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Why has economic growth been more pro-poor in some states of India than others?

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Abstract

We use 20 household surveys for India's 15 major states spanning 1960–1994 to study how the sectoral composition of economic growth and initial conditions interact to influence how much growth reduced consumption poverty. The elasticities of measured poverty to farm yields and development spending did not differ significantly across states. But the elasticities of poverty to (urban and rural) non-farm output varied appreciably, and the differences were quantitatively important to the overall rate of poverty reduction. States with higher elasticities did not experience higher rates of non-farm growth. The non-farm growth process was more pro-poor in states with initially higher literacy, higher farm productivity, higher rural living standards (relative to urban areas), lower landlessness and lower infant mortality. © 2002 Elsevier Science B.V. All rights reserved.

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1. Introduction

While cross-country comparisons indicate that measures of absolute poverty in developing countries tend to fall with economic growth, there is considerable variance in the poverty-reducing impact of a given rate of growth. For example, on studying successive household surveys for a set of developing countries, Ravallion and Chen (1997, Table 6) obtain a point estimate of (minus) three for the elasticity of the

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proportion of the population living below US$1/day (at 1985 Purchasing Power Parity) to the survey mean income or consumption. Their 95% confidence interval, however, goes from about 1 to 5. On further factoring in the variance in how much GDP growth translates into growth in average household incomes (Ravallion, 2001), one sees why a rate of growth that brings rapid poverty reduction in one country can largely leave the poor behind in another.

Why is growth more pro-poor in some economies than others? Answering this question with cross-country data raises many problems, including weak comparability of the primary data used for poverty measurement and the explanatory variables. This paper pursues an alternative route where we compare the evolution of poverty measures across major states of India, for which it is possible to construct a long time series of 20 reasonably comparable surveys spanning a 35-year period. We test for inter-state differences in the poverty impact of various sources of growth in India, and we try to explain the differences in impact.

There are clearly countrywide factors that have influenced growth and poverty reduction in India, and comparisons of experiences over time in different states cannot throw much light on those factors. However, the diverse experiences of these states in poverty reduction can illuminate one important question: are these diverse experiences mainly due to differences in the rate and sectoral pattern of economic growth, or are there important differences in the poverty-reducing impact of that growth? Conditional on finding the latter factor to be important, we further explore the extent to which differences in initial conditions at state level account for differing poverty-reducing impacts of economic growth.

We build on our past work on poverty in India. Consistent with cross-country evidence for developing countries, measures of absolute consumption-poverty in India tend to fall with economic growth (Ravallion and Datt, 1996). But one also finds that:

(i) the *sectoral composition of growth* matters to the aggregate (country-wide) rate of poverty reduction: the aggregate time series data for India indicate that poverty measures have responded more to rural economic growth than urban economic growth (Ravallion and Datt, 1996),[1] and

(ii) differences in *initial conditions* related to rural development and human resource development accounted for a sizable share of the long-run differences between states in rates of rural poverty reduction (Datt and Ravallion, 1998a).

However, initial conditions entered *additively* with growth in Datt and Ravallion (1998a); favorable conditions meant a higher rate of poverty reduction (by a fixed mark-up) at any rate of growth, but a given growth rate was deemed to have the same impact on the rate of poverty reduction whatever the initial conditions. Clearly, this type of

[1] "Rural (urban) economic growth" refers to growth in mean consumption in rural (urban) areas; Ravallion and Datt (1996) also find that "primary" and "tertiary" sector growth had greater impact on poverty than "secondary" sector growth. Thorbecke and Hong-Sang (1996) come to a similar conclusion for Indonesia, using a different method based on simulations with a Social Accounting Matrix. There is a large literature, and much debate, on the role of agricultural growth in poverty reduction (Lipton and Ravallion, 1995, Section 5.2; Datt and Ravallion, 1998b).

specification cannot tell us how initial conditions might influence the impact on poverty of economic growth and how that impact might depend on the sectoral composition of economic growth.

Here we test an empirical model of the evolution of the aggregate (urban plus rural) poverty measures at state level that allows for *multiplicative* interactions of the sectoral composition of growth with initial conditions in determining the evolution of state-level poverty measures. In addition to helping us understand what makes growth in a given sector of the economy more pro-poor, we will be able to test for possible trade offs; for example, do certain conditions foster a more pro-poor agricultural growth process, but a less pro-poor *non-farm* growth process?

The next section discusses the arguments that have been made in the past as to why existing inequalities in various dimensions matter to the prospects for poverty-reducing economic growth. We do not attempt to unify these arguments in a formal model, but we do draw out some implications for the measurable factors that might be expected to influence how much impact economic growth has on poverty. Turning to our data for India, we then establish that there are significant differences between states of India in the extent to which the poor have benefited from (urban and rural) non-farm economic growth. We then test for interaction effects between non-farm growth and initial conditions.

2. What makes growth pro-poor? Arguments from the literature

It is widely agreed that economic growth is not sufficient for poverty reduction. A number of other factors influence whether the growth is more or less poverty reducing. The issue here is whether the extra things needed enter additively or multiplicatively. Is it a matter of doing as many things as possible from a list of poverty-reducing actions, with extra impact as each one is ticked off? Or are there important interaction effects, such that only certain combinations do the trick? And what are the key combinations?

It is evident that the distribution of consumption matters to the level of consumption poverty at a given level of mean consumption. But does initial distribution also matter to the subsequent rate of poverty reduction? One way it could matter is through the rate of growth in the mean. A long-standing view — though for long periods a minority view amongst economists — has held that inequality can be harmful to the pace of economic growth in poor countries. For example, in the 1920s and 1930s, Gunnar Myrdal believed that "...an equalization in favor of the low-income strata was also a productive investment in the quality of people and their productivity" (Myrdal, 1988, p. 154). A number of arguments have been made as to why high inequality can impede growth (Aghion et al., 1999). A plausible argument (in this context) is that credit market failures mean that the poor are unable to exploit growth-promoting opportunities for investment in (physical and human) capital. The higher the proportion of poor (and hence credit-constrained) people in the economy, the lower the rate of growth.[2]

[2] Versions of this argument can be found in Stiglitz (1969), Loury (1981), Binswanger et al. (1995), Benabou (1996) and Aghion et al. (1999), amongst others.

In addition to its implications for the rate of growth, high initial inequality is a plausible candidate in explaining why the same rate of economic growth might be less effective in reducing poverty in one setting than another. Quite generally, the elasticity of any measure of poverty to change in the mean of the distribution on which poverty is measured will depend on other properties of that distribution. These effects are hard to characterize in general terms. However, in an economy where inequality is persistently low, one can expect that the poor will tend to obtain a higher share of the gains from growth than in an economy in which inequality is high. There is supportive evidence from cross-country distributional data that higher initial income inequality entails a lower (absolute) elasticity of poverty to average incomes (Ravallion, 1997; Timmer, 1997; World Bank, 2000). For example, a country with a Gini index of 0.25 can expect an elasticity of the headcount index to mean household income of around -3.3, while for a country with a Gini index of 0.60, the elasticity is -1.8 (Ravallion, 1997). But what specific aspects of "inequality" are likely to matter? The Gini index for incomes can be thought of as a product of various dimensions of inequality. Some inequalities may matter more than others to how much the poor share in economic growth.

Asset distribution is likely to influence the extent to which poor people participate in economic growth. Indeed, the credit-market failure argument discussed above as to why initial distribution matters to the rate of growth suggests that it will be the asset poor who are most locked out of growth prospects. Greater initial asset poverty will then mean that the growth that does occur is less (income) poverty reducing. Land is clearly an important asset in this context, so we might expect greater landlessness to entail that the poor share less in the gains from economic growth.

Human capital is possibly no less important. Low basic education attainments are often identified as a source of income inequality.[3] Education will also influence how much the poor are equipped to participate in (relative to farming) skill-demanding non-farm growth. This too is not a new observation. In the 1950s, Jacob Viner wrote that "The first requirements of high labor productivity under modern conditions are that the masses of the population shall be literate, healthy, and sufficiently well fed to be strong and energetic" (Viner, 1953, p. 100). More recently, the view that there are important synergies between human resource development and growth-oriented policy reforms has been a prominent theme in writings on development; examples include Drèze and Sen (1995) writing on India, and Thorbecke and Hong-Sang (1996) on Indonesia. The World Bank's approach to poverty reduction has also emphasized the importance of combining human resource development with policies promoting economic growth (World Bank, 1990, 2000; Bruno et al., 1998).

Another potentially important factor in developing countries is the extent of the income disparities between urban and rural sectors. The existence of earnings and other income disparities between urban and rural sectors is clearly an important dimension of overall inequality in developing countries (Fields, 1980; Bourguignon and Morrison, 1998, who provide supporting evidence from cross-country comparisons). Ravallion and Datt (1999) outline a simple dual economy model with this feature. Poverty reduction in this model

[3] See, for example, the discussions in Tinbergen (1975) and Atkinson (1997). Evidence from cross-country comparisons of income-inequality reducing effects of average education attainments can be found in Li et al. (1998).

takes the form of absorption of poor farm-sector workers into the non-poor non-farm sector. The model assumes that any farm worker who wants to participate in the non-farm sector incurs a cost in doing so. This cost determines the equilibrium earnings differential between the farm sector and the non-farm sector. It is evident that such a cost lowers overall output. But this cost also reduces labor absorption into the non-farm sector, thus implying a higher poverty rate. Moreover, the intersectoral wage gap also makes output *gains* less pro-poor. The higher the initial wage gap (in turn implying a higher initial poverty rate), the lower the rate of poverty reduction from a given rate of non-farm economic growth. Arguably, dualism also limits prospects for pro-poor growth. There is a long-standing view (though not a dominant one it would seem) that rural underdevelopment constrains prospects for industrialization; see, for example, Clarke (1940). Again factor market distortions also entail that urban–rural inequality impedes poverty reduction through non-farm economic growth.

Consider, for example, the classic model of Harris and Todaro (1970) in which wages in the non-farm sector are fixed above market clearing levels. While there is mobility between the urban and rural sectors, rural workers who move to the city will not all be able to get the new jobs, and so they will face unemployment, or turn to relatively low-paid urban informal sector activities. Greater labor market dualism (as measured by the intersectoral wage differential) means that there will be less growth, and that less of the growth that does occur will benefit the poor.

The initial population distribution between urban and rural sectors can also be expected to matter to the impact on poverty of economic growth. In general, a change in the share of the population living in urban areas will shift the Lorenz curve in a dual economy. The direction of that effect is, however, theoretically ambiguous. For example, under the Kuznets Hypothesis, inequality will be low at both low and high levels of urbanization (Robinson, 1976; Fields, 1980; Anand and Kanbur, 1993).

Urbanization is often viewed as a positive factor in promoting rural non-farm economic growth, by expanding markets. Schultz (1953) noticed that rural non-farm activities tend to be more developed in the periphery of urban-industrial centers, and this has been confirmed in many countries. Enterprises are probably attracted to urban areas because of the larger local product markets, the availability of a skilled workforce, the wider variety of production inputs, the possibility of technological spillovers, and better infrastructure (Lanjouw and Lanjouw, 1997).

It can be argued that these same factors will also matter to the impact on poverty of growth in mean output. It is plausible that the poor will tend to be more constrained in their access to markets and infrastructure than the non-poor, and that the poor will tend to gain more from relaxing those constraints than do the non-poor. Assuming that the level of urbanization in an area reflects these differences in access to markets and infrastructure, one can expect that (other things being equal) the poor will be able to benefit more from non-farm growth when they live in a more urbanized area. On the other hand, it is also arguable that greater initial level of urbanization may lead to further concentration of non-farm growth in the urban centers that are already better-off, and hence may dampen the poverty alleviation impact of that growth (relative to a situation where that growth is more evenly spread). The overall effect of initial urbanization on the elasticity of poverty to mean output could thus be positive or negative.

Another factor influencing the impact on poverty of non-farm economic growth is the productivity of the main competing sector for workers, namely farming. For example, by allowing multiple cropping, irrigation and the spread of high-yielding varieties will probably increase aggregate demand for agricultural labor, thus bidding up wages for new entrants into an expanding non-farm sector.

Motivated by these diverse arguments from the literature, the rest of this paper tries to see what the experience of India's states suggests about the factors influencing how much impact economic growth has on poverty.

3. Econometric model and results

There is a large literature studying the evolution of India's rural poverty measures over time, following (and debating) the seminal contribution of Ahluwalia (1978); Datt and Ravallion (1998b) survey this literature. In addition to updating and revising the data, our main points of departure are that: (i) we model the aggregate (urban and rural) state-wide poverty measures and (ii) we relax the almost universal assumption in past work that the poverty-reducing impact of growth is the same across all states.[4] Thus, we allow for state-specific elasticities of poverty, which vary with initial conditions. We deliberately condition out interstate differences in the levels of poverty, by including state fixed effects. We also allow for state-specific time trends as well as state effects in other time-varying factors that could well bias our results if they were omitted. With this specification, we can focus on whether changes over time in aggregate farm and non-farm outputs had different impacts on poverty in different states and (if so) whether observed differences in initial conditions can account for the heterogeneity in impacts.

If there are no significant inter-state differences in the elasticities of poverty, then we will not have much to explain. So we first test for such differences.

3.1. Testing for inter-state differences in the elasticities of poverty

We have estimated various measures of absolute consumption-poverty for each of India's 15 main states using 20 rounds of the National Sample Survey (NSS) spanning the period 1960–1961 to 1993–1994 at intervals of 0.9–5.5 years. We will be concerned with measures of absolute poverty, by which we mean that the poverty line is kept fixed in real terms (or in terms of the standard of living it commands) over the entire (spatial and temporal) domain of poverty measurement (Ravallion, 1994). The standard of living is measured by real per capita consumption. We construct three different measures of poverty within the Foster et al. (1984) class of measures: the headcount index (H), the poverty gap index (PG) and the squared poverty gap index (SPG). We have collated the survey data with data on farm yields, non-farm output, government spending, and variables describing initial conditions. Appendix A provides more details.

[4] The only exception appears to be Van de Walle (1985) who relaxes the pooling restrictions in the Ahluwalia (1978) model to allow the elasticities of rural poverty to agricultural output to vary between states. No attempt is made to explain the revealed differences.

Table 1
Trend rates of poverty reduction by state, 1960–1994

	Trend rates of poverty reduction (percentage per annum)		
	Headcount index	Poverty gap index	Squared poverty gap index
Andhra Pradesh	−2.179	−3.371	−4.295
Assam	0.060	0.054	0.025
Bihar	−0.107	−1.027	−1.797
Gujarat	−1.568	−2.744	−3.619
Karnataka	−1.114	−1.694	−2.159
Kerala	−2.733	−4.447	−5.675
Madhya Pradesh	−0.633	−1.412	−2.070
Maharashtra	−1.013	−1.522	−1.887
Orissa	−1.586	−2.712	−3.697
Punjab and Haryana	−2.547	−3.746	−4.679
Rajasthan	−1.154	−1.883	−2.423
Tamil Nadu	−1.508	−2.315	−2.930
Uttar Pradesh	−0.876	−1.531	−2.115
West Bengal	−1.965	−3.073	−4.015
Jammu and Kashmir	−1.023	−1.382	−1.635

Trends calculated as the OLS regression coefficients of logarithms on time.

Table 1 gives the trend rates of poverty reduction by state. There is a wide range, from a trend rate of reduction in the headcount index in Kerala of 2.7% per year (with Punjab–Haryana close behind) to trends close to zero for Assam and Bihar.[5] We will attempt to explain these differences below.

In testing for inter-state differences in the elasticities of poverty, the natural starting point is an econometric specification in which the log of the poverty measure is regressed on the log of mean income, allowing the regression coefficient to vary across states. We want to extend this specification to allow for differences in the elasticities with respect to different sectoral components of aggregate income, and for inflationary shocks. Since we are interested in describing (and later modeling) the elasticities of poverty with respect to its determinants rather than levels of poverty, we also control for differences between states in the initial level of poverty. (So when we later try to explain the inter-state differences in elasticities, we will not be confusing this question with that of the effects of initial conditions on the initial level of poverty.) This is done by including a complete set of state dummy variables in all regressions.[6] As usual in fixed effects regressions, this also means that our results are robust to any correlation between the explanatory variables and the time-invariant error component. For example, we need not be concerned with bias arising from the endogeneity of rates of economic growth to any latent time-invariant factors at state level that also influence subsequent progress in poverty reduction.

[5] To help put these numbers in perspective, the results of Chen and Ravallion (in press) indicate that the percentage of the population of the developing world living below US$1 per day (at 1993 Purchasing Power Parity) fell at a compound annual rate of 1.7% over 1987–1998 (1.0% excluding China).

[6] Alternatively, one can think of our regressions as models of the deviations from time mean or the rates of poverty reduction (difference in logs) as functions of the similarly transformed (state- and time-specific) explanatory variables.

However, bias will remain due to any correlations between the explanatory variables and time-varying omitted variables. To allow for time-trended omitted variables, we include a state-specific trend.

Combining these features, our test equation takes the form:

$$\ln P_{it} = \beta_i^{\mathrm{NFP}} \ln \mathrm{NFP}_{it} + \beta_i^{\mathrm{YLD}} \ln \mathrm{YLD}_{it} + \beta_i^{\mathrm{GOV}} \ln \mathrm{GOV}_{it} + \gamma_i \mathrm{INF}_{it} + \pi_i t + \eta_i + \varepsilon_{it} \quad (1)$$

where P_{it} is the measure of absolute consumption poverty (on a per capita basis) in state i ($=1,\ldots,N$) at date t ($=1,\ldots,T$), NFP_{it} is real non-farm product per head of the population in state i at date t, YLD is farm yield (output per hectare),[7] GOV is real state development expenditure per capita, and INF is the inflation rate. (All these variables are defined more precisely in Appendix A.) Consistently with Datt and Ravallion (1998a), we found that the fit was improved using the 2-year moving averages of lnYLD and lnNFP, and the lagged value of lnGOV, which also addresses a possible endogeneity concern about current spending. We initially assumed that ε_{it} was an AR1 error term, allowing for the uneven spacing of the surveys (following Datt and Ravallion, 1998a). However, the autoregression coefficient was not significantly different from zero so we set it to zero to simplify the estimation method.

To be as flexible as possible, we initially write the β_i's as linear functions of a vector of state dummy variables. Since we have state fixed effects and state-specific time trends as well as differing effects of inflation, estimating Eq. (1) is equivalent to running a separate regression for each state.

However, we found that a degree of pooling was consistent with the data. In particular, we could not reject the null hypothesis of constant coefficients at the 10% level for all variables except non-farm output per person and the state effects in the intercept.[8] We could, however, reject the null hypothesis that the coefficients on NFP are the same across states.

Thus, we impose a constant-coefficients restriction for YLD, GOV, INF and the time trend, leaving the coefficient on NFP free to vary between states and retaining the state fixed effects in the intercepts. An implication of our finding that only the non-farm elasticities vary significantly across states is immediate: we can reject the idea of significant trade-offs; it is not the case that states with higher elasticities with respect to non-farm growth tended to have lower elasticities to agricultural growth or development spending.

Table 2 gives the estimated parameters of the restricted model. Higher farm yields and higher development spending reduce all three poverty measures, and the coefficients are highly significant. Higher non-farm output per person lowers poverty in all states. Inflation is poverty increasing. The significance of inflation confirms the results of Datt and Ravallion (1997, 1998a,b). In Datt and Ravallion (1998b), we argued that the main

[7] In past work on these data (Datt and Ravallion, 1998a,b), we have found that farm output per hectare is a better predictor of poverty than output per person; on decomposing log output per person into output per hectare and hectares per person, the latter is insignificant. Output per hectare is probably the better measure of farm productivity (for further discussion, see Datt and Ravallion, 1998b).

[8] The failure to reject the null hypothesis of constant coefficients for all except NFP was statistically convincing; probabilities for the tests were no lower than 0.15, and most were above 0.25.

Table 2
Regressions for the state poverty measures allowing for inter-state differences in elasticities to non-farm output

Variable	Headcount index		Poverty gap index		Squared poverty gap index	
	Coefficient	*t*-Ratio	Coefficient	*t*-Ratio	Coefficient	*t*-Ratio
Real agricultural output per hectare of net sown area (current + lagged) (YLD)	− 0.110	− 4.74	− 0.201	− 5.46	− 0.271	− 5.35
Real per capita state development expenditure (lagged) (GOV)	− 0.140	− 2.57	− 0.241	− 2.79	− 0.338	− 2.86
Real non-agricultural output per person (current + lagged) (NFP)						
Andhra Pradesh	− 0.291	− 8.89	− 0.425	− 8.19	− 0.524	− 7.37
Assam	− 0.199	− 5.05	− 0.259	− 4.13	− 0.314	− 3.65
Bihar	− 0.130	− 2.59	− 0.335	− 4.21	− 0.501	− 4.58
Gujarat	− 0.285	− 6.93	− 0.444	− 6.81	− 0.550	− 6.14
Karnataka	− 0.249	− 7.06	− 0.360	− 6.42	− 0.444	− 5.77
Kerala	− 0.542	− 14.80	− 0.859	− 14.79	− 1.087	− 13.64
Madhya Pradesh	− 0.184	− 4.92	− 0.318	− 5.35	− 0.421	− 5.16
Maharashtra	− 0.191	− 5.04	− 0.248	− 4.13	− 0.270	− 3.27
Orissa	− 0.330	− 9.67	− 0.531	− 9.80	− 0.700	− 9.42
Punjab and Haryana	− 0.343	− 10.09	− 0.466	− 8.65	− 0.554	− 7.49
Rajasthan	− 0.336	− 7.39	− 0.493	− 6.84	− 0.605	− 6.11
Tamil Nadu	− 0.277	− 7.97	− 0.397	− 7.20	− 0.479	− 6.33
Uttar Pradesh	− 0.253	− 6.12	− 0.359	− 5.47	− 0.444	− 4.93
West Bengal	− 0.618	− 11.57	− 0.937	− 11.06	− 1.204	− 10.35
Jammu and Kashmir	− 0.176	− 5.12	− 0.230	− 4.21	− 0.273	− 3.65
Inflation rate (INF)	0.419	5.19	0.587	4.58	0.704	4.00
Time trend	0.017	6.46	0.027	6.51	0.036	6.21
Root mean square error	0.0940		0.1491		0.2047	
R^2	0.918		0.918		0.910	
Test for equality of non-farm output elasticities across all states: $F(14, 238)$ (p-value)	14.39 (0.00)		14.28 (0.00)		12.94 (0.00)	

All variables are measured in natural logarithms. The dependent variables are log poverty measures. A positive (negative) sign indicates that the variable contributes to an increase (decrease) in the poverty measure. The estimated model also included state-specific intercept effects, not reported in the table. The number of observations used in the estimation is 272.

channel through which inflation mattered to India's poor was through its short-term adverse effect on the real wage rate for unskilled labor. We also find a significant positive independent time trend. One possible interpretation is that it reflects an adverse distributional effect of population on poverty (Van de Walle, 1985). This is consistent with the fact that our time trend became insignificant when we introduced log population as an additional variable in our model.

Fig. 1 gives the estimated (absolute) elasticities of poverty to non-farm output. (Notice that the elasticities are twice the β_i estimate because lnNFP enters as the sum of the current and the lagged values.) For the headcount index, the absolute values of the implied non-

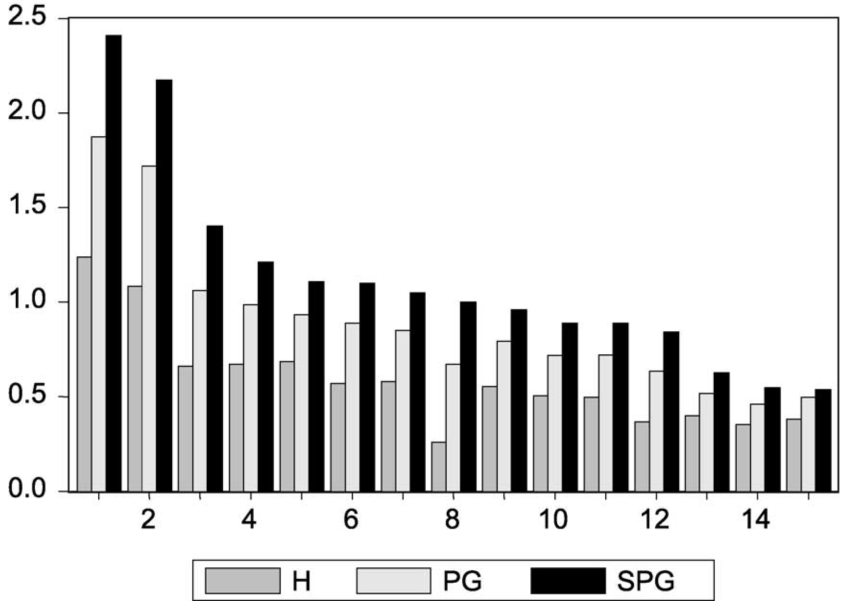

Fig. 1. Elasticities of poverty to non-farm output. Absolute values of the elasticities by states of India implied by Table 2 for the headcount index (H), poverty gap index (PG) and squared poverty gap index (SPG). States ranked by elasticity for SPG. 1 = West Bengal; 2 = Kerala; 3 = Orissa; 4 = Rajasthan; 5 = Gujarat; 6 = Punjab and Haryana; 7 = Andhra Pradesh; 8 = Bihar; 9 = Tamil Nadu; 10 = Uttar Pradesh; 11 = Karnataka; 12 = Madhya Pradesh; 13 = Assam; 14 = Jammu and Kashmir; 15 = Maharashtra.

farm growth elasticities vary from a low of 0.26 in Bihar to a high of 1.08 in Kerala and 1.24 in West Bengal. For all states, the elasticities are higher (in absolute value) for PG than H, and higher still for SPG. This implies inequality-reducing gains below the poverty line. For SPG, the lowest elasticity is for Jammu and Kashmir (0.46) and the highest is for West Bengal (2.41, though with Kerala close behind at 2.18).

To quantify the importance of the elasticity differences to the overall rate of poverty reduction, we simulated rates of poverty reduction, in which we artificially set the non-farm output elasticities of all states to a reference value (denoted $\beta^{\mathrm{NFP}*}$) set alternately at the lowest and highest elasticities across all states:

$$\frac{d\ln P_i^*}{dt} = \frac{d\ln P_i}{dt} + 2(\beta^{\mathrm{NFP}^*} - \beta_i^{\mathrm{NFP}})\frac{d\ln\mathrm{NFP}_i}{dt} \tag{2}$$

where $(d\ln P_i/dt)$ and $(d\ln\mathrm{NFP}_i/dt)$ are the trend rates of poverty reduction and non-farm output per capita, respectively. This calculation assumes that the changes in elasticities leave other variables in the model unchanged. That is questionable. Consider the simulations when all states are given the highest elasticity of any state. If the more favorable initial conditions for the elasticities would have also led to higher (lower) growth rates, then these simulations will have under (over) estimated the gains to rates of poverty reduction.

Table 3 compares the national average trend rate of poverty reduction with the simulated rates of poverty reduction using Eq. (2). Recall from Table 2 that the lowest (absolute) elasticities are for Bihar (for the headcount index) and Jammu and Kashmir (for the other two poverty measures). If all states had Bihar's low elasticity, then the mean rate of poverty reduction would have been only 0.3% per year for the headcount index (versus the observed mean of 1.3%). Under the Jammu and Kashmir elasticities, the average annual rate of decline would have been 0.9% and 1.1% for PG and SPG, respectively (versus actual means of 2.2% and 2.9%).

At the other extreme, if all states had West Bengal's elasticity, then the headcount index would have fallen at a trend rate of 3.5% instead of 1.3% per year. The trend rate of reduction in SPG would have been 7.2% per year instead of 2.9%.

Was there more growth in the non-farm economy in states where that growth would have greater impact on poverty nationally? To determine the impact on poverty in India of the same rate of growth in two different states, one must weight the elasticities in Table 2 by the shares of national poverty in those states. These share-weighted elasticities give the impact of non-farm growth in any state on the national rate of poverty reduction. Table 4 gives these calculations, and also the trend rates of growth in non-farm output per person.

It can be seen that the impact on national poverty of non-farm growth has varied greatly across states. A 1% growth rate of non-farm output in West Bengal brings down the national poverty rate by 0.078% (reflecting both that state's high elasticity of poverty to growth and its high population share). At the other extreme, the same growth rate in Jammu and Kashmir (with both a low elasticity and low share of poverty) would have negligible effect. The differences are even more pronounced using the squared poverty gap (which is sensitive to the severity of poverty, as well as its depth and incidence). Then we find that non-farm growth in Kerala has the highest impact on national poverty — many times that for most other states. Thus, the geographic distribution of growth in the non-farm economy matters to the overall rate of poverty reduction in India.

We can also see from Table 4 that the trend rates of non-farm growth have not tended to be higher in states with higher (weighted) elasticities of poverty. Indeed, it is notable that

Table 3
Actual and simulated mean trend rates of poverty reduction across states

Trend rates of change in poverty measure (percentage/year)	Headcount index	Poverty gap index	Squared poverty gap index
Actual mean across all states	− 1.330	− 2.187	− 2.865
Simulated mean with lowest elasticity amongst all states	− 0.287	− 0.865	− 1.130
Simulated mean with highest elasticity amongst all states	− 3.495	− 5.514	− 7.245

The first row shows the unweighted mean of the actual rates of poverty reduction across states. The second and third rows show unweighted means across states of the simulated rates of poverty reduction, evaluated using state-specific trend growth rates of non-farm output per person (based on regressions of log NFP on time) and the lowest and highest elasticities of poverty (w.r.t. non-farm output growth) across all states.

Table 4
Impacts of non-farm economic growth by state on national poverty

	Trend growth rate in non-farm output per person, 1960–1994 (percentage per annum)	Impact on the national rate of poverty reduction of a 1% annual growth rate in non-farm output per person (percentage per annum)		
		Headcount index	Poverty gap index	Squared poverty gap index
Andhra Pradesh	4.166	− 0.060	− 0.094	− 0.120
Assam	3.148	− 0.008	− 0.006	− 0.005
Bihar	1.961	− 0.030	− 0.078	− 0.115
Gujarat	3.350	− 0.029	− 0.044	− 0.054
Karnataka	3.657	− 0.026	− 0.037	− 0.044
Kerala	3.418	− 0.055	− 0.107	− 0.154
Madhya Pradesh	3.294	− 0.029	− 0.049	− 0.065
Maharashtra	3.512	− 0.039	− 0.053	− 0.059
Orissa	3.151	− 0.030	− 0.050	− 0.069
Punjab and Haryana	4.367	− 0.020	− 0.023	− 0.024
Rajasthan	2.414	− 0.036	− 0.057	− 0.075
Tamil Nadu	3.883	− 0.051	− 0.081	− 0.108
Uttar Pradesh	2.917	− 0.071	− 0.092	− 0.106
West Bengal	2.058	− 0.078	− 0.091	− 0.094
Jammu and Kashmir	3.971	− 0.002	− 0.002	− 0.002
Total	3.285	− 0.563	− 0.865	− 1.093

The trend rates of growth are the regression coefficients of log real non-agricultural state domestic product per person on time. The right panel gives the non-farm output elasticity of poverty (from Table 2) times the initial share of poverty. The totals give the rate of poverty reduction nationally if non-farm output per capita in all states grew at 1% per annum.

two of the three states with the highest (most negative) share-weighted growth elasticities of the headcount index (West Bengal, Uttar Pradesh and Kerala) had below average trend rates of non-farm growth. And similarly, two of the three states with the highest growth rates (Punjab and Haryana, and Jammu and Kashmir; the third is Andhra Pradesh) had below average weighted elasticities. Overall, there is no significant correlation.

So it is clear that, in the longer term, growth in India's non-farm economy has not been concentrated in states where it would have the most impact on poverty nationally. In short, the geographic pattern of non-farm economic growth has not been pro-poor.

Next we try to explain these differences in the poverty impact of non-farm growth.

3.2. Initial conditions and the non-farm output elasticities of poverty

We now postulate that the elasticities of poverty to non-farm output depend on initial conditions. Motivated by the discussion in Section 2, we let β_i^{NFP} depend on the values around the beginning of the period of NFP, YLD, the urban population share (URB), the ratio of urban to rural average consumption (CDIF), and the share of the rural population that is landless (LLESS) in the state, the state's infant mortality rate (IMR) and the literacy rate; we use the female literacy rate (FLIT) following our previous work (Datt and Ravallion, 1998a), though it makes little difference if one uses the male rate or the average.

Table 5
Initial conditions around 1960

	Female literacy rate (%)	Urbanization rate (%)	Urban–rural mean consumption ratio	Landlessness (percentage rural households)	Infant mortality rate (per '000)	Agricultural output per hectare	Non-farm product per person
Andhra Pradesh	12.0	17.4	1.24	6.8	96.2	19.3	1.06
Assam	16.0	7.2	1.25	27.8	72.1	52.0	1.60
Bihar	6.9	8.4	1.09	8.6	91.7	30.3	0.91
Gujarat	19.1	25.8	1.10	14.7	70.4	6.3	2.60
Karnataka	14.2	22.3	1.01	18.6	91.0	12.8	1.32
Kerala	38.9	15.1	1.19	30.9	67.3	96.4	1.02
Madhya Pradesh	6.8	14.3	1.14	9.1	130.1	8.0	1.10
Maharashtra	16.7	28.2	1.46	16.0	95.4	8.0	4.45
Orissa	8.6	6.3	1.01	7.8	95.3	18.3	1.10
Punjab and Haryana	14.1	20.7	0.97	12.3	87.3	16.7	1.50
Rajasthan	5.9	16.3	0.96	11.8	119.4	3.6	0.97
Tamil Nadu	18.2	26.7	1.47	24.2	98.7	51.0	1.80
Uttar Pradesh	7.1	12.9	0.94	2.8	179.2	41.9	1.19
West Bengal	16.9	24.4	1.46	12.6	64.4	76.0	4.86
Jammu and Kashmir	4.3	16.6	1.08	10.9	64.8	47.3	0.86

The units of initial farm yield are Rs. '000 per hectare at October 1973–June 1974 all-India rural prices, and those of initial non-farm product are Rs. '000 per person also at October 1973–June 1974 all-India rural prices. See Appendix A for further details on data and sources.

Table 5 gives the data we will use on these initial conditions.[9] Table 6 gives the results when we replace the state dummy variables in the sub-function for β_i^{NFP} by the variables described above. All of these variables are entered in log form.[10]

We find that non-farm growth is more pro-poor in states with higher initial farm yields, higher female literacy rates, lower infant mortality, lower urban–rural disparities in consumption levels and lower initial landlessness. Controlling for these variables, we do not find the initial urbanization rates or the initial non-farm product to exert a significant influence on the non-farm output elasticity of poverty. The restriction that the effects of these two factors is jointly insignificant is easily accepted statistically. Table 6 also gives a restricted form of the model imposing this joint restriction.

On comparing the R^2 values of Tables 2 and 6, it can also be seen that the variables we have used in explaining the inter-state differences in the non-farm output elasticities of poverty account for a large share of the variance. For example, with full state dummy

[9] Note that we do not include the economic and human resource development indicators in time-varying form as additional explanatory variables in our model for two reasons. First, there are gaps in the available time series data on these variables over the period covered by our analysis. But, even if a complete time series were available, these indicators in time-varying form would be arguably endogenous to the model.

[10] Notice that there is also a (positive) intercept coefficient in the effect of non-farm output on poverty; this is the elasticity when all initial conditions are set at zero.

Table 6
Explaining inter-state differences in the elasticity of poverty to non-farm output

	Headcount index				Poverty gap index				Squared poverty gap index			
	Coefficient	*t*-Ratio	Coefficient	*t*-Ratio	Coefficient	*t*-Ratio	Coeffient	*t*-Ratio	Coeffient	*t*-Ratio	Coeffient	*t*-Ratio
Real agricultural output per hectare of net sown area: current + lagged (YLD)	−0.103	−3.92	−0.105	−4.04	−0.192	−4.57	−0.186	−4.47	−0.258	−4.52	−0.246	−4.34
Real per capita state development expenditure: lagged (GOV)	−0.046	−0.78	−0.056	−0.97	−0.156	−1.64	−0.137	−1.48	−0.261	−2.02	−0.215	−1.70
Real non-agricultural output per person: current + lagged (NFP)	0.160	0.30	0.192	0.58	−0.209	−0.24	0.292	0.55	−0.375	−0.32	0.358	0.49
NFP * initial female literacy rate (FLIT)	−0.149	−6.01	−0.153	−6.89	−0.251	−6.35	−0.233	−6.58	−0.320	−5.95	−0.285	−5.89
NFP * initial urban–rural population ratio (URB)	−0.020	−0.77	–	–	0.021	0.52	–	–	0.067	1.19	–	–
NFP * initial urban–rural mean consumption disparity (CDIF)	0.183	2.09	0.166	2.33	0.196	1.40	0.277	2.44	0.216	1.14	0.371	2.39
NFP * initial percentage of rural landless households (LLESS)	0.074	2.79	0.072	2.81	0.120	2.85	0.115	2.82	0.157	2.74	0.153	2.74
NFP * initial infant mortality rate (IMR)	0.101	2.14	0.101	2.17	0.173	2.30	0.162	2.20	0.233	2.28	0.216	2.14
NFP * initial yield per hectare (YPH)	−0.029	−2.27	−0.027	−2.37	−0.032	−1.54	−0.042	−2.37	−0.038	−1.36	−0.060	−2.44
NFP * initial per capita non-agricultural output (NFP)	0.001	0.02	–	–	0.036	0.79	–	–	0.055	0.89	–	–
Inflation rate (INF)	0.372	4.00	0.377	4.07	0.578	3.89	0.565	3.83	0.725	3.59	0.698	3.46
Time trend	0.010	3.49	0.011	3.72	0.018	3.78	0.017	3.70	0.024	3.76	0.022	3.52
Root mean squared error		0.1108		0.1104		0.1767		0.1768		0.2405		0.2409
R^2		0.883		0.883		0.882		0.881		0.872		0.871
Test for joint significance of omitted variables: $F(2, 245)$ with p-value in ( )				0.31 (0.73)				0.57 (0.57)				1.43 (0.24)

Absolute *t*-ratios in parentheses; 272 observations. All variables are measured in natural logarithms. A negative (positive) sign on the interaction terms indicates that the variable contributes to more (less) pro-poor growth. The regressions also included state-specific intercepts.

variables, the value of R^2 in the regression for the headcount index is 0.918. Using our explanatory variables, it drops to 0.882 indicating that only 3.6% of the variance in the poverty measures is accounted for by omitted variables (including measurement errors) influencing the measured non-farm output elasticity of poverty.

We know already that inter-state differences in elasticities with respect to non-farm output were quantitatively important to the rates of poverty reduction. From Tables 5 and 6, we can also say something about the relative importance of the various initial conditions we have identified in explaining the differences in elasticities. Consider the state with the lowest elasticity for the headcount index, namely Bihar with an absolute elasticity of 0.25, well below Kerala's elasticity of 1.08. What non-farm output elasticity of poverty would we have seen in Bihar if it had Kerala's initial conditions? The female literacy rate in 1960 was in Bihar was 6.9%, while it was 38.9% in Kerala. If Bihar had Kerala's literacy rate, then the parameter estimates in Table 6 (restricted form) imply that the (absolute) elasticity of the headcount index to non-farm output per person in Bihar would have risen roughly three-fold, from 0.25 to 0.79.[11]

Performing the same calculation for the other initial conditions, we find that if Bihar had Kerala's infant mortality rate, then Bihar's elasticity would have risen by 0.06, while with Kerala's higher initial farm yields, Bihar's elasticity would have risen by a further 0.06. However, the urban–rural consumption disparity and landlessness was higher in Kerala; so Kerala's values for these initial conditions would have *reduced* Bihar's (absolute) elasticity by 0.02 and 0.18, respectively. So maintaining the literacy difference between the two states but equalizing the four other factors would have meant an even lower elasticity in Bihar relative to Kerala. In other words, the difference in literacy was the overwhelming factor in explaining the difference in the poverty impact of non-farm output growth.

4. Conclusions

Using state-level poverty measures for India spanning 1960 to 1994 and allowing for state fixed effects, we find that higher farm yields, higher state development spending, higher (urban and rural) non-farm output and lower inflation were all poverty reducing. Except for non-farm output, we could not reject the null hypothesis that all these variables had the same elasticity across states for a given poverty measure. Farm yield growth, for example, was poverty reducing but with a similar elasticity in states with dissimilar initial conditions; thus it was the differences in the rate of agricultural growth that mattered to the poor.

However, the elasticity of poverty to non-farm output growth varied significantly across states; growth in this sector brought much larger proportionate reductions in consumption-poverty measures in some states than others. Thus, we have been able to derive a state-specific measure of how pro-poor economic growth has been in India over this period.

Differing non-farm output elasticities of poverty appear to have had a powerful longer term impact on the prospects of escaping absolute poverty in India. We have simulated the rates of poverty reduction if all states had the non-farm output elasticity of West Bengal,

[11] The number of literate women per 1000 adult women is logged, so $0.79 = 0.26 + 0.306x(5.96 - 4.23)$ (recalling that the regressor is the sum of current and lagged output).

which had the highest elasticity of any state (with Kerala a close second). Then the trend rate of reduction in the headcount index over this 35-year period would have been more than two percentage points higher. For a state with the national average poverty incidence in 1960 of 48%, this difference in trend rates of poverty reduction would have meant a difference in the poverty rate by the mid-1990s of almost 16 percentage points; the poverty rate would have fallen to 14% instead of 30%.

Our results also indicate that the national rate of poverty reduction depended on the geographic composition of growth as well as its overall rate. However, the geographic pattern of growth in India has not been pro-poor, in that the rate of growth in the non-farm economy has not been any higher in states where it would have greater impact on national poverty.

Consistent with arguments found in the literature, we find that the inter-state differences in the impact of a given rate of non-farm economic growth on consumption poverty reflect observed differences in initial conditions. Low farm productivity, low rural living standards relative to urban areas, greater landlessness in rural areas, and poor basic education and health all inhibited the prospects of the poor participating in growth of the non-farm sector. Taken as a whole, our results suggest that non-farm economic growth was less effective in reducing poverty in states with poorer initial conditions in terms of rural development (in both absolute terms and relative to urban areas), human resources and land distribution. The sectoral composition of economic growth was clearly more important to poverty reduction in states with poor initial conditions.

Rural and human resource development and a more egalitarian distribution of land appear to be strongly synergistic with poverty reduction though an expanding non-farm economy. Amongst the initial conditions we have found to matter significantly to prospects for pro-poor growth, the role played by literacy is particularly notable. For example, nearly two-thirds of the difference between the elasticity of the headcount index of poverty to non-farm output for Bihar (the state with lowest absolute elasticity) and Kerala is attributable to the latter's substantially higher initial literacy rate.

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Appendix A

This appendix describes the main features of our data. A complete description of the data set assembled for this study (including sources of all variables) can be found in Özler et al. (1996) and the data and manual can be found at the following web site: http://www.worldbank.org/poverty/data/indiap aper.htm.

We have used a consistent series of absolute poverty measures based on distributions of consumption per capita from 20 rounds of the National Sample Survey (NSS) spanning the period 1960–1961 (round 16) to 1993–1994 (round 50). All 20 rounds of the survey are covered for all 15 major states with the exception of Jammu and Kashmir, for which surveys were not held for the 48th and 50th rounds due to the prevailing political unrest. Punjab and Haryana had to be treated as a composite state because Haryana emerged as a separate state only in 1964. For NSS rounds since then, the poverty measures for the two states have been aggregated using population weights derived from the decennial censuses. Altogether, we use data from 298 consumption distributions to construct state-level poverty measures.

There is considerable variation in the sample sizes. For all states, the samples range from 6330 households for the 16th round (July 1959–June 1960) to 157,928 households for the 32nd round (July 1977–June 1978), with a median sample size of 25,761 households for the 43rd round (July 1986–June 1987). The smallest sample size for any state is 172 households for Assam for the 16th round. Assuming a simple random sample, this implies a standard error, for a headcount index of 50%, of 3.8 percentage points.

The poverty lines we use are those proposed by the Planning Commission (GOI, 1979). These lines were defined at the per capita monthly expenditure levels of Rs. 49 for rural areas and Rs. 57 for urban areas (rounded to the nearest rupee) at October 1973–June 1974 all-India prices. The Planning Commission followed the "food-energy method" in deriving the rural and urban lines; these poverty lines thus corresponded to levels of per capita total expenditure at which certain caloric norms were typically attained in the rural and urban sectors. The norms correspond to a per capita food energy intake of 2400 calories per day in rural areas and 2100 calories per day in urban areas. Poverty lines constructed this way have sometimes been found not to have the same purchasing power in urban and rural areas (Ravallion, 1994). However, independent estimates of the urban–rural cost of living differential for 1973–1974 (see Bhattacharya et al., 1980) came up with a similar figure of about 16% higher urban cost of living implicit in the Planning Commission poverty lines (see Datt, 1997, for further discussion).

A substantial effort was invested into the construction of a consistent set of price indices across states and survey periods, using monthly data on consumer price indices from the Labour Bureau (disaggregated to the center level for the urban index) over the whole 35-year period. Our primary deflators were the Consumer Price Index for Industrial Workers (CPIIW) for the urban sector and the *adjusted* all-India Consumer Price Index for Agricultural Labourers (CPIAL) for the rural sector. The adjustment carried out to the CPIAL was for the price of firewood that has been held constant in the official CPIAL series since 1960–1961. The nominal state-level distributions were further normalized for inter-state cost of living differentials estimated separately for urban and rural areas, anchored to the consumption pattern of households in the neighborhood of the poverty line. However, since a single price index is used for a given state and sector, we do not allow for differences between expenditure groups (as would arise from non-homothetic preferences with changes in relative prices). For further details on the construction of the price indices, see Özler et al. (1996), Datt (1997), and Datt and Ravallion (1998a). The poverty measures are estimated from the published grouped distributions of per capita expenditure using parameterized Lorenz curves; for details on the methodology, see Datt and Ravallion (1992).

As discussed above, the poverty measures are hypothesized to depend on both a set of time-dependent variables as well as a set of initial condition variables that determine how poverty-reducing the time-dependent variables are. Building on the empirical approach used in our earlier work (Datt and Ravallion, 1998a), we use time-dependent variables related to agricultural and non-agricultural growth, public spending on economic and social services and inflation. The specific variables used are as follows:

(i) mean farm yield, given by real agricultural state domestic product (SDP) per hectare of net sown area in the state (denoted YLD),[12]

(ii) non-farm output, measured by real non-agricultural state domestic product per person (NFP),

(iii) rate of inflation in the rural sector measured as the change per year in the natural log of the (adjusted) CPIAL,[13]

(iv) real state development expenditure per capita (GOV); development expenditure includes expenditure on economic and social services. The economic services include agriculture, rural development, special area programs, irrigation and flood control, energy, industry and minerals, transport and communications, science, technology and environment. The social services include education, medical and public health, family welfare, water supply and sanitation, housing, urban development, labor and labor welfare, social security and welfare, nutrition, and relief for natural calamities.

The data on SDP and state development expenditure are available on an annual basis, while the NSS surveys are not only not annual but they also do not always cover a full 12-month period. To match the annual data with the poverty data by NSS rounds, we have log-linearly interpolated the annual data to the mid-point of the survey period of each NSS round.

We also identify a number of social and economic variables to describe initial conditions around 1960 (that we will later use in attempting to explain the growth elasticities of the poverty measures by state).[14] The following variables (all measured in natural logs) describe these initial conditions:

(i) the female literacy rate in 1961 defined as the number of literate females per thousand females in the total state population (FLIT),
(ii) the percentage of landless rural households in 1961–1962 (LLESS), as a measure of initial asset inequality in rural areas,

[12] All real values were calculated using the (adjusted) state-specific CPIAL as the deflator. For further details on the State Domestic Product (SDP) data, see Datt and Ravallion (1998a).

[13] This is state specific. However, the bulk of the effect is clearly through inter-temporal variation in the rate of inflation. We also tried adding the log of the ratio of the CPIIW to the (adjusted) CPIAL as an additional regressor, but that turned out to be insignificant.

[14] The initial condition variables were assembled from a number of diverse data sources including the 1961 Census, the Statistical Abstract (Central Statistical Organization) for various years, and reports from a number of NSS surveys dealing with village statistics, land holdings and utilization, fertility, and infant mortality.

(iii) the proportion of urban population in 1961 (URB),
(iv) the ratio of the initial urban real mean consumption to that in the rural sector, where the initial real mean consumption in each sector is formed as an average over the first three NSS rounds available for that state (CDIF), as a measure of initial inter-sectoral disparity,
(v) the percentage of operated area which was irrigated in 1957–1960 (IRR),
(vi) the initial levels of YLD and NFP (for 1960–1961).

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