjacent value is similarly defined, extending downwards from the 25th percentile. From a purely statistical perspective, observations that lie outside the upper and lower adjacent values might be considered outliers.

[34] This *normalized* measure of log state real income per capita is calculated for each state i for any given year as follows

$$\log\left(\frac{\text{MA of real per capita income of state } i}{N^{-1}\Sigma_{i=1}^{N}\text{real per capita income of state } i}\right)$$

where N is the total number of states in the sample.

[35] Some researchers, for example Sala-i-Martin (2002), use the Gaussian kernel. I also estimated all the densities with the Gaussian kernel, and the identical bandwidth. The results were almost identical, and so are not reported here. In any case, for most purposes the choice of kernel is not as important as the choice of bandwidth.

[36] The 'optimal' bandwidth is calculated using the formula

$$bw = \frac{0.9m}{n^{\frac{1}{5}}}$$

where

$$m = \min\left(\sqrt{variance_x}, \frac{interquartile\ range_x}{1.349}\right).$$

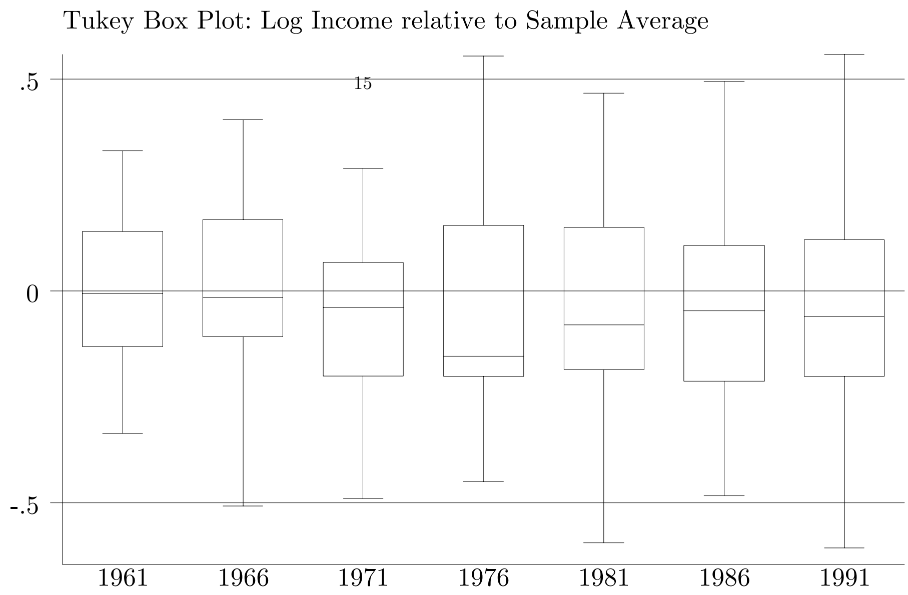

Figure 5: DISPERSION OF THE CROSS-STATE INCOME DISTRIBUTION

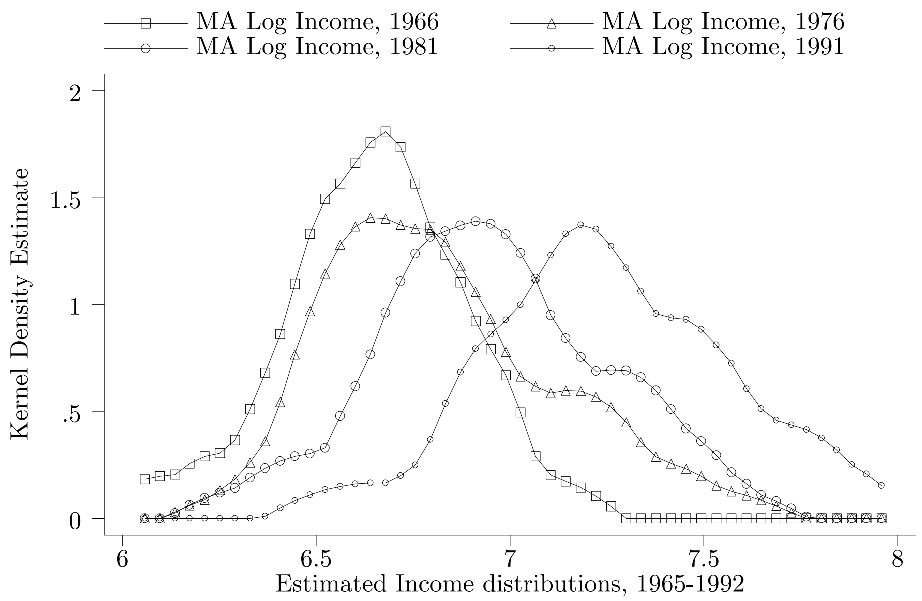

Figure 6: KERNEL DENSITY ESTIMATES OF THE CROSS-STATE INCOME DISTRIBUTION

6 it can be seen that the distribution becomes fatter over time, and the 'primary' mode of the distribution has become smaller. This is evidence of the increased dispersion or polarization within the cross-state income distribution. The third point of interest is the possible emergence of a second mode in the distribution towards the high income end. This is most obviously visible in the density estimates of 1976 and 1981.[37] In 1991, even with the second mode, the right tail is considerably fatter. Overall, this suggests that at least part of the $\sigma-$divergence that we have documented so far can be attributed to an emerging multimodality – perhaps because a small group of states at the higher end of the income distribution is pulling away from the rest.[38]

Closer analysis of the income distribution reveals the identity of this *elite* group of states. Between 1965 and 1992, the two agricultural powerhouse states Punjab (state==15) and Haryana (state==5), along with the industrialized Maharashtra (state==11) have been consistent members of the top 25% of the income distribution.[39] In the same period, these are the only 3 states in the sample which have clocked a growth rate in excess of 3%. That these rich states have grown as fast, and on occasion faster than the sample average, has ensured that their place at the top of the income distribution has been maintained, and may be one of the key reasons why we found little evidence of unconditional $\beta-$convergence in the last section.

However, this picture of the rich growing richer is by no means the whole story. West Bengal (state==21) was the richest state in 1960, but by the early 1990s it had fallen behind to sixth position in the income distribution. The two states which had edged ahead were Gujarat (state==4) and Tamil Nadu (state==18). Gujarat had been an early favorite – an above average industrialized state, geographically contiguous to Maharashtra (state==11) and renowed for its entrepreneurial workforce – it grew especially rapidly in the 1980s and 1990s in a more liberal industrial policy environment. By contrast, Tamil Nadu overtook West Bengal in terms of levels of income only in the early 1990s. In fact, Tamil Nadu (state==18) is one of a group of three southern Indian states which grew extremely rapidly in 1980s and continued growing strongly in the 1990s. For example in the decade of the 1980s, per capita income in Karnataka grew by 3.5%, in Tamil Nadu by 4.5%, and in Andhra Pradesh at the relatively dizzying rate of 5%. Consequently, all three states are, as of the mid-1990s, firmly ensconced in the top half of the cross-state income distribution. Together, Andhra Pradesh (state==1), Karnataka (state==8) and Tamil Nadu (state==18) constitute the best evidence of convergence or catch-up that we

[37] Bandyopadhyay (2001) documents the existence of twin-peaks in income in her study of distribution dynamics across Indian states for a similar time period.

[38] The possible multimodality in figure 4 is almost surely understated. It is well known that the 'optimal' bandwidth oversmoothes the density estimates in case the underlying true density is highly skewed or multimodal. (Pagan and Ullah, 1999, ch.2).

[39] In fact, using additional data on incomes between 1980 and 1996 (used in Trivedi (2000)), it is possible to confirm that these trends persist at least until 1996.

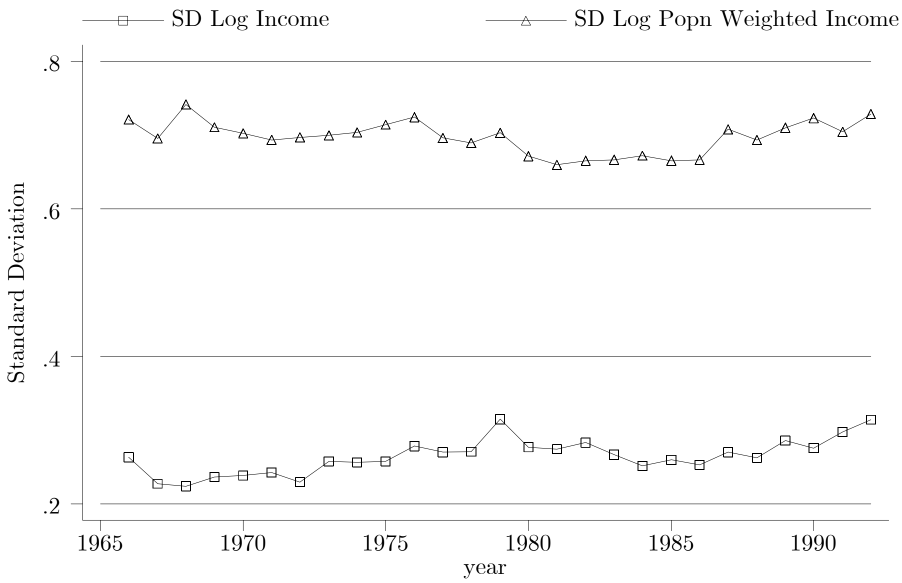

Figure 7: STANDARD DEVIATION OF THE CROSS-STATE INCOME DISTRIBUTION (RAW AND POPULATION WEIGHTED)

see in this period.

4.3 The Population Qualification

Section 4.2 has documented the increasing income disparity between states over time. However, it would be erroneous to conclude, on the basis of this evidence, that individual income inequality has increased between 1960 and 1992. This is because the unit of comparison so far has been states rather than people. To move from making an analysis of inequality of income across states to drawing a conclusion about inequality of income across people is a complex research exercise, but it is possible to offer some preliminary insights based on some simple adjustments.

Figure 7 plots the standard deviation of the log of the population-weighted (real state per capita) income for the 16 states in the sample. For comparability, it also reports the unweighted measure shown in figure 4. The figure shows that in the standard deviation of the weighted measure, there is no clear upward trend over time, until about the mid-1980s after which the unweighted measure and the weighted measure seem to move together. (Note that no importance should be attached to the level of inequality shown in figure 7.) Since the population-weighted figure implicitly assumes that all individuals in a given state have the same level of income, it obviously understates the true level of individual income inequality. In fact, even the trend as an indicator of individual income inequality would be misleading if within-state income inequality changed significantly over time. If however, within-state income inequality did not change significantly over the period, then the movement in the standard deviation of the population-weighted measure of income would depict, more or less accurately, movements in individual income inequality.

At the all India level, there is some evidence that measured rural income inequality has fallen marginally between 1961 and 1992, but urban income inequality has not changed very much at all.[40] A very similar pattern also holds at the state level.[41] Hence, one can be reasonably confident about the trend movements in the population-weighted income measure. These suggest that the increasing cross-state income disparity between 1960 and 1992 did not lead to a corresponding increase in individual income inequality until 1985, after which there is a marked rise in both.

The dissonance between the standard deviation in the weighted and unweighted measures before 1985 can be partly explained by the convergence of the numerically important southern states, which was referred to earlier. Together, Andhra Pradesh (state==1), Karnataka (state==8) and Tamil Nadu (state==18) make up approximately 21% of the total (sample) population. On the other hand, the co-movement of the variance of the weighted and unweighted measures post 1985 appears chiefly to be the result of a 'growth collapse' in Bihar (state==3) post 1985. Between 1961 and 1985 per capita income growth in Bihar was 1%. However, between 1985 and 1992, per capita income in Bihar contracted by -0.7%. Since Bihar is an important state in terms of population – in the sample of 16 states Bihar alone accounts for approximately 11% of the population – once it starts falling off the graph after 1985 it induces an increase in the variance of both the weighted and the unweighted measures.[42]

5 Concluding Remarks

The stated aim of this paper was to provide a comprehensive empirical account of convergence and catch-up among the major states within India between 1960 and 1992. At least four important conclusions from can be noted from the empirical results presented. First, there is no evidence of unconditional $\beta-$convergence. In contrast to some previous studies we find no tendency for initially poorer states to grow faster. Different estimators were used to confirm that this finding is robust, in the sense that it holds across time periods,

[40] Drèze and Sen (1995) report that between 1960-61 and 1990-91, the Gini coefficient for rural income inequality has fallen from 33 to 28; while the Gini coefficient for urban income inequality has fallen from 35.6 to 34.

[41] Analyzing the state-level rural Gini coefficients reveals that of the all states, five had small statistically significant time trends, all negative. For the urban Gini coefficients, there were three states with small statistically significant time trends, two positive and one negative.

[42] Bihar's 'growth collapse' has continued well into the 1990s. Between 1990 and 1996, Bihar's State Domestic Product contracted by approximately -0.02%.

and is not sensitive to outliers or variations in sample size. An equally robust finding is the existence of conditional $\beta-$convergence. After holding constant proxies for educational and non-educational human capital, and physical capital, initially poorer states do converge faster to their differing steady-states. The addition of fixed effects reinforces the conditional convergence effect, and highlights the importance of initial conditions to the future growth experiences across states. A third conclusion is the finding of $\sigma-$divergence. Analysis of measures of dispersion and the shape of the cross-state income distribution, show that over time, state incomes are moving further away from each other. It also appears that a small group of states is pulling away from the rest, resulting in an incipient second peak in the income distribution, although this will only be completely clear as we get data for future years. The final conclusion cautions that the increased income disparities between states do not always imply increased personal income inequality in the whole country. However, the evidence does suggest that from the mid-1980s both kinds of income inequality might have risen.

These *overall* or *average* trends are instructive, but they are not the complete story. It is equally important and interesting to pinpoint what lies behind them. Throughout the paper, the analysis has tried to identify particular states which might be responsible, to a greater degree than others, for generating these aggregate patterns in the data. In so doing, we have uncovered examples of catching-up and falling behind within the income distribution, at the same time as movements towards greater polarization at both the extremities of the income distribution.

A Data and Sources

The data set covers the 16 major states of India, in most cases for a period of 32 years, between 1960 and 1992. Most of these states were reorganized along linguistic lines to currently specified boundaries in 1956,[43] and have existed as such until the year 2000.[44] In 1960 Bombay State was split into Gujarat and Maharashtra. In 1965-66 the core Punjabi Suba was split up into Punjab, Haryana and Himachal Pradesh; and data for both Punjab and Haryana commences in 1965 for most variables. Data on Jammu and Kashmir is patchy in the early years and in the early 1990s for most explanatory variables in the conditional convergence regressions of table II. Hence it is dropped from the sample under estimation for table II. Out of the 16 states, it is the smallest and not of special economic significance either. In this limited statistical sense, it is the least painful to omit. Table A-1 below provides a list of the states in the sample with the average per capita income, and the average annual growth rate of per capita income during the sample period.

[43] The States Reorganisation act, 1956, specified 14 states within the Indian Union. For more on the linguistic reorganisation of states in India, see Paul Brass (1990).

[44] In the year 2000, three of the states in the sample were bifurcated. Uttaranchal, Jharkhand, and Chattisgarh were carved out of Uttar Pradesh, Bihar and Madhya Pradesh, respectively.

Table A-1: Summary Characteristics (1960-1992)

State	State Code	Annual Growth rate of Real Per Capita Income	Log Real Per Capita Income	Population Weight in Sample
Andhra Pradesh	1	2.101	6.879	0.082
		[6.718]	[0.228]	[0.002]
Assam	2	2.319	6.791	0.027
		[6.936]	[0.225]	[0.001]
Bihar	3	0.568	6.435	0.106
		[10.208]	[0.175]	[0.002]
Gujarat	4	2.360	7.049	0.050
		[13.719]	[0.239]	[0.001]
Haryana	5	3.237	7.262	0.019
		[8.533]	[0.259]	[0.001]
Jammu & Kashmir	7	-0.986	6.920	0.009
		[11.706]	[0.234]	[0.000]
Karnataka	8	1.764	6.921	0.055
		[6.689]	[0.194]	[0.000]
Kerala	9	1.924	6.741	0.039
		[6.264]	[0.204]	[0.001]
Madhya Pradesh	10	1.185	6.711	0.078
		[10.839]	[0.214]	[0.001]
Maharashtra	11	2.083	7.134	0.095
		[7.199]	[0.254]	[0.001]
Orissa	14	1.475	6.751	0.040
		[12.802]	[0.206]	[0.001]
Punjab	15	3.226	7.432	0.025
		[6.286]	[0.255]	[0.000]
Rajasthan	16	1.505	6.653	0.050
		[14.494]	[0.172]	[0.002]
Tamil Nadu	18	2.023	6.890	0.075
		[10.096]	[0.248]	[0.004]
Uttar Pradesh	20	1.165	6.764	0.169
		[8.161]	[0.164]	[0.003]
West Bengal	21	0.928	7.079	0.083
		[6.794]	[0.173]	[0.000]
Total		1.638	6.894	0.063
S.D. overall		[9.587]	[0.318]	[0.0389]
S.D. between		[1.023]	[0.247]	[0.0401]
S.D. within		[9.537]	[0.213]	[0.0015]

Standard Deviations in parentheses.

A.1 Income/Growth

The two sources for the incomes data are

- Ozler, Datt, and Ravallion (1996): This data set compiles a consistent set of figures on incomes, price indices, population, *inter alia* for the rural and urban areas of India's sixteen major states spanning the period 1958-1992.

- *Estimates of the State Domestic Product,* Central Statistical Organization, various issues. Estimates after 1981 are from diskettes obtained directly from the CSO office, Sardar Patel Bhavan, New Delhi.

Real state per capita income is calculated in the following manner. A deflator is constructed using different price indices for agricultural labourers (SCPIAL1) and industrial workers (STCPIW1) by state and year from the Ozler *et al*(1996) data set, and by weighing them by the respective rural and urban population shares (POP1 and POP2). The population data comes from the decennial census estimates. Between any two censuses it is assumed to grow at a constant rate of growth derived from the respective population totals. Like almost all other variables in the paper the deflator is also time-varying and state-varying.

$$deflator_{i,t} = \frac{\text{POP1}}{\text{POP1+POP2}} \times \text{SCPIAL1} + \frac{\text{POP2}}{\text{POP1+POP2}} \times \text{STCPIW1}$$

Estimates of the Net State Domestic Product (computed at factor cost and current prices) for each state and all sectors and year are then divided by the total population and the deflator to obtain consistent estimates of real state per capita income. Growth rates are calculated by taking log differences of the real state per capita income, and divided by the number of intervening years.

A.2 Education Measures

High School enrollment data comes from the serial publication, *Education in India,* Department of Education, Government of India. The data relates to boys and girls between 11 and 14 years of age. The enrollment rates are calculated as the percentage of students enrolled in classes $6-8$ to the estimated child population in the age group 11 to 14. Schooling in this age group is sometimes also categorized as 'upper primary'.

A.3 The Infant Mortality Rate

Data on infant mortality rates from the Sample Registration Survey (SRS) was collected from various issues of the *Sample Registration Bulletin,* Office of the Registrar General, Government of India; and from Bose, A., *India's Basic Demographic Statistics: 177 Key*

Tables with Graphics, 1996. Data on infant mortality rates from the Civil Registration (CR) sample is taken from various issues of the publication, *Vital Statistics of India,* Office of the Registrar General, Government of India.

In India, vital statistics are recorded under two alternative systems: the Civil Registration system (CR) and the Sample Registration System (SRS). Civil Registration data are severely deficient primarily due to incomplete coverage, the extent of which varies in different states. In contrast, the SRS is a reliable dual record system which became operational in 1969-70, covering about 3700 sample units.[45] The number of sample units has been increasing over the years. As of 1995 it stood at 6300 sample units covering well over 2 million people. The SRS estimates are far more accurate than the CR estimates, but the CR estimates have the advantage of being available before 1970. Fortunately, since data from the CR sample are available even after the commencement of the SRS, it is possible to infer the degree of inaccuracy in the CR data for different states.[46] Comparing birth and death rates from the two samples in 1988 reveals that the states with the biggest inaccuracies (more than 70%) are Assam, Bihar, Rajasthan, Uttar Pradesh and West Bengal.

A consistent series of the infant mortality rate is constructed by using a spliced series for the pre-1970 observations and using the SRS estimates for the post 1970 observations. This has the advantage of retaining the variation within the original CR data, while appropriately rescaling it to make up for the deficiency in sample coverage. The splicing is done separately for each state, via a scaling factor constructed as an average from the ratios of overlapping observations of CR and SRS data. West Bengal had the fewest number of overlapping observations (5), followed by Jammu and Kashmir, (7). All other state scaling factors were constructed with about 15 years of overlapping observations. There is thus little chance that randomness in any given year would affect the scaling factors and distort the data. Reassuringly, plotting the spliced pre-1970 series against the CR estimates reveals that the biggest adjustments are in states where the CR deficiency is the greatest.

A.4 Physical Infrastructure

The data on 3 electricity measures used to compute the index of physical infrastructure have been collected from various issues of the *Statistical Abstract of India* (SAI), pub-

[45] A sample unit in rural areas is a village or a segement of a village if it had a population of 2000 or more. In urban areas, a sample unit is a census enumeration block with a population ranging from 750 to 1000.

[46] In fact the official publication using CR data – *Vital Statistics of India* – routinely tabulates the ratio of vital statistics obtained via the CR system and SRS. The discrepancy is not minor. For example, in 1988 the infant mortality rate at the all-India level computed from CR data is 70% below the corresponding figure obtained from the SRS.

lished by the Central Statistical Organization (CSO), Department of Statistics, Ministry of Planning, Government of India.[47] The measures are:

- PEIPCAP: total installed capacity of electricity generation plants ('000s kilowatts);
- PEIPGEN: total energy generated (crores of kilowatt hours);
- PEIPINDH: sale of high voltage power to industry (crores of kilowatt hours).

Each measure is divided by state population to obtain a per capita number. In addition, the physical infrastructure index includes data on total state highways – PTIPSHW – taken from various issues of the SAI, CSO, Department of Planning, Government of India. The acknowledged primary sources change over the years – Ministry of Transport and Communications, Ministry of Transport, Ministry of Shipping and Transport, and finally, Ministry of Surface Transport.[48] I also collected data on Surfaced State Highways – PTIPSSHW – which are a subset of total state highways, and have the desirable feature of measuring both the quantity and quality of the roads infrastructure of states. However, since in the early part of the sample period there were few surfaced state highways to speak of, it is difficult to get a consistent series over the whole period. Hence we restrict attention to total State Highways,[49]

- PTIPSHW: length of total State Highways (km.) as a proportion of total state land area.

Missing values for each state, the bulk of which are in the early 1960s, are linearly interpolated using within state growth rates.

[47] The primary source until 1970-71 was the *Central Water & Power Commission,* Ministry of Irrigation and Power, Government of India. After 1971-72, the source is acknowledged to be the *Central Electricity Authority,* Ministry of Energy, Government of India.

[48] Highways appear to be strategically more important for the economy than conventional road networks. For instance, according to the CMIE (1998) report, *Infrastructure in India*, national highways constitute only about 2% of the total road network, but carry close to 40% of the total road traffic.

[49] In fact, the series on total state highways, PTIPSHW, and total surfaced state highways, PTIPSSHW, are highly correlated, with a correlation coefficient of 0.73. The worry in omitting to use PTIPSSHW was that we would not capture effectively the role of a state which while not expanding the total length of highways, channelled its resources into converting the existing unsurfaced highways into surfaced highways. On the whole, however, it appears as if states that do more to improve the roads infrastructure tend to do more of both.

TABLE A-2

Correlation Matrix of Physical Infrastructure Measures

	PEIPCAP	PEIPGEN	PEIPINDH	PTIPSHW
PEIPCAP	1			
PEIPGEN	0.976	1		
PEIPINDH	0.847	0.859	1	
PTIPSHW	0.570	0.586	0.538	1

Table A-2 is a correlation matrix of the infrastructure variables. One immediately striking feature is the very high pairwise correlation coefficients between the different electricity variables. This suggests that rather than including the different physical infrastructure variables in each regression, it might be preferable to construct one composite index of physical infrastructure which might proxy for the level of physical capital in each state. Hence, a principal components measure of physical infrastructure is constructed by combining the four infrastructure variables.[50] Table A-3 calculates the proportion of variation explained by each computed principal component, and it is clear that the 1^{st} principal component is massively dominant – it explains 81% of the sum of the individual variances of the infrastructure measures.

TABLE A-3

Eigenvalues and Explained Variance

Principal Component	Eigenvalue	Proportion	Cumulative
1	3.220	0.805	0.805
2	0.569	0.142	0.948
3	0.187	0.047	0.994
4	0.023	0.006	1.000

Moreover, since its eigenvector yields coefficient weights which are all positive, as reported in Table A-4, it is the principal component which can most easily be interpreted as a general measure of physical capital.[51] Rather serendipitously, the relative weights for each of the infrastructure measures are more or less equal in the first principal component: the lowest weight (0.40) for state highways is not that different than the highest weight

[50] The use of Principal Components is fairly standard in situations such as this – where the aim is to create an index which extracts the largest possible signal from a number of proxies. Lubotsky and Wittenberg (2001) have recently suggested that in large samples it can sometimes be preferable to simultaneously include all the proxies in the regression, and to combine the coefficient estimates *ex post*. However, in finite samples there is a trade-off between the increase in noise and the lost degrees of freedom from including too many proxies, and any increased precision gained by putting them all in.

[51] Principal Components is a statistical technique and so one should not put a strong theoretical interpretation on them, as such. However, one's theoretical priors would suggest that any principal component which is a serious candidate for representing a broadly defined measure of physical capital would be increasing in each measure of physical infrastructure, and would therefore assign positive weights to each measure.

(0.54) for electricity generation.

TABLE A-4

Eigenvectors and Factor Loadings

Principal Component	1	2	3	4
Variable				
PEIPCAP	0.535	-0.238	-0.432	0.686
PEIPGEN	0.539	-0.215	-0.368	-0.727
PEIPINDH	0.510	-0.247	0.823	0.035
PTIPSHW	0.403	0.915	0.023	0.017

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