Why Were Some Indian States So Slow to Participate in the Turnaround?

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In earlier research we identified the start of the growth turnaround in the late 1980s. This is consistent with the pattern of (particularly trade) policy liberalisation at the time. Since then there has been a remarkable improvement in per capita incomes. But a puzzle remains. The change in policy should have had a symmetric effect across India. Yet the participation of different states in the turnaround has been very uneven. In this paper we examine whether the relative size of shifts in growth across states could have been predicted from data on state characteristics, measured before the turnaround. We use the "robustness" techniques first proposed by Sala-i-Martin. As might be expected, higher initial literacy, urbanisation and access to ports all predicted stronger growth. But we also find that relatively high shares of both agriculture and registered manufacturing predicted weaker growth across all sectors of a given state, suggesting negative externalities. We guess, along with some other evidence, that this reflects the negative impact of state intervention.

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Introduction

In the past 25 years there has been a remarkable turnaround in Indian growth. From 1960 to 1987 output per capita in India (measured by real net domestic product[1]) grew at an average rate of only 1.3% per annum. On the same measure US output per capita grew at 2.4%, so that India and the US were steadily diverging. In marked contrast, from 1987 to 2011 Indian output per capita grew on average at 4.9% per annum, while US per capita growth slowed to only 1.2%. Thus in this more recent period India has been converging towards US output per capita levels, at a distinctly more rapid rate than it was diverging in the earlier period.

By 2001 India had regained all the ground lost, in terms of relative output, during the period of the "Hindu Rate of Growth", and since then has gained considerably more ground than it had previously lost. While concern has been expressed about some slowing of growth from the unprecedentedly high growth rates of the mid-2000s, provisional data for 2011-12 show that per capita income growth, at just over 5%, was still somewhat above its average over the past quarter-century. If India could sustain this growth rate, real income per capita would double roughly every 14 years.[2]

In an earlier paper (Ghate and Wright 2012) we presented evidence, derived from a large disaggregated data set, that the growth turnaround started around 1987. We showed that this pattern matched the time path of reforms (particularly trade liberalisation) much more clearly than had been found in previous research, which had mainly analysed aggregate data. The majority of states and the majority of sectors participated in the turnaround. However we also showed that participation in the turnaround at the state level was distinctly uneven. By the end of our original sample period, in 2004, a minority of states had shown little or no sign of a sustained pickup in growth. Several were still failing to converge on the global frontier. However, as we shall show, since the end of our original sample, even these lagging states had begun to participate in the turnaround – in at least one case, Bihar, dramatically so.

What explains this disparate performance of the major Indian states? In our earlier paper we provided some regression-based evidence that shed at least some light on the disparate nature of state participation in the turnaround, by finding indicators at the state level that appeared collectively to predict differences in growth rates across states. However while we found some evidence of collective predictive power, there was a limit to how much we could say about individual indicators using conventional regression analysis.

In this paper we supplement our earlier findings in two ways.

First, using our original data set, we provide evidence of the robustness of the relationship between individual indicators and participation in the turnaround. We follow a methodology originally suggested by Sala-i-Martin (1997) in relation to the econometrics of growth. The econometric literature on growth and convergence is now so massive that the number of potential regressors in cross-sectional regressions easily exceeds the number of countries that can be included, and hence far exceeds the number of regressors that can feasibly be included in any given growth regression. Thus in statistical terms we simply have too many explanatory factors. A similar problem arises in our data set: we wish to explain the range of experience across 15 states, but we have too many potential state-level indicators to isolate the effects of each of these in a single regression framework.

Following Sala-i-Martin's approach, we address this problem by running large numbers of regressions that differ according to the subset of potential explanatory factors that are included. We then examine the distribution of coefficients on individual state-level regressors in all such regressions. If a large part, or all, of the distribution of the resulting coefficients lies to the right (or left) of zero, we follow Sala-i-Martin in taking this as evidence that the indicator has a robust positive (or negative) relationship with the growth turnaround in individual states.

The second contribution of this paper is to provide a provisional assessment of experience since the end of our original data set, in 2004. Strikingly, several of the states that had not participated in the turnaround from the outset have grown much more rapidly in more recent data, such that, since 2004, all major states have been converging towards the global frontier. There is however still little sign of convergence between the states – an issue we shall revert to later in the paper.

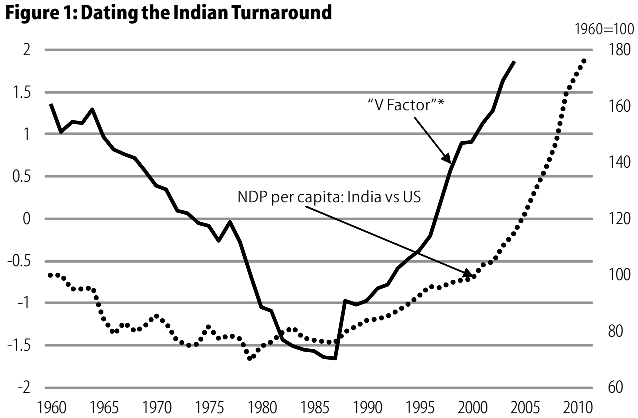
This recent pattern provides us with a rough-and-ready out-of-sample test of our techniques. We focus in particular on the experience of the four poorest states, and show that this more recent pickup in growth is broadly consistent with shifts in state-level indicators that we had found to be robust on our earlier data set: most notably, a falling dependence on agriculture, strong improvements in literacy, and a continuing trend to urbanisation. But we have to acknowledge that our available indicators still provide an incomplete explanation of the disparate experience of Indian states; we suggest that there is still plenty of scope for future research.

Dating the Turnaround

Figure 1 summarises one of the key findings of our earlier paper Ghate and Wright (2012, hereafter GW). It also illustrates nicely the contrast between our methodology for dating the turnaround and the findings of earlier research.

A number of earlier authors (see, for example, Rodrik and Subramanian (2005); Virmani (2006); Balakrishnan and Parameswaran (2007)) had identified what appeared to be a puzzle. Basing their analysis on aggregate data, they pointed to an apparent turning point in Indian output as early as the late 1970s. This feature is illustrated in Figure 1, which shows the ratio of India's real net domestic product per capita to the same series for the US (which we can use as a proxy for the global frontier), expressed as an index equal to 100 in 1960, the first year of our sample. This series shows clearly the long period of steady decline in relative incomes during the period of the "Hindu Rate of Growth", followed by a revival, which, as Figure 1 illustrates, resulted in a full recovery of lost ground by 2001, with the rate of catch-up accelerating thereafter.

Figure 1: Dating the Indian Turnaround



* Second principal component derived from 139 real net national product per capita series, disaggregated into 14 sectors and 10 major states.

The puzzle that Figure 1 also illustrates is that if we use the low point of this series to identify the date of the turnaround, it suggests a date of 1979 – well before any identifiable shift in policy.

In GW we used a different approach, based on a much larger data set[3] of up to 207 real output series, disaggregated both by 15 major states, and 14 industrial sectors.[4] To summarise the properties of such a large number of series, we used a "common factor" representation. Each of the individual output series is assumed to be driven by two factors that capture common long-term movements, plus an idiosyncratic component. We represent the *i*th output series, y_{it}, in period *t*, by

$$Y_{it} = \alpha_i + \beta_{iG}G_t + \beta_{iV}V_t + \omega_{it}$$

where G_t, the "G Factor" captures long-term growth at a rate which changes little throughout the sample. The second common factor, V_t, which we dubbed the "V Factor", captures shifts in the growth pattern. The remaining variation in each series is captured by an idiosyncratic component, ω_{it}.

To estimate the common factors we used the method of principal components as advocated by Bai (2004); and Bai and Ng (2004). The G factor and V factor are identified as, respectively, the first and second principal components of the data set.[5] For each individual series, the first "factor loading" β_{iG}, captures the long-term growth trend in the *i*th output series, via the G Factor. The second factor loading, β_{iV}, captures the impact of the V Factor. In GW we show, using panel unit root tests, that the remaining variation in each series, captured by ω_{it}, appears stationary, implying that the two factors do capture the key long-run properties of each series.

Figure 2: Growth in Per Capita Real NDP, by State

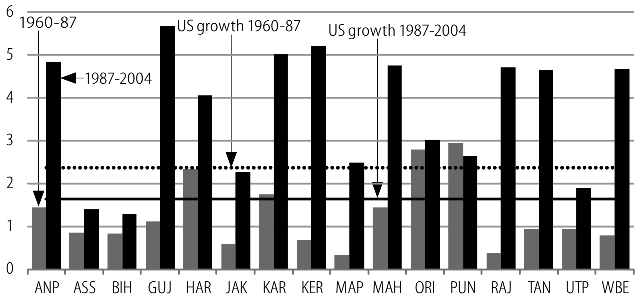


Figure 1 illustrates the time profile of the V Factor.[6] It captures both the period of relative decline of the "Hindu Rate of Growth", from 1960 to the mid-1980s, and the subsequent turnaround. However Figure 1 also illustrates a key contrast with the other series, the ratio of Indian to US output at an aggregate level. As noted above, this has a low point in 1979, whereas the V Factor reaches a minimum considerably later, in 1987.

How can we reconcile our results with those from past research? Basu (2008) notes the crucial role of a single year, 1979 in affecting inferences based on aggregate data, largely due to a sharp fall, then sharp recovery, in agricultural output. This year also shows up strongly in our disaggregated approach, however our results are much less affected by this particular year, since agriculture is weighted equally with all other sectors. As shown in Figure 1, our estimate of the V factor also shows a sharp fall in 1979-80; but then continues to fall, only reversing this decline in the second half of the 1980s. The later turnaround captured by the V Factor is thus representative of a shift that was much more pervasive throughout the economy. In GW we showed (see GW Figures 5 and 6) that the G Factor and the V Factor capture well a large part of the pattern of growth shifts both across states and sectors.[7] We also showed that the difference in timing in the turnaround is strongly statistically significant.[8]

The dating of the turnaround in the V Factor derived from disaggregated data resolves the apparent puzzle presented by aggregate data in earlier research. A turnaround in 1987 is very much more consistent with what we know about the historic pattern of reforms. In particular (see GW Figure 7) we showed that there was a strongly negative correlation between the V Factor and the average tariff rate, implying a particularly significant role for international trade liberalisation. This is also consistent with the narrative of trade reform in Pursell (1992) and Panagariya (2004). The mid-1980s also saw a significant relaxation in the "licence raj" (Aghion et al 2008). Thus, in contrast to earlier research, our results suggest that the timing of the growth turnaround is consistent with the timing of policy liberalisation.

Uneven Participation in the Turnaround

Given that the policy liberalisation was at a national level and the results summarised above also show strong evidence of a strongly pervasive change in the Indian economy, it might be expected that the response to this change would have had a fairly similar impact throughout India. However, Figure 2 summarises a key feature also identified in our earlier work, namely, the uneven nature of the growth turnaround across Indian states, at least in its early stages.

Figure 2 shows output growth in two sub-samples for the 16 major states, which collectively represent 97% of the Indian population.[9] We split our data sample at the point identified as the start of the turnaround at the low point of the V Factor, in 1987, as shown in Figure 1, and show growth rates from 1960-87, and from 1987 to the end of our original data set in 2004 (we discuss more recent developments below).

The chart displays very clear dividing lines, both across time and across states. They are most revealing if expressed in terms of convergence towards the global frontier, which we proxy by the US. Figure 2 also shows growth rates of the equivalent measure of US output per capita over the same sub-samples. Using this as the benchmark, only three Indian states, Haryana, Punjab and Orissa, showed any tendency to even marginal convergence in the first sub-period: they would be better described as just holding their own.[10] The remaining states were all growing less rapidly than the frontier – indeed some, like Madhya Pradesh, were barely growing at all – so that almost all were actually diverging systematically from the global frontier. (We have already shown, in Figure 1, that this was also the case for India as a whole.)

For the majority of states the contrast in the second period is very striking. Nine states (Andhra Pradesh, Gujarat, Haryana, Karnataka, Kerala, Maharashtra, Rajasthan, Tamil Nadu and West Bengal) had per capita growth rates in the neighbourhood of 4% to 5%, and were thus unambiguously converging towards the global frontier. Two others, Madhya Pradesh and Jammu & Kashmir, achieved significant shifts in growth, but from such a low base that they were still at best barely converging (partly due to a somewhat lower rate of growth in the US). In the remaining states, however, growth remained at a similar rate to that in the previous sub-period. Within this group, Figure 2 shows that three states, Punjab, Orissa and Uttar Pradesh did achieve modest rates of convergence; but Assam and Bihar continued to lose ground.

Predictors of State-wise Participation in the Turnaround: Previous Results

In our earlier paper we also used regression analysis to investigate the variation in state-wise participation in the growth turnaround.

We first ran simple cross-sectional regressions where the dependent variable is the change in the average growth rate of our 207 real NDP per capita series (again disaggregated by 15 states[11] and 14 sectors) between the two sub-samples 1970-87 and 1987-2004. If dummy variables for both individual sectors and individual states are included, both sets of dummies are strongly significant, both in combination and in isolation (for details, see GW Table 3). Thus differences between individual states are strongly statistically significant.

We then investigated whether identifiable state characteristics could have predicted this disparate performance across

Table 1 State-Level Indicators Included in Robustness Analysis

A	Solow/Malthus Indicators Real income per capita, 1987
	Population Growth, 1971-81
	Population Level, 1981
B	Climatic and Geographical Indicators Average rainfall, 1983-87
	Dummy for landlocked states (equal to unity for all series for Assam, Bihar, Haryana, Madhya Pradesh, Punjab, Rajasthan, Uttar Pradesh, and zero otherwise)
C	Social Indicators Urbanisation in 1981 (%)
	Literacy Rate in 1981 (%)
D	Composition of Output % Share of Agriculture, 1987
	% Share of Registered Manufacturing, 1987
E	Other indicators Development spending as % of output (1981)
	Aghion, Burgess, Redding, and Zilibotti's (2008) "pro-worker" dummy.

the states. We retained the sectoral dummies, but included 11 different state characteristics (all measured at or before the turnaround), in place of the state dummies.[12] The overall goodness of fit of the resulting equation barely differs from the regression with state dummies: that is, the state-level regressors jointly predict all significant variation in growth rates across states. However, we also showed (see GW Table 3, equation (4)) that most individual predictors in this regression are statistically insignificant. This is unsurprising since we have nearly as many regressors as states,[13] and the regressors are mostly quite strongly mutually correlated. Thus it was hard to say with any precision, from regression evidence alone, which state-level indicators are doing the work of explaining state-wise participation in the turnaround.

What Predicts State-wise Participation in the Turnaround? New Evidence Using Robustness Analysis

We now supplement the findings in GW by following a line of research first proposed by Sala-i-Martin (1997) in the context of growth regressions. When there is an excess of explanatory factors, regression analysis may produce many different specifications with a very similar degree of predictive power, but each with a somewhat different list of regressors. Sala-i-Martin proposed a resolution: simply estimate all possible regressions, each with a different combination of regressors, and then examine the properties of the coefficient estimates on different regressors, in all of the resulting regressions. If a given indicator turns out to have a notional significance level (as captured by the *p*-value, or a *t*-test of the null hypothesis that the coefficient is zero) that is consistently strong, and coefficients are all, or predominantly, of the same sign, then this indicator is deemed to be "robust". It should be noted that the significance level used is purely notional because the methodology is clearly not consistent with classical hypothesis testing; rather it should be viewed as a short-hand measure of predictive power.

We use this technique here to provide us with more information about the relative importance, and robustness, of different state-level indicators in predicting the extent to which different Indian states participated in the turnaround. We consider the same set of state-level indicators as in GW, all measured before or at the turnaround in growth, as shown in Table 1.[14] We discuss the rationale for each of these indicators below, in relation to the results.

As in our earlier work, each of the regressions carried out in this exercise again has as the dependent variable the change in the average growth rate of our 207 state-sectoral real NDP per capita series between the two sub-samples 1970-87 and 1987-2004. In each regression we also include dummies for each of the 14 industrial sectors. We then include five state-level regressors,[15] all measured in or before 1987. The first is the variable of interest. The second and third are always two "top tier" regressors: the shares of agriculture and registered manufacturing, since in GW we found these to be strongly significant. The remaining two "second tier" regressors are picked from the set of the remaining eight regressors. We then carry out a regression for every combination of two out of eight possible regressors: thus we run 28 regressions including each "second tier" indicator; and a total of 252 (28 times 9) regressions for each of the "top tier" indicators.[16]

Table 2 and Figure 3 (p 122) summarise the results of this exercise.

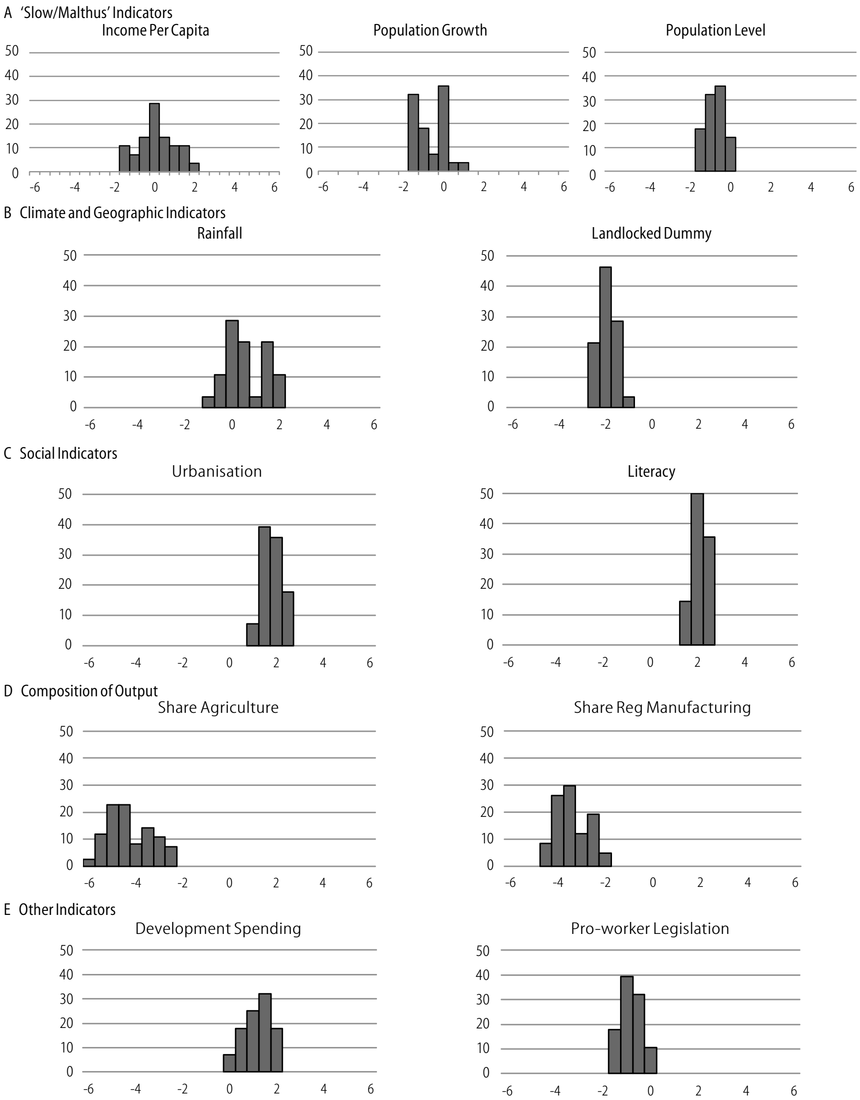
Table 2: Summary Properties of Coefficient Estimates*

Regressor	% Negative Coefficients	% Positive Coefficients	Impact on Growth of One Standard Deviation Difference in Regressor			t-statistics			Average CDF(0)**
			Minimum	Maximum	Average	Minimum	Maximum	Average	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Real state income per capita, 1987	61	39	-0.59	1.03	0.00	-1.75	1.59	-0.18	0.56
Population growth, 1971-81	93	7	-0.47	0.30	-0.24	-1.79	0.83	-0.86	0.76
Population, 1981	100	0	-1.12	-0.02	-0.39	-1.86	-0.08	-1.05	0.83
Average rainfall, 1983-87	43	57	-0.47	0.66	0.10	-1.33	1.94	0.33	0.41
Landlocked dummy	100	0	-0.93	-0.54	-0.78	-2.72	-1.47	-2.19	0.98
% urban population, 1981	0	100	0.25	1.19	0.66	0.63	2.47	1.57	0.07
Literacy rate, 1981	0	100	0.45	0.86	0.68	1.25	2.40	1.86	0.04
Share of agriculture, 1987	100	0	-2.58	-1.43	-2.05	-6.12	-2.76	-4.53	1.00
Share of reg manufacturing, 1987	100	0	-2.32	-1.15	-1.75	-4.92	-2.21	-3.64	1.00
Development spending, % of NDP, 1981	7	93	-0.13	0.56	0.29	-0.27	1.73	0.91	0.21
Aghion et al's pro-worker dummy	100	0	-0.50	-0.02	-0.33	-1.71	-0.04	-1.08	0.84

*The dependent variable in all regressions is the change in the average growth rate of our 207 state-sectoral real NDP per capita series between the two sub-samples 1970-87 and 1987-2004. Each regression also includes dummies for each of the 14 industrial sectors, and five state-level regressors. The table summarises the distribution of coefficients across all combinations of different regressors, as described in main text of the paper.

** Average across all regressions of analytical CDF(0), given coefficient estimate and associated standard error, assuming normality (see Sala-i-Martin 1997).

Figure 3: Robustness of State-wise Correlates of the Growth Turnaround (in %)
Frequency distribution of t-statistics of coefficient estimates across different regressions*



* Dependent variable in all regressions is change in average log growth in state-sectoral real NDP per capita between 1970-87 and 1987-2004.

Figure 3 plots the frequency distribution, for each of the potential explanatory factors, across all regressions including this indicator, of the *t*-statistic that tests the (notional) null hypothesis that the coefficient on this indicator is zero. Recall that, to a good approximation, in a classical hypothesis test, the null hypothesis is rejected at conventional significance levels if this statistic is greater than 2, or less than -2. Thus, if an indicator is robust, it will tend to have a high proportion of *t*-statistics that are (notionally) significant on this measure; and at a minimum will have all coefficients (and hence *t*-statistics) of the same sign. As noted previously, the *t*-statistics resulting from this exercise cannot be regarded as true hypothesis tests; presenting the results in this form simply allows easier comparability between different regressors. All panels in Figure 3 have the same range, again, to ease comparisons.

Table 2 provides a range of summary statistics of the distribution of coefficients in the regressions. Columns (1) and (2) show the percentages of coefficient estimates that are either positive or negative. When all, or the greater part, of the distribution lies to the left or right of zero, we follow Sala-i-Martin in taking this as evidence of robustness.[17]

As an indicator of the range of implied economic, as opposed to statistical significance of different regressors across different regressions, columns (3) to (5) standardise the results for different regressors by showing the impact on predicted growth of a difference in the regressor of one standard deviation across the cross section, using the average coefficient estimate, and the minimum and maximum value of the estimated coefficients (we provide some specific examples below). Consistent with Figure 3, columns (6) to (8) give the same information in terms of notional *t*-statistics.

Finally, column (9) follows Sala-i-Martin (1997) in deriving the average of the analytical cumulative distribution functions (CDF) evaluated at zero: i e, for any regression we calculate the (notional) implied probability that the associated coefficient is less than zero (assuming a normal distribution, hence using only the coefficient estimate and its calculated standard error). A number close to zero (or 1) implies a very low (or very high) notional probability that the coefficient is negative. A number close to 0.5 implies a roughly equal probability that the coefficient is positive or negative.[18] The figure shown is the average of these calculated probabilities across all regressions.[19]

The first panel of Figure 3 shows the results for the "Solow/Malthus" indicators often included in growth regressions, and provides a clear demonstration that these indicators are *not* robust explanatory factors of participation in the turnaround.

In a conventional growth regression, the initial level of output is expected to be negatively correlated with subsequent growth if there is convergence between the different output series.[20] The first plot in Panel A shows that, in contrast, in our regressions, the coefficient on output is more or less symmetrically distributed around zero. Thus, while these regressions provide no evidence in favour of systematic convergence between the Indian states, nor do they provide evidence of divergence. This feature can also be inferred directly from the disparate performance of both rich and poor states illustrated in Figure 2. For example, Maharashtra, a rich state, and Rajasthan, a poor state, both saw sharp increases in growth, while Punjab (rich) and Bihar (poor) both showed barely any shift in growth.

Figure 3 shows that there is a similar lack of robustness in the evidence for a role for population growth, as would be implied by a conventional Solow growth model, with coefficients again of both signs, depending on the specification of the regression. There is somewhat more evidence, albeit still very weak, for a role for the *level* of the population; but, while the coefficient on population is always negative (indicating that states with large populations tended, other things equal, to have a below-average shift in growth), only a small proportion of the associated *t*-statistics are even close to being notionally significant. Table 2, column (3) shows that the lowest *t*-statistic in all the regressions is -1.86, and column (5) shows that the average estimated impact on growth across all regressions is also quite small in economic terms.

Panel B of Figure 3 shows a more mixed picture for the very limited indicators we have of geographical and climatic characteristics. While there is no evidence for any robust relationship between the growth turnaround and rainfall (as a proxy for exogenous factors affecting agriculture in particular) there does appear to be a reasonably robust negative relationship with a simple dummy variable that is equal to one if a state is landlocked, and zero otherwise. Given the evidence we reported above from GW that the timing of the turnaround matches the timing of trade liberalisation measures, it is perhaps unsurprising that states with less easy access to ports may have been at a disadvantage, at least initially, in reaping the benefits of trade liberalisation.

Panel C of Figure 3 shows that there is reasonably robust evidence that both social indicators, urbanisation and literacy rates, were positively correlated with participation in the turnaround. For both indicators, Table 2 shows that coefficients were always positive; and there was a reasonably high proportion of notionally significant coefficients, with *t*-statistics greater (although not much greater) than 2. The average estimated economic impact on growth of differences in literacy and urbanisation across states (shown in column (5)) is also non-trivial. These effects are consistent with a large body of international evidence that increases in both indicators are strongly associated with sustained pickups in growth.[21]

Panel D of Figure 3 shows that, as noted above, there is a much stronger evidence of robustness *and* explanatory power, for our two measures of the composition of state output. It shows that the sectoral shares of both agriculture and registered manufacturing in any given state's output before the turnaround were very strongly negatively related to their subsequent participation in the turnaround. Indeed Table 2 shows that this predictive power was not just statistically significant, but also implies quantitatively very significant predicted impacts on growth. Column (5) of Table 2 shows that, on the basis of the average coefficient estimate, a difference of one standard deviation (roughly 10 percentage points) in the share of agriculture between two states in 1987 implied a predicted difference in average growth rates between 1987 and 2004 of around two percentage points. The impact of the registered manufacturing share had nearly as strong a negative impact. Columns (3) and (4) show that, for both indicators, the range of estimated impacts across equations is relatively small.

Note that the negative impact of agriculture does not reflect any direct effect of the resulting high weight of agriculture in dampening growth of state NDP (given the relatively low growth rate of agriculture), since the regression results give each sector an equal weight. Rather it suggests that the mere fact that a state was predominantly agricultural was itself an obstacle to that state's participation in the turnaround in growth across all sectors. Nor does the negative predictive power of the registered manufacturing share reflect the relatively slow growth of that sector. In both cases high shares of the two sectors in a given state predicted weaker growth across *all* sectors of that state. This suggests that these sectors imposed a negative externality on growth in other sectors.

We can only speculate on what this (very strong) predictive power tells us. One possible explanation for the case of agriculture is that, in a state that is dominated by farming, productive resources – for example, infrastructure spending or free electricity – will tend to flow disproportionately into agriculture, and may in so doing act as an effective tax on other sectors. Thus if, for example, free electricity to farmers leads to power cuts, and these are more likely to happen in predominantly agricultural states, this will impose external costs on other sectors.

Role of Registered Manufacturing

At first sight, a more surprising feature is the negative role of registered manufacturing. Indeed this result directly contradicts those of Rodrik and Subramanian (2005). They posited that the impetus for the turnaround (which, it will be recalled, they dated significantly earlier) was a shift to a pro-business orientation, which they proxied in their regressions by the share of registered manufacturing in aggregate state-level data. Our results suggest that, far from having a positive effect on subsequent growth, a high share of registered manufacturing in any state just before our later estimated turnaround date actually appears to have had a significantly negative effect on growth in that state. This is clearly more striking than if it simply played no role at all.

Just as in the case of agriculture, we can again only speculate about the explanation for this apparent negative externality. A common feature of both sectors is that they were both relatively slow-growing. They were also both subject to considerably more extensive state intervention than was the rest of the economy. Panagariya (2004) makes the forceful point that even in recent years government intervention in registered manufacturing remains extensive. Our results suggest that, in both cases, a common pattern of state intervention and (at least by intent) preferential treatment of these sectors had negative knock-on effects in other sectors, which were stronger, the larger were the shares of agriculture and registered manufacturing. Viewed another way, our results suggest that in the rest of the Indian economy (predominantly services) there were *positive* spillover effects between sectors, that were stronger, the larger was the services sector.[22,23]

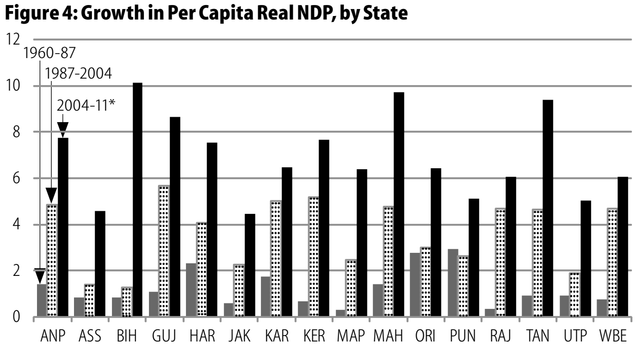
Finally, Panel E of Figure 3 provides further, if rather weaker evidence, of the – at best – mixed role of government intervention in impacting on any given state's ability to participate in the turnaround. It shows that there is very little evidence of any positive role for development spending in the turnaround: while coefficients are predominantly positive, they are, at very best, of marginal significance – both in economic and (notional) statistical terms.

At the same time there is somewhat stronger evidence that government intervention in the labour market, as in registered manufacturing, had a negative impact on growth. We proxy this using a dummy variable constructed by Aghion et al (2008), which captures in numerical form, based on a range of indicators, their subjective assessment of the extent to which labour legislation in any given state was "pro-worker". This dummy variable ranges in value from -2 (strongly pro-employer) to +2 (strongly pro-worker). While the results are not very economically significant for most states, they do suggest non-trivial impacts on growth for those states with extreme values of this indicator. Thus, our results suggest that, based on average coefficient estimates, the difference between, e g, West Bengal's value of +2 (strongly pro-worker) and Tamil Nadu's value of -2 (strongly pro-employer) lowered growth in West Bengal by around 1.3 percentage points. However, a clear caveat to this point estimate is that in a high proportion of regressions the impact of this indicator was much closer to zero.

Insights from More Recent Experience

One unintended consequence of the long lags involved in bringing academic research to final publication in a journal is that, very commonly, the data sets used are already more than a little out of date by the time the research is actually published. Our research is no exception. The full data set used in our original paper, and which we used to conduct the robustness exercise summarised in the previous section of this paper, runs only up to 2004. Subsequent growth performance (from 2004 to 2011) provides a natural out-of-sample cross-check on the results reported above. This test is all the more powerful, because the growth experience of the Indian economy in more recent years appears to have entered another phase.

Figure 4: Growth in Per Capita Real NDP, by State



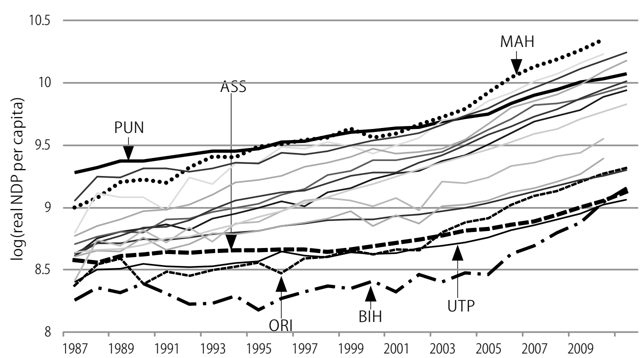
* 2004-10 for Gujarat, Maharashtra, Madhya Pradesh and Rajasthan.

Figure 4 supplements the information shown in Figure 2 above, to include data on growth rates of the 16 major states between 2004 and 2011. It shows that, in contrast to both earlier periods, in this more recent (albeit distinctly shorter) period, *all* major states have achieved sufficiently strong growth rates to put them on convergent paths relative to the US.

All states have also seen increases in growth, relative to the period 1987-2004, even those starting from a high base. Some increases have been very dramatic. Crucially, in terms of welfare, the four poor and slow growing states identified in our earlier sample period have all shifted towards strong growth in the most recent period. This is most striking in the case of Bihar, which saw an increase of nearly nine percentage points in its average growth rate, with the result that recent years have seen the striking, and unprecedented phenomenon of Bihar, until recently the poorest Indian state, growing more rapidly than the richest state, Maharashtra.

More generally, however, the fact that growth rates have increased across the board means that, despite the sharp increase in growth rates in the poorer states, the gap between rich and poor states has not in general been narrowing: indeed the cross-sectional standard deviation of output levels has actually increased somewhat. This should not in itself be surprising. Figure 5 shows that the states that were both poor and slow-growing during the period 1987-2004 (Assam, Bihar, Orissa and Uttar Pradesh) appear now (albeit only on the basis of seven years of data) to have shifted onto a strongly convergent path towards the global frontier. For three out of four of these states (the conspicuous exception, noted above, being Bihar) this higher growth has been at rates similar to

Figure 5: Per Capita Real Output in the 16 Major Indian States*



* All series are in logs, so that equal increases over time imply equal growth rates in percentage terms, irrespective of initial level. Note that we deliberately highlight only those states explicitly mentioned in the paper.

those seen by the faster-growing states in the earlier period 1987-2004. However, Figure 5 shows that a number of the previously faster-growing states have typically grown even faster in more recent years. Thus there is still no general tendency to convergence *within* India.

At the same time, as in the earlier period, there is also no general evidence of *di*vergence. For example, Figure 4 shows that Punjab, which in 1987 was still the richest Indian state, has had one of the weakest growth performances since the turnaround, and Figure 5 shows that as a result it has in recent years been overtaken by four other states.

In Fic, Ghate and Wright (2012) we offered an explanation of the earlier experience of the growth turnaround that also appears consistent with this more recent experience. In a standard convergence framework a rise in growth can in principle arise as a result of a shift in the long-run equilibrium level of output, or as a result of a more rapid rate of convergence to a given long-run equilibrium. The liberalisations from the centre that started in the late 1980s affected all states; hence we argued that they should in principle have affected long-run equilibrium levels of output largely symmetrically across the states. That being the case, other things being equal, we would have expected to see a symmetric participation in the turnaround. Figure 2, above, shows that this did not occur. We argued that this must have reflected a very disparate pattern of frictions in different states, which impeded some states from being able to participate in the process of convergence to a new equilibrium. The results of this paper suggest (with varying degrees of robustness) that states with lower shares of agriculture and registered manufacturing, higher literacy and urbanisation, and better access to ports, were better equipped to adjust towards the new equilibrium.

Are recent shifts in growth in this group of previously slow-growing poor states compatible with this argument? That is, have there been shifts (in the correct direction) in state-wise indicators that appeared in our earlier analysis to predict relatively stronger growth? On the basis of available state-level indicators, we can tentatively answer in the affirmative.

Our robustness results showed that the single-most important determinant of relative growth performance between 1987 and 2004 was the initial share of agriculture in any given state, with a high share of agriculture predicting relatively lower growth. Figure 6 shows that all four of the poor-and-slow-growing states had agriculture shares that were above (in some cases far above) the average of all major states. By 2004, in contrast all four states had, to varying extents, significantly reduced their dependence on agriculture, to levels well below the previous average. In Bihar, in particular, the shift away from agriculture has continued in more recent years.

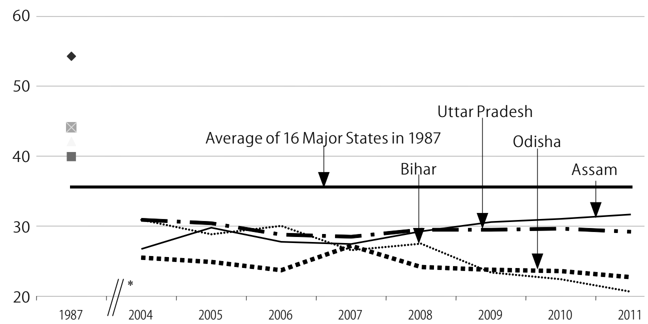
Figure 7 shows a similar pattern, with reversed sign, in literacy. In 1981, the last census before the turnaround, all four states had below-average rates of literacy. Since then literacy has risen strongly to levels well above the prevailing average across states in 1981. Figure 8 shows that, at least in three out of four states, there have also been steady increases in urbanisation, although all four states remain less urbanised than the average across states in 1981.[24]

Figure 9 shows that there is less of a clear-cut relationship with the share of registered manufacturing; but this is perhaps not entirely surprising, since the original result may well have been specific to the particular time period. But it is striking that all four states have managed strong growth with shares of registered manufacturing that have remained relatively small. Furthermore, Bihar, the most rapidly growing state in recent years, has achieved this growth with a still negligibly small share of registered manufacturing. Thus it is at least clear that registered manufacturing has had little or no *positive* role to play in the growth turnaround in these states.

The evidence of Figures 6 to 9 appears consistent with our results for the earlier period, in the sense that, on the basis of recent shifts in these indicators, all four states would have been predicted to have grown more rapidly, and have indeed done so. It also appears consistent with our arguments in Fic, Ghate and Wright (2012), that, these shifts have corresponded to reductions in frictions that had previously impeded convergence to a new long-run equilibrium.

While we cannot make excessive claims on this score, even the *relative* size of growth shifts in this group of states corresponds reasonably well with these recent developments. If (heroically) we assume all other state characteristics have remained unchanged, and (even more heroically) that the predictive model for growth over the period 1987-2004 is equally valid for this later period, then Table 3 shows that, if we plug in the changes in the four indicators summarised in Figures 8 to 9 into our equation, it explains the relative pattern of

Figure 6: Share of Agriculture (in %)



* Break in time axis

Figure 7: Literacy Rates

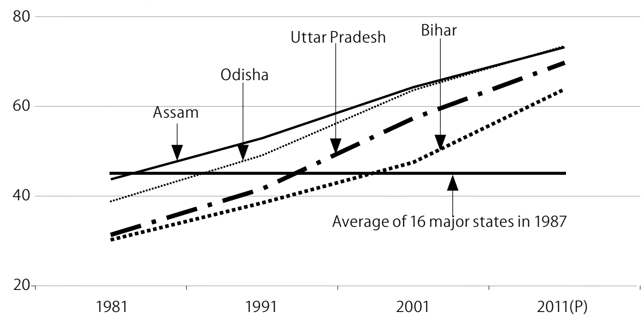


Figure 8: Urbanisation, Percentage of Population

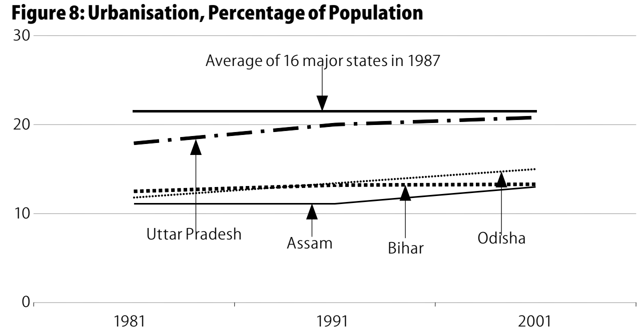
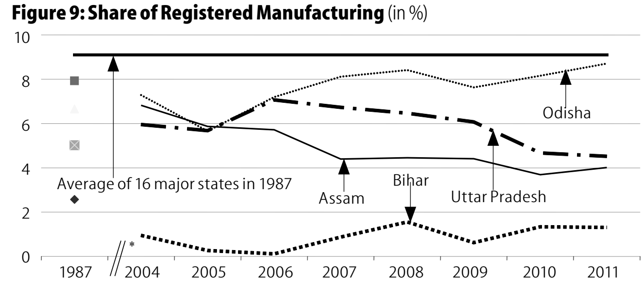


Figure 9: Share of Registered Manufacturing (in %)



* Break in time axis.

subsequent shifts in growth rates reasonably well – particularly the much stronger growth performance of Bihar.

The fit of these predictions is by no means perfect, but nor would we expect it to be. There are two major caveats to the above exercise. First, Table 3 uses average coefficient values from different regressions, which may not be strictly additive in their effects; second, the analysis solely relates to aggregate state figures, whereas our econometric results relate to the disaggregated data.[25] If the exercise were repeated on more recent disaggregated data, ideally with a larger data set of state-level indicators, this might tell us more about the relative success of different states in more recent periods, and might thereby give guidance on likely future performance. We would encourage other researchers to pursue these issues further.

Table 3: Predicted Impact on Growth of Shifts in Four Indicators*

Predicted Impact on Growth of Change in	Assam	Bihar	Orissa	Uttar Pradesh
Share of agriculture	2.7	4.8	3.8	2.3
Share of reg manuf	0.4	0.6	-0.9	0.3
Literacy	1.0	1.2	1.3	1.6
Urbanisation	0.3	0.1	0.4	0.3
Predicted impact of all four factors	4.4	6.8	4.7	4.4
Change in growth, 2004-11 vs 1987-2004	3.2	8.9	3.4	3.1

* Predicted impact on average growth of shifts in regressors between 1987 and 2004 (agriculture and registered manufacturing) and 1981-2001 (literacy and urbanisation) using average coefficient estimates from regressions summarised in Table 2.

Conclusions

In Ghate and Wright (2012) we used a disaggregated data set of state-sectoral real output per capita to identify a turning point in Indian output per capita around 1987. But we also noted the uneven participation of Indian states in the growth turnaround, at least up until the end of our data set in 2004. In this paper we have extended our earlier work on the same data set by using an approach suggested by Sala-i-Martin (1997) to test whether the relationship between a range of state-level indicators has a robust predictive relationship with participation in the turnaround, by examining the distribution of coefficients on a given predictor in a wide range of econometric specifications. Those predictors with coefficients all of one sign, and predominantly strong notional statistical significance, are deemed robust.

Both our negative and positive results using these techniques are revealing. On the negative side, we find no evidence either of convergence *or* divergence between the Indian states: thus participation in the turnaround appears to have been unrelated to initial income level. Nor do demographics appear to have played a role. But we do find strong evidence that states with a high share of agriculture participated less in the growth turnaround; in contrast higher literacy, urbanisation, and (a proxy for) access to ports all appear to have been helpful (albeit that the evidence for some of these characteristics, while unambiguous as to sign, is distinctly less strong in terms either of statistical or economic significance).

Our results suggest that the role of the state in the turnaround was at best ambiguous; indeed the balance of evidence (most notably that shares of both agriculture and registered manufacturing were both negatively correlated with participation in the turnaround) suggests a negative role. This seems consistent with our earlier findings that the timing of the turnaround appears strongly linked to liberalising policies.

Our full data set runs only to 2004. Since then participation in the turnaround appears to have widened significantly, most significantly in some of the poorest and previously slow-growing states. On the basis of partial evidence on state-level indicators for more recent years, this recent growth performance appears broadly consistent with our earlier results.

NOTES

1 Throughout this paper we use net domestic product as our measure of output since the longest and most consistent output measures for India at both state and sectoral levels are on this basis.

2 If US per capita income continued to grow at only 1% per annum, relative income levels would double roughly every 17 years.

3 All data used in this paper are taken from a new panel data set for Indian states assembled by the authors comprising roughly 200 regional economic and social indicators for Indian states. For a detailed description of the data set see Ghate and Wright (2008). The data set is downloadable from Stephen Wright's web page, http://www.ems.bbk.ac.uk/faculty/wright

4 Observant readers may note that, with 15 states and 14 sectors we should have had 210 series in all; however we had to discard three series due to clear data problems.

5 The first principal component is the linear combination which captures the largest proportion of the total variance in the data set; the second, which by construction is uncorrelated with the first, the largest proportion of the remaining variance.

6 The G Factor, not shown in the chart, is very close to being a straight line time trend: see GW Figure 4. Note that the estimated V Factor over the full sample illustrated here is derived from data for only 10 states, but from the same 14 sectors. In GW we also reported results from shorter samples, with larger numbers of states, as well as using the alternative methodology proposed by Bai and Ng (2004), which is robust to nonstationarity in the idiosyncratic components: results are very similar.

7 The first factor loading, β_{iG}, captures trend growth; the second, β_{iV}, captures participation in the turnaround. Given the time profile of the V Factor, illustrated in Figure 1, a positive value of β_{iV} for any given series implies that it grew more rapidly after the turnaround, a zero or (in a few cases) negative value implies it was unaffected, or even grew more slowly.

8 In the sense that if the true turnaround had actually been as early as 1979, there would have been a very low probability of identifying our turning point in 1987.

9 The sixteen states are: Andhra Pradesh (ANP), Assam (ASS), Bihar (BIH), Gujarat (GUJ), Haryana (HAR), Jammu and Kashmir (JAK), Kerala (KER), Karnataka (KAR), Madhya Pradesh (MAP), Maharashtra (MAH), Odisha (ORI), Punjab (PUN), Rajasthan (RAJ), Tamil Nadu (TAN), Uttar Pradesh (UTP), and West Bengal (WBE). We have made adjustments to output series to allow for changes in state definitions.

10 Of these three states, closer inspection of the data shows that the fastest growing state, Odisha, had shown extremely rapid growth during the 1960s, but thereafter showed no tendency to converge.

11 We were unable to include Jammu and Kashmir due to lack of data.

12 We cannot include a full set of both state dummies and state characteristics, since in a cross-sectional regression the resulting matrix of regressors would be singular.

13 Note that, despite the fact that we have 207 observations, the best we can possibly hope to do with state-level regressors is to match the explanatory power of the state dummies. If we had 15 indicators, we would be able to match precisely the fit of the regression with dummies. Even with only 11 indicators, the fit is virtually identical – indeed the R-Bar-Squared of the regression actually increases somewhat, due to the increase in degrees of freedom.

14 All data are again taken from the data set described in Ghate and Wright (2008).

15 Given the strong mutual correlations between our regressors, five regressors virtually always capture the great majority of the state-wise variation. For more than nine out of 10 such regressions the implied F-test of the restrictions against the equation with the full set of state dummies is not rejected at a notional 5% level, implying a consistently high degree of goodness-of-fit.

16 This is a rather modest number compared to the 30,856 regressions per indicator – two million in total – run by Sala-i-Martin.

17 We do not attempt to weight each regression by goodness-of-fit, but focus on the unweighted distribution. Ciccone and Jarocinski (2010) show that likelihood-based model averaging, as in, for example, Doppelhofer, Miller and Sala-i-Martin (2004), can lead to a very high weight being placed on a very small number of regressions. At least some of these problems had indeed already been alluded to in Sala-i-Martin's (1997) original paper, leading him to give more prominence to the unweighted coefficient distribution.

18 We differ slightly from Sala-i-Martin in our presentation of this statistic. For any calculated probability less than 0.5, he uses 1-CDF(0), rather than CDF(0), so that whereas our probability ranges between zero and 1, his ranges between 0.5 and 1. Thus in Sala-i-Martin's calculations, a figure close to unity implies a strongly robust indicator, irrespective of sign.

19 These figures should be viewed as useful summary statistics rather than anything resembling a true probability, given that (a) the true distribution may not be normal, and (b) we are, as noted above, a very long way from the classical hypothesis testing framework. Note that, given the non-linearity of the normal cumulative distribution function, any *t*-statistic greater than around 3 in absolute value implies essentially a zero probability that the true coefficient is zero.

20 Given that we also include sectoral dummies and other state indicators, a negative value would imply "conditional" convergence.

21 See, for example, Spence ed. (2008), and references therein.

22 All the regressions could be written in equivalent form in terms of a *positive* impact of the share of the remaining sectors of the economy, along with a negative impact of registered manufacturing (on which the coefficient in our regressions is systematically more negative than for agriculture). Note that in the last resort we are simply capturing features of the data. The pattern of regression coefficients matches the property that, for example, Kerala achieved a larger growth shift than Maharashtra, despite having a much larger agricultural sector, with the predicted impact of differences in agriculture being offset by the much larger share of registered manufacturing in Maharashtra.

23 Gupta and Kumar (2012) argue that key aspects of the Industrial Disputes Act, such as Chapter VB, apply to establishments (as defined in the Factories Act) in the manufacturing sector. In contrast, the services sector comes under the Shops and Establishments Act. They also suggest that there are no known cases in which the modern services in the organised sector have been affected by the application of labour laws. They write "Anecdotal evidence suggests that in the fast-growing modern sectors – IT, finance, and communications – labour is not unionised and labor unions do not even exist".

24 Note that while literacy figures are available on a provisional basis from the 2011 Census, the latest available figures for urbanisation are from the previous census in 2001. Note also that the urbanisation and literacy figures for Bihar in 2001 and 2011 are population weighted averages of the figures for Bihar and Jharkhand, to ensure comparability with earlier periods.

25 Thus even using the original data set and sample, with output disaggregated into states and sectors, the state dummies convey essentially the same information as the total effect of the state-wise indicators (by construction they cannot convey less). But there is by no means a perfect match between these state dummies in disaggregated data, and relative growth shifts in *total* state output.

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