Income and the Environment in Rural India: Is There a Poverty Trap?

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Abstract. We study the relationships between rural income distributions and changes in environmental conditions in South, West and Central India. Other than the relatively rich, we find that all income strata benefit from an improved environment and intermediate expenditure households benefit more than the very poor in absolute terms. Higher median consumption expenditures and "richness" are estimated to increase environmental decline, but we generally do not find a significant impact of income poverty on local environmental health. The results generally do not support the "poverty trap" conjecture, with environmental degradation driving expenditure reductions that promote offsetting aforestation (which benefits the poor).

Keywords. deforestation, environment, income, poverty, satellite data

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The "poverty-environment nexus" has become a pillar of contemporary academic and policy debate on economic development (see, for example, Duraiappah, 1998; Dasgupta and Maler, 1994; Nelson and Chomitz, 2004; Dasgupta, et al., 2005). The poor have lower costs of harvesting the resources of open access and common property forests due to both lower wages (the opportunity cost of labor in these activities) and less potential for sanction when these activities are not legally authorized (due to fewer assets and income). They also have a greater incentive to engage in these activities because their very subsistence and survival may depend upon them. As a result, according to this logic, the poor rely particularly heavily on the natural environment. Moreover, as the natural environment on which they depend deteriorates, the poor become poorer. And as the poor become poorer and more numerous, their exploitation of the environment rises and environmental degradation hastens. These feedbacks create a vicious cycle between poverty and the natural environment, the nexus or "poverty trap."

The importance of these feedbacks in practice is potentially enormous. If an accurate description of the economic mechanisms at work, the nexus implies that poverty reduction – whether achieved with education, health or income support programs – is at the heart of global interests in environmental preservation. Conversely, environmental improvement, achieved without disenfranchising the poor from the bounty of environmental resources, is a key to poverty reduction. Key questions for scholars thus concern the veracity and relevance of the conjectured feedbacks in the developing world.

Are the poor the principal harvesters of the commons? And if they are, do they only exploit these resources or do they pursue traditional strategies to preserve them?

In this paper, we undertake a direct empirical examination of linkages between the natural environment and poverty (and other measures of income distribution) using a rural district-level dataset from South, West and Central India. We examine changes in environmental health between 1994-95 and 2000-01 using two satellite-based measures of "greenness," one of which captures overall biomass and the other of which captures the upper tail of vegetative biomass and reflects the density, quality, and extent of forest cover. We examine changes in rural income distribution (poverty, median levels of consumption expenditure, and "richness") over the same time interval, and control for a variety of relevant socio-economic, natural and climatic factors. We study how initial income distribution affects environmental change, and how environmental conditions and changes affect the income distribution.

For a number of reasons, India is a particularly appropriate study region for our analysis. Approximately 72 percent of India's population resides in rural areas (2001 Census of India). Despite a number of rural poverty alleviation programs, rural poverty is pervasive, with 22.7 percent of rural residents below official (and exceptionally low) poverty lines in 2004-05 (Sundaram, 2007). A variety of evidence documents the dependence of India's rural population, especially the rural poor, on open access and common pool natural resources (Rao, 1994; Jodha, 2000; Narain, et al., 2008). In our study region, 69 percent of rural households have proximate forests and proximate commons that are at least .1 hectare per household; 47 percent collect fuelwood from these commons and 20 percent graze livestock on them (NSSO, 1999). Government initiatives, of which Joint Forest Management (JFM) is perhaps the most prominent, reflect official recognition of the need to address rural poverty alleviation and environmental conservation in a unified framework.[1] The inter-linkages that we study are thus central aspects of India's rural economy.

There is a vast literature on poverty and the environment.[2] Most closely related to our study is research focusing on the extent to which different income groups (poor vs. rich) depend upon income derived from common property, community and open access land and forest resources. Micro-level studies confirm the dependence of the poor on common pool resources for fuelwood, dung, fodder, construction materials, flowers, nuts, and other uses.[3] However, recent work also documents the dependence of relatively rich households on these natural resources (Cavendish, 2000), some finding evidence for a U-shaped relationship between resource dependence and income (Narain, et al., 2008; Adhikari, et al., 2004). Different income groups are also found to depend upon different types of resources, with the rich depending upon high value (and more degrading) activities such as charcoal and timber sales (Fisher, 2004), while the poor depend upon lower value and higher cost activities such as collecting dung and leaves (Narain, et al., 2008).

This work suggests possible heterogeneous effects of environmental degradation on different income groups, because groups that are more dependent upon environmental resources are likely to suffer more when these resources are depleted. However, these impacts are not clear-cut. For example, when natural commons are degraded, the poor may face less competition for access and thereby *benefit* from the degradation despite higher costs of resource collection. Similarly, even if the rich obtain a greater level (or even share) of income from natural resources, their portfolio of activities and resilience to shocks are likely to be much more robust than their less-resource-dependent middle-income counterparts. Hence, environmental degradation need not harm a given income group because that group is resource dependent and need not harm one group more than another because the first group is more resource dependent. This logic – while clearly speculative – gives reason to examine directly the impact of changes in natural resource health on the well-being of the poor and the rich.

Conversely, resource dependence does not necessarily imply environmental degradation. If the poor depend upon natural resources for their subsistence, they have incentives to protect them (as stressed, for example, in discussions of traditional Indian cultures by Gadgil, Berkes, and Folke (1993), Rao (1994), Jodha (2000), and Berkes, Colding, and Folke (2000)). Again, there is reason to examine directly the impact of income distribution (poverty and "richness") on environmental health.[4] In this paper, we study these direct relationships, both ways, in rural India.

Hypotheses

Consider rural households that obtain income from wage labor, production within the household, and other sources (such as returns to asset holdings, remittances, or salaried labor). Household production of "forest goods" (including fuel, foods, and household items) is accomplished by labor effort in resource extraction and depends upon the health of the local environment. The produced goods can be consumed within the household or sold.

In this setting, a variety of economic phenomena can affect the link between a household's income and resource exploitation incentives. Benefits of exploitation may change with income, for example due to altered survival and risk reduction motives for resource collection by the poor, who lack access to insurance markets. Access to complementary inputs in resource collection can also change with incomes; for example, access to automotive transport, tools, hired labor, and credit markets, can rise with income (Baland and Platteau, 1997). In addition, different income groups bear different costs of illegally exploiting public environmental resources: The poor are likely to face no sanctions for illegal resource collection because they have no income to give up; the rich are likely to face no sanctions because they can acquire legal rights to resource use; intermediate income groups optimally engage in illegal resource collection on the commons and face the prospect of some sanction.[5] If so, the relationship between expected sanctions from resource exploitation and income levels has an inverse U-shape (low sanctions for low and high incomes, high for intermediate incomes).

These forces imply effects of income change, for different income strata, on resource depletion. Lowered incomes of the poor reduce possible sanctions from illegal resource collection, elevate survival motives for resource use, and thus raise exploitation incentives. Increased incomes of the rich yield improved access to complementary inputs (transport, tools, labor, and credit), enable increases in legal entitlements (lowering expected sanctions from resource exploitation), and thereby raise exploitation incentives. In sum:

<u>Hypothesis 1</u>. Increased poverty leads to increased deterioration of open access and common property land and forest resources. Increased incomes of the relatively well-to-do can also lead to increased environmental deterioration.

Other forces may confound or reinforce these effects. Increased poverty can render more of the poor in such a severe category of deprivation that resource collection activities cease, and may also shift the type of resource exploitation activities from those that are more degrading (and tend to occupy the relatively rich) to those that are less degrading, for example, from timber clearing to collection of twigs, leaves and plants (Fisher, 2004).

Regarding the other direction of effect (environment to income), an improved environment increases the economic well-being of any household that engages in resource collection. This is a simple "envelope theorem" result. However, the extent of benefit will not be uniform either in magnitude or as a share of income. The very poor have low opportunity costs of labor, potentially large survival benefits from resource collection, and limited prospects for sanction. They may therefore engage in more resource collection than other income groups, be more dependent on the natural environment, and benefit the most from an environmental improvement, both absolutely and proportionately (as a share of income):

Hypothesis 2. All income groups that engage in resource extraction activities suffer reduced incomes when the environment deteriorates, and the poorest suffer proportionately the most.

The last claim of Hypothesis 2 must be qualified because "the poor" include those who are so deprived that their poverty limits all possible resource extraction activity and thus also limits their losses from marginal environmental degradation. Also potentially confounding this claim are incentives for more wealthy households to increase their legal entitlements to environmental resources, and substitute low cost labor for their own in resource collection, when environmental conditions improve. Such incentives can enable the rich to benefit more from environmental improvement than the poor.

We have so far considered household-level behavior that has no market effects. In our empirical work, however, we necessarily focus on local environmental aggregates (at the level of Indian districts) and corresponding measures of local income distribution. If markets for products from resource collection activities are local, then local income distributions can affect demand for these products and private provision of the forests from which the products derive (Foster and Rosenzweig, 2003). On one hand, higher incomes that drive higher demand for forest products can, by raising prices, raise incentives for exploitation of common property resources. On the other hand, they can raise incentives for private provision of forests (Foster and Rosenzweig, 2003). The income effects posited in Hypothesis 1 can thus be tempered or reinforced. The extent of market effects can depend upon the extent of market integration. For example, Alix-Garcia, et al. (2011) identify a tempering effect of greater market integration (due to better road infrastructure) on the deforesting impact of higher local incomes from a Mexican cash transfer program. This leads us, in our empirical work, to consider the intermediating role of road infrastructure in driving local income effects on the environment.

Hypothesis 2 implies that environmental degradation fuels income reductions. If income reductions in turn harm the environment, we have a "poverty trap." Hypothesis 1 implies that reduced incomes of the poor harm the environment, but reduced incomes of the rich may improve it. This tension cannot be resolved by theory. The empirical question for us, in the context of rural India, is whether the environment-to-income-to-environment feedbacks are reinforcing – the poverty trap conjecture – or not.

Hypothesis 3 (the poverty trap). An exogenous deterioration in the environment causes income reductions that in turn spur further environmental degradation.

A final issue concerns the impact of initial environmental health on the subsequent change in environmental status, improvement or degradation. The state of the initial environment alters both resource extraction incentives and environmental regeneration. Unless the forest resources are exceptionally deteriorated, standard biological modeling (with the Gordon growth model) implies a negative effect of increased initial environmental health on growth. With an improved environment also increasing extraction incentives, we have the Boserup (1965) / Simon (1996) conjecture, countering any "poverty trap":[6]

Hypothesis 4. Reduced initial environmental health leads to subsequent environmental improvement.

Data

We use district level data from eight states in the southern, western and central regions of India. The eight states are Andhra Pradesh, Tamil Nadu, Karnataka, Kerala, Maharashtra, Gujarat, Rajasthan and Madhya Pradesh.[7] Adjusting for district redefinitions and missing data gives a usable sample size of 162 districts.[8] Our data set exhibits enormous variation in climatic as well as socio-economic conditions. For example, normal annual rainfall varies from 31 cm to 350 cm and rural literacy rates vary from 13 percent to 96 percent in our sample districts. Table 1 describes the variables used in this study and summary statistics. As our study is related to rural environmental conditions and rural consumption expenditures affected by these conditions, the analysis focuses primarily on data from the rural sectors of our sample districts.[9]

Measuring Environmental Quality

To measure rural district-level environmental quality, we use the Normalized Difference Vegetation Index (NDVI) derived from satellite data. The NDVI, a measure of "greenness," is highly correlated with plant matter, takes on higher values when forest vegetation is present, and is robust to topographical variation, the sun's angle of illumination, and atmospheric phenomena such as haze. Satellite-based vegetation indices are increasingly used by scholars to measure forest and vegetative cover (Pfaff, 1999; Foster and Rozensweig, 2003; Narain, et al., 2008) and have been shown to be highly correlated with not only the condition of the canopy, but also of the non-timber forest (NTF) environment beneath the canopy, including genetic diversity of NTF species; the density and size distribution of key NTF plants; and the vegetation composition and structure (see, for example, Skanker, et al., 2004). The NDVI is measured on a 10-day composite basis and at fine resolution (with each pixel eight square kilometers).[10] Images are obtained from the National Aeronautics and Space Administration (NASA) and processed using Geographic Information System (GIS) techniques to obtain district-specific index values. Monthly composite images downloaded from NASA are reprojected into geographic format. Using the political map of India, district NDVI averages and standard deviations (across pixels and one or two year timeframes) are extracted from the pixel-level data.

There are two key advantages of satellite-based measures of environmental quality. Satellite images provide accurate and frequent data on vegetation. In contrast, forest area surveys are infrequent and notoriously unreliable. Second, the NDVI captures differences in vegetative quality across space and time. If a designated forest area is degraded over time or old growth forest is replaced by new plantations or a forest is evergreen, tropical and dense as opposed to sparse and denuded, the NDVI reflects the differences and changes in form, while the traditional measure, area under forest, does not.

Using the NDVI, we construct two indicators of environmental health. The first is the average district-level NDVI, a measure of overall biomass. The second, the z-NDVI, is our proxy for forest cover. The z-NDVI is monotonically related to the proportion of time-pixels that are above a critical NDVI value, reflecting the higher quality and more stable biomass that characterize forests as opposed to agricultural vegetation.

The z-NDVI is constructed using the following procedure. The average NDVI value (μs) and standard deviation (σs) are calculated from all monthly pixels in our study region. A critical NDVI index, N, is then constructed such that approximately 20 percent of the study region's month-pixel NDVI values are higher than this index: $N = \mu s + n_{.20}\sigma s$ where $n_{.20}$ = critical value of a standard normal random variable such that the upper tail has a 20 percent probability ≈ 0.84. We use a 20 percent “upper tail probability” because approximately 19.1 percent of our study region was in forest in 1995 and approximately 21 percent of India’s land was forested in 1990-91. For any given time interval of interest (e.g., 1994-95), a "z-NDVI" is derived for each district as follows:

z-NDVI for district j = $z_j = (\mu_j - N)/\sigma_j$, where μ_j = district j average of time-pixel NDVI and σ_j = district j standard deviation of time-pixel NDVI.[11] This "z-score" is a measure of high-NDVI frequency that is commonly used by GIS geographers (see Yool, 2001).

We construct district-level average NDVI and z-NDVI over two two-year intervals: 1994-95 and 2000-01. Changes in respective index values between these two periods (2000-01 minus 1994-95) give us our measures of environmental change. Initial (1994-95) NDVI values vary across our study region from a low of 139.7 (Bikaner in Rahasthan) to a high of 198.8 (Wayanad in Kerala), averaging 174.3. As indicated in table 2, State-level averages of the district biomass index values rise as one moves from the arid north of our study region (Rajasthan and Gujurat) to the more tropical south (Kerala and Tamil Nadu). Similar geographic patterns are observed for the initial z-NDVI. Changes in the NDVI from 1994-95 to 2000-01 range from a low of -19 (Ujjain in Madhya Pradesh) to a high of 8.5 (Ramanathapuram in Tamil Nadu), averaging -10.3 overall across our sample districts. Only four of our 162 sample districts showed improvement in the NDVI (two districts in Rajasthan and two in Tamil Nadu) or z-NDVI (one in Rajasthan and three in Tamil Nadu). State-level average changes in both indices are all negative, with the smallest average declines seen in Tamil Nadu and the largest in Kerala and Madhya Pradesh.

Within-district standard deviations of the initial (1994-95) pixel-level NDVI values (across space and seasons) average 16.61, less than ten percent of the average district level NDVI. These standard deviations are quite stable across both our sample region and our study period. For example, State-level averages (from table 2) range from 13.03 (in Tamil Nadu) to 19.2 (in Madhya Pradesh), and the overall standard deviation of the within-district standard deviations is 2.77. Over our study period, the standard deviations rose on average by 12.6 percent (1.85 in levels). Loosely speaking, these statistics suggest that much of the within-district variation in pixel-level NDVI is due to inter-seasonal changes.[12]

Measuring Income and Poverty

Household level monthly consumption expenditure data are obtained from the National Sample Survey of India (NSSO) for 1994-95 (round 51) and 2000-01 (round 56). From these data, we construct district level measures of rural expenditure distributions.[13] We restrict attention to districts that have a minimum NSSO sample size (of 100 households) and consider two types of indicators for the consumption expenditure distribution. The first set uses deciles and quartiles of a district's sample of consumption expenditures. Using State-level poverty lines at the beginning and end of our study period (to measure inflation), we calculate real changes in respective deciles and quartiles. We consider five decile/quartiles to capture the different tails of the expenditure distribution, 10th Percentile (the per capita consumption expenditure below which 10 percent of sampled residents in a district belong), 25th Percentile, 50th Percentile, 75th Percentile, and 90th Percentile. Real changes in these critical values over our study period (1994-2000) are denoted $\Delta 10^{th}$Percentile, $\Delta 25^{th}$Percentile, and so on.

The second class of expenditure distribution measures employs the logic of the Foster-Greer-Thorbecke (Foster, et al., 1984) indices. For poverty, we have:

(1) $$\text{Poverty Index} = Y_a = \sum_{(y_i < p)} [(p - y_i)/p]^a / n,$$

where y_i is the consumption expenditure of the i^{th} individual, p is the poverty line, n is the population (NSSO sample) size, and α is a non-negative parameter. If α = 0, Y_α gives the headcount ratio (HCR), the proportion of the local population that has expenditures below the poverty line. If $\alpha = 1$, Y_α gives the Poverty Gap Index (PGI), the average positive shortfall from the poverty line, expressed as a percentage of the poverty line.[14] The upper-tail ("richness") analog to the poverty index is as follows:

(2) $$\text{Richness Index} = Y_\alpha = [\sum_{y_i > p} (y_i - p)/p]^\alpha / n.$$

Using α=1, we construct the "Richness Gap Index" (RGI) from equation (2). Finally, we construct an average "per capita consumption expenditure" (PCE) index:

(3) $$\text{PCE Index} = Y_\alpha = [\sum_i y_i/p]/n.$$

In India, poverty lines are designed to capture rural-urban and inter-State differentials in cost of living and are therefore at a State level and specific to rural and urban sectors. The official poverty lines are presented in table 3. Note that these lines are very tight, constructed to represent the minimum expenditure needed for bare survival. For example, the 2000-01 average rural poverty line represents expenditure of roughly 25 U.S. cents per person per day. Hence, substantially higher expenditure levels also reflect impoverished circumstances. As a baseline, we use twice the government's official poverty lines (from table 3) to construct our expenditure distribution measures. However, we also present estimations using FGT distribution indices constructed using exactly (one times) the poverty line, and 1.5 times the poverty line.

To interpret our expenditure distribution measures, note the following: (1) average levels of the 25th Percentile value are slightly higher than the average official rural poverty line for our sample states (365 Rupees vs. 318 in 2000-01), roughly US$7 to US$8 per person per month; (2) average levels of the median (50th Percentile) are about the same as 1.5 times the average official poverty line (470 vs. 477 Rupees), roughly US$10.50 per person per month; and (3) average levels of the 75th Percentile are about the same as two times the average poverty line, our baseline (630 vs. 636 Rupees), roughly US$14 per person per month. All of these measures are indicative of impoverished circumstances; the 10th Percentile, 25th Percentile, and FGT poverty indices based on one times official lines (the headcount ratio, HCR, and poverty gap index, PGI) measure extreme poverty.

Over our sample period, the real expenditure percentiles declines on average for all measured decile / quartiles (see Δ 10th Percentile, Δ 25th Percentile, and so on in table 1).[15] In absolute terms the declines were larger for the higher expenditure classes; for example, the 10th Percentile fell on average by 9.62 Rupees (in 1994 Rupees) and the 90th Percentile fell by 76.13 Rupees. In percentage terms, the declines were also larger for the higher expenditure classes; the average real decline in the 10th Percentile was 3.5 percent; analogs were 6.3% (for the 25th Percentile), 8.4% (50th Percentile), 11.1% (75th Percentile), and 10.3% (90th Percentile). These numbers suggest that average changes in per capita consumption expenditures over our sample period were substantially driven by declines in expenditures in the upper tail of the expenditure distributions. However, there was also significant cross-district heterogeneity in these changes. Cross-district standard deviations of the expenditure decile / quartile changes are many multiples of the corresponding average changes (see table 1). For example, real changes in the 10th Percentile range from -163 Rupees to +106 Rupees; the corresponding range for changes in the 90th Percentile was -689 to +777 Rupees. The econometric model we describe below aims to explain this variation.

Socio-Economic, Agronomic and Land-Use Data

District level sector-specific (rural and urban) socio-economic data is obtained from Human Development Reports published by the National Council for Applied Economic Research (NCAER) of India, the data portal site www.indiastat.com, reports of the International Institute for Population Sciences (IIPS), and the 1991 Census of India. In addition, using World Bank data (as updated by Duflo and Pande, 2007), we construct a district level measure of annualized changes in value-weighted agricultural yields per hectare for our sample period, 1994-2000; this indicator permits us to study determinants of changes in agricultural productivity and technology (see Section 5 below).

Climatic Data

We use actual annual and monthly rainfall data to capture climatic variations across time and districts. Rainfall data are available for meteorological subdivisions of India. Each subdivision is defined according to climatic features and contains several districts. Because there are only 19 subdivisions in our study region – and "greener" districts are likely to have higher rainfall – we approximate district-level rainfall using subdivision rainfall and district NDVI data as follows:

$$Rain_{ij} = Rain_j * (NDVI_i / NDVI_j);$$

where $Rain_{ij}$ = estimated rainfall for district i in subdivision j, $Rain_j$ = annualized 1994-2001 rainfall of subdivision j, $NDVI_i$ = average NDVI of district i (1990-91), $NDVI_j$ = average NDVI of subdivision j (1990-91). Average (1994-2000) district temperatures and elevations are obtained from the International Research Institute for Climate and Society.

On District-Level Data

Indian districts are the finest level at which our consumption expenditure and explanatory data are available. Although our satellite-based environmental data can be obtained at finer resolution, our other data cannot be tied to finer geographic areas. Indian districts are therefore our finest possible unit of analysis, similar to the use of U.S. counties. Although one might prefer smaller geographic units for study, our research question requires *some* geographic aggregation for a meaningful study of how income distribution affects a local environment that is exploited by many agents.

There are two potential implications of our implicit aggregation to districts.[16] First, to the extent that we are summing multiple (within district) local effects, our aggregation compromises precision by reducing degrees of freedom. Second, there may be spillovers across subregions within districts; incomes in one subregion can affect the market for another subregion's forest products (as discussed in Section 2). The potential loss of precision implies that we need to be careful in interpreting a lack of statistical significance (as one always must be), but does not introduce bias per se. Spillovers imply that we are measuring combined effects of (1) "within" subregion consumption expenditures on the environment, which include both household production impacts and local forest product demand effects, and (2) neighboring subregion expenditures, which only include product demand effects. However, note that we include a measure of local urban consumption expenditures within each district and find no evidence of urban expenditure effects on local rural environments, which would be expected were there significant cross-subregion spillovers.

The Empirical Model

Because we have a two-date district-level panel for our endogenous variables (environmental health and consumption expenditure indicators), we first difference these variables to remove district-specific effects on environmental and expenditure levels, respectively. To test the foregoing hypotheses, we therefore estimate two types of equations, both with differences/changes on the left hand side. First are changes in a district's consumption expenditure distribution:

(4) $$\Delta CEDM_j = \alpha_j + \beta_j \Delta E + \eta_j E + \gamma_j X_I + \varphi_j CEDM + \varepsilon_j,$$

where $\Delta CEDM_j$ represents the change in the jth consumption expenditure distribution measure (*CEDM*), *CEDM* is the vector of initial (pre-determined) expenditure distribution indicators, ΔE denotes contemporaneous environmental change, E denotes the initial state of the environment, and X_I represents a set of other explanatory variables. Changes are measured over our 1994-95 to 2000-01 study period. We predict positive effects of initial environmental conditions (E) and contemporaneous changes (ΔE) on expenditures of the different groups (Hypothesis 2). Because consumption expenditures can potentially respond to both current and anticipated future income, we include the lagged change in environmental conditions (ΔE from the prior four years) in estimating our models in order to capture all available information about the anticipated trajectory of environmental conditions.

Second is an environmental change equation in which consumption expenditure patterns are key:

(5) $$\Delta E = \alpha_E + \theta_E CEDM + \eta_E E + \gamma_E X_E + \varepsilon_E.$$

Hypothesis 1 implies that increased poverty will degrade the environment. Hypothesis 4 implies that a more degraded initial environment will spur environmental improvement (η_E<0).

Equation (5) omits contemporaneous changes in the consumption expenditure distribution. In an expanded paper, we exhaustively study impacts of jointly endogenous expenditure changes and population growth on changes in our environmental indicators.[17] We find no significant effects of any of the expenditure changes and, consistent with the literature, robust negative effects of population growth on environmental change.[18] These results are perhaps not surprising as it is more likely that cumulative levels of poverty and income – rather than short-run income changes – drive resource extraction activity. To focus the present paper in view of these results, we measure income effects in our environment equation using lagged (initial) expenditure distribution measures only.

On their face, equations (4) and (5) are a triangular system that could be estimated by least squares. However, omitted from these equations is population growth which, although not our focus, has key implications for our model construction and methods.

Population growth can affect per capita income changes by redirecting labor to child care and by altering incentives for use of child labor. Changes in income can also alter incentives to have children, as the poor seek more child labor resources and old age security (Schultz, 1997; Dasgupta, 1995; and many others). On the environmental side, population growth can promote increased resource extraction effort (Brander and Taylor, 1998), both because there are more mouths to feed and because availability of child labor can reduce costs of resource collection. As is well documented, population growth can therefore have a deleterious effect on the environment. Moreover, the relationship between population and the environment goes both ways (e.g., see Dasgupta, 1995; Bhattacharya and Innes, 2008).[19]

Population links to incomes and the environment have two implications for our models. First, both equations (4) and (5) are quasi-reduced forms that substitute out the effects of endogenous population change. For our purposes, this is desirable because we are interested in the "total" (net) effects of environmental change on the consumption expenditure distribution (equation (4)) and of the expenditure distribution on environmental change (equation (5)), including impacts that are attributable to resulting changes in population. However, it also means that our explanatory variables need to encompass determinants of population decisions. Second, although equation (5) is a pure reduced form with no jointly endogenous regressor on the right-hand side, the same cannot be said for equation (4), despite our apparent triangular structure. The reason is that environmental change contains population growth effects that are also relevant to changes in consumption expenditures. We therefore need to treat environmental change as an endogenous regressor and identify with instruments that are uncorrelated with changes in both population and consumption expenditures, other than due to forces for which we control. We discuss our identification strategy in detail below.

Our equation (4) exogenous variables include a variety of socio-economic factors relevant to income and population changes: initial (pre-study-period) measures of the distribution of per-capita consumption expenditure; literacy rates; female workforce participation; average household size; the sex (female to male) ratio; the tribal population proportion and the religious makeup of the population. Tribal populations are generally regarded as relatively poor, with relatively high population growth rates, and to be resource conserving. Because Hindus and Muslims represent over 95 percent of the Indian population, we use the Muslim population share as our indicator of a district's religious composition. We include three measures of health status: infant death rates, overall population death rates and life expectancy at birth. Potential congestion effects are captured by including population density. In addition, Dasgupta (1995) observes that urbanization may affect the outward orientation of a district's population, which may affect attitudes toward the environment (and attendant dependence on natural resources), trade, and child bearing. We therefore include a district's urban population share.[20] Finally, the extent of agricultural cultivation may reflect the supply of common lands in rural areas and local economic opportunities. We therefore include the district's initial percentage net sown area (NSA) (Chopra and Gulati, 1997). Initial income distribution measures are available at the start of our study period (1994-5); most other demographic variables are available from the 1991 census.

For equation (5), a variety of socioeconomic and natural factors can drive environmental change. Rural labor availability for resource-based household production is affected by demographic determinants of labor allocations. For example, lower rural sex ratios and higher rural female workforce participation imply reduced availability of female labor that is traditionally used for resource-gathering activities. Other potential determinants of environmental change include predetermined (1991) population densities, literacy (that may promote environmental awareness), the urban population share (a measure of "openness"), the tribal population share, and the percentage net sown area. To control for natural and climatic processes, we use data on rainfall, temperature, elevation, and prior environmental change (1990-1 to 1993-4). Finally, to capture local income effects – from beyond the borders of a district's rural area – on demand for the products from a district's environmental resources (as stressed in Foster and Rosenzweig, 2003, for example), we include the district's urban per-capita consumption exenditure (among other urban sector indicators) and the State's rural and urban per-capita expenditures.

Identification Strategy

While our environmental change equation (5) is a pure reduced form that can be estimated by ordinary least squares, environmental change is a jointly endogenous regressor in the income change equation (4) (as discussed above). To identify environmental change, we use district level average annual rainfall (over 1994-2001). To judge the merits of this instrument, several issues arise.

First, is the instrument highly correlated with environmental change? Intuitively, plant growth is positively related to rainfall. Following standard practice (Bound, Jaeger and Baker, 1995), we assess the instrument's strength from its performance in first stage regressions of environmental change on all exogenous variables. The instrument performs well in these regressions, always with a positive and strongly significant estimated impact on our two environmental measures. First-stage F statistics for the instrument range from 15.64 to 26.86 (see tables 8-10 below), far above the rule-of-thumb cut-off for weak instruments ($F^*=10$, see Staiger and Stock, 1997; Stock and Yogo, 2005).

Second, is our instrument exogenous to population decisions and consumption expenditure changes? Rainfall clearly affects agricultural productivity, which in turn affects rural incomes and population decisions. Using rainfall as an identifying instrument for environmental change in our expenditure equation (4) may thus seem to violate the most basic tenet for identification. We must therefore carefully explain the logic for exclusion of rainfall from equation (4).

Agronomic research indicates that agricultural productivity is affected by deviations of rainfall outside of normal bands (see Azzam and Sekkat, 2003). We therefore control for potential effects of rainfall on agricultural productivity by constructing two rainfall deviation variables that we include in our expenditure change equations; specifically, we sum positive and negative deviations of annual rainfalls, over the period 1994 to 2001, from average annual rainfall (calculated over 1981 to 2000).[21] With these deviation controls, our rainfall instrument captures systematic cross-district differences in *normal* rainfall.

Now remember that our consumption expenditure equations are in *change* form. While normal rainfall clearly affects agricultural productivity, crop mix decisions, and resulting expenditure *levels*, we focus on *changes* that net out fixed effects in expenditure *levels*, including fixed effects of cross-district variation in normal rainfall. This said, expenditure changes perhaps reflect *changes* in agricultural productivity and crop mix that may be driven to some extent by changes in technological adoption (including use of irrigation and high yielding varieties).[22] Technological change, and associated changes in agricultural productivity, may in turn be correlated with normal rainfall. Higher rainfall areas may be better positioned to take advantage of agricultural technologies, for example.

The relationship between agricultural technology change and normal rainfall is far from clear, however. A key point of Fan, Hazell, and Haque (2000) is that, while some advances in agricultural practices are most advantageous in higher rainfall areas (fertilizer use, for example), others are most advantageous in lower rainfall areas (such as irrigation). Net effects of rainfall on the productivity impacts of induced technological change are therefore ambiguous. In Fan, Hazell, and Haque (2000, tables 2 and 3), there is no obvious correlation between changes in agricultural technology and normal rainfall, with one exception: total factor productivity change appears positively correlated with rainfall over the 1970-1994 period, and even over the shorter interval, 1990-94. This relationship is also illustrated in our data with a raw correlation between district-level total agricultural factor productivity growth and normal rainfall, in our study region, over 1990-94, equal to .53. However, this correlation ignores other physical and socioeconomic variables that drive productivity change. To investigate this correlation further, we constructed a State-level six date panel (1970, 1974, 1978, 1982, 1986, 1990) of technology change and income distribution indicators. The technology indicators are (1) total factor productivity change, (2) change in gross irrigated acreage proportions, and (3) change in high yielding variety proportions. In panel (random effects) regressions of the technology change indicators on lagged levels of technology, lagged expenditure indicators and normal rainfall, we conclude that rainfall impacts are not significantly different from period to period, and are generally not significantly different from zero. The one exception to the last rule is that normal rainfall has a significant (at 10%) negative effect on gross irrigated acreage changes, consistent with the logic that irrigation is most advantageous in low rainfall areas.

This anecdotal evidence of a tenuous relationship between normal rainfall and productivity change is reinforced by estimations reported in table 4, where we regress value-weighted yield growth over our sample period on various sets of explanatory variables.[23] Note that the coefficient on average rainfall is not significant in any specification, and is very close to zero. Moreover, p-values for these estimated coefficients are much larger when our rainfall deviation controls – one of which is significant in all specifications – are included.

A second potential criticism of our rainfall instrument is that rainfall may be correlated with disease (such as malaria), which in turn may affect income outcomes and population decisions. However, there are two components to such potential effects, and we control for both. The two components are (1) systematic (cross-district) differences in rainfall, and (2) exceptional rainfall, within the sample period, that causes (for example) floods or droughts. Our rainfall deviation measures control for the second set of effects. To control for systematic effects of health status, whether due to rainfall or other factors, we include relevant health measures (infant death rates, overall death rates, and life expectancy) in our expenditure change equations.

Results

Tables 5-7 present results from our estimation of the environmental change equations (equation (5)) and tables 8-10 present results from estimation of the expenditure change equations (equation (4)). In all cases, we present two specifications, one using the NDVI (vegetative biomass) to measure environmental conditions, and the other using the z-NDVI (forest cover). All models incorporate relevant rural sector exogenous data and urban sector counterparts (to capture potential urban-rural spillovers); alternative specifications (for example with only the rural covariates) yield similar results.

The Environment Equation

Table 5 presents our baseline estimations for our two environmental change measures (*ΔNDVI* and *Δz-NDVI*) using different combinations of the decile / quartile distribution measures. The headcount ratio for the poor (HCR) is included in all models; alternate specifications capture tails of the expenditure distribution using the 10 percent and 90 percent deciles; the 25 and 75 percent deciles; and the 50 percent decile (the median) combined with the Gini coefficient of inequality.[24] Table 6 presents estimations using the FGT-based indices of the expenditure distribution, with alternate poverty lines (one, 1.5 and two times the official poverty lines, respectively). In table 7, we investigate how district road density intermediates the impact of expenditure distribution measures on environmental change.[25] Our road density indicator captures the extent of a district's market integration and may also reflect ease of access to environmental resources for those who have automotive transport. To the extent that markets are integrated and the effects of consumption expenditures on the environment are driven by demand for environment-related products (Foster and Rosenzweig, 2003; Alix-Garcia, et al., 2011), one may expect local expenditure effects (on environmental change) to be attenuated by market integration. However, ease of access may strengthen resource-depletion effects of higher consumption expenditures.

Tables 5-7 give rise to the following conclusions:

(1) *The initial headcount of poverty (HCR) has a significant negative effect on environmental change* (see coefficients on HCR in table 5). Because the meaning of

"units" of NDVI and z-NDVI is not at all clear, gauging the size of these impacts is not straightforward. Following contemporary practice, we look to standard deviations as units by which to gauge magnitudes of effect. For example, consider a five percentage point rise in the initial headcount ratio, which represents almost 7 percent of the average poverty rate but only one-third of the standard deviation for the change in the headcount ratio. Resulting deteriorations in the NDVI and z-NDVI, respectively, are predicted to be between 8.8 and 13.2 percent of the standard deviation for the NDVI change, and 7.5 to 13.4 percent of the standard deviation for the z-NDVI change. These changes are not large as a fraction of the *range* of initial NDVI / z-NDVI; the standard deviations of NDVI / z-NDVI changes equal 8 and 5 percent of initial NDVI / z-NDVI ranges, respectively. However, bear in mind that the effects we estimate are over one 6-year period; hence, a persistent change in the HCR over a longer term will multiply the estimated impacts; this is why we gauge magnitudes using standard deviations of changes.

From table 6, we see that the significant effects of headcount poverty persist when using lower poverty lines – 1.5 times the official lines – but do not persist when using exactly (one times) the official lines. Recall that the lowest (one times) poverty lines capture extreme poverty (per capita expenditures less than \$7.50 per month) and represent only 15 percent of the public on average in our sample districts.

(2) *Higher levels of initial expenditure have a significant negative effect on both types of environmental change*. From table 5, there are negative coefficients on all decile / quartile expenditure values for both environmental change measures, and these coefficients are statistically significant for the upper tail indicators (75th Percentile and

90^{th} Percentile), as well as the median (50^{th} Percentile), but not for the lowest tail (extreme poverty) indicator (10^{th} Perentile). Using Models 3 and 6 of table 5, a one standard deviation increase in median consumption expenditures – roughly a twenty percent rise equal to 67 Rupees per person per month (US$1.50) – is estimated to reduce the NDVI (z-NDVI) by 41.4 percent (47.2 percent) of the standard deviation for the respective NDVI (z-NDVI) change.

Expenditure inequality (as measured by the Gini coefficient in Models 3 and 6 of table 5) is estimated to have a significant negative effect on both of our environmental indicators. Based on our other models, we attribute these impacts primarily to the upper tail of the expenditure distribution. Regardless of how one measures the "upper tail," higher incomes of the relatively rich have significant negative effects on environmental change (see coefficients on 90^{th} Percentile in table 5 and on the richness gap index in table 6). For example, using Models 2 and 5 of table 5, a one standard deviation change in the 90^{th} Percentile expenditure value – roughly 28 percent of the average level of this percentile equal to 172 Rupees per person per month (US$4) – is estimated to reduce the NDVI (z-NDVI) by 34.4 percent (29.9 percent) of the standard deviation for the NDVI (z-NDVI) change.

These results give us mixed evidence on our Hypothesis 1. Hypothesis 1 predicts negative effects of poverty on environmental change and possibly also negative effects of "richness." Although we find evidence of the latter "richness" impacts and that higher poverty counts (HCR) worsen the environment, we do not find evidence that lower incomes of the poor (higher poverty gap indices or lower median expenditures) worsen the environment (tables 5 and 6). Recalling that the negative effects of headcount poverty evaporate when we use the lowest poverty lines (one times the official levels), our results suggest that the estimated negative effects of headcount poverty are attributable to the border-line poor, not the extreme poor.

For the extreme poor (with per capita incomes less than US$7.50 per month), worsened incomes are likely to reflect severe economic and related health deprivation that limits activity, particularly physically taxing efforts to exploit environmental resources. On the other hand, greater prevalence of less extreme poverty (per capita incomes roughly between US$7.50 and US$15 per month) may lead to the modeled effects underpinning Hypothesis 1, with lowered incomes raising incentives to exploit common access resources due to reduced penalties from doing so and an increased threat to basic survival.

(3) As predicted by Hypothesis 4, *initial scarcity of environmental resources spurs subsequent improvement in these resources* (see coefficients on the environmental variables in table 5). We find significant negative effects of the initial NDVI (z-NDVI) and prior change in the NDVI (z-NDVI) on subsequent environmental change. Our estimates indicate that approximately 50 to 60 percent of prior period environmental degradation is offset by subsequent environmental improvement during our six-year study period.[26]

(4) *Greater road density tends to attenuate the impact of poverty on the environment, but reinforces impacts of increased expenditures by the upper tail (relatively rich) households.* In table 7, the road density interactions with at least one of the poverty measures (25^{th} Percentile or HCR) is significant and positive – that is, opposite in sign to the coefficient on the poverty indicator. However, coefficients on the road density

interactions with the upper tail expenditures (75th Percentile in Models 1 and 3) or inequality (Gini in Models 2 and 4) are negative and significant. One possible interpretation of these impacts is that greater road density improves access to environmental resources for those with ready access to automotive transport, which in turn makes these resources more (less) sensitive to the circumstances of the relatively wealthy (poor).

The Income Change Equations

Tables 8 and 9 present estimations for changes in district-level decile / quartile expenditure distribution values. Table 8 estimates environmental impacts using our biomass measure, NDVI, and table 9 estimates using our forest measure, z-NDVI. Table 10 presents estimations for changes in the FGT-based expenditure distribution measures, including the headcount ratio (poverty share, HCR), the poverty gap index (PGI), and the richness gap index (RGI). Estimations are presented for measures constructed using exactly (one times) the official poverty lines (extreme poverty), as well as 1.5 times and twice the official lines. We use a two step generalized method of moments (GMM) estimator that produces heteroskedasticity-robust standard error estimates that account for the normal bias associated with two-stage estimators (Murphy and Topel, 2002).

The estimations yield the following outcomes:

(1) *Improved environmental conditions significantly reduce poverty*. In tables 8 and 9, the environmental change variables (*ΔNDVI* / *Δz-NDVI*) have significant and positive coefficients on real changes in the median expenditure value, and positive but insignificant estimated coefficients on real changes in the lower (10th and 25th) percentiles. In table 10, the environmental changes have significant and negative

estimated impacts on all poverty gap indices, whether measured with one, 1.5 or two times official poverty lines. However, headcount ratios (the share of the poor in the local population) are significantly reduced by environmental improvement only when measuring poverty with the higher (1.5 or two times) poverty lines, with the most pronounced impacts for the highest (baseline, two times) poverty line. In sum, we do *not* find statistical evidence that the *relative number (population share) of the extreme poor* is affected by changes in environmental conditions as we measure them. However, even for the extreme poor, we find evidence that the *extent* of income poverty, as measured by the poverty gap index (with one times the official poverty line), is reduced by environmental improvement. Moreover, both the relative number and extent of expenditure deprivation for the "less extreme" poor (with per-capita monthly expenditures between $7 and $15) are reduced by the environmental improvements that we measure.

To illustrate the economic significance of these estimates, consider a one standard deviation improvement in the NDVI change (4.64) or z-NDVI change (.35), respectively. From Model 3 of tables 8 and 9, the estimated direct impact of these changes is to raise real median expenditures by 13.6 percent (NDVI) and 13.9 percent (z-NDVI) of the initial (1994-5) sample mean (of the median, 326 Rupees), or 65.7 percent (NDVI) and 67.4 percent (z-NDVI) of the corresponding standard deviation (67 Rupees). From Models 1 and 2 of table 10c, the estimated impact is to reduce the poverty gap index (PGI, measured using twice the poverty line) by 21.3 percent (NDVI) and 22.1 percent (z-NDVI) of its initial sample mean (.25), and by 66.6 percent (NDVI) and 69.1 percent (z-NDVI) of the corresponding standard deviation.

(2) *Improved environmental conditions also improve incomes of the non-poor*. However, we do not find statistical evidence that the "rich" benefit from an improved environment. In tables 8 and 9, environmental change is estimated to have a significant and positive impact on the real change in the 75th percentile value, and a positive but insignificant impact on real change in the 90th percentile. In table 10, environmental change is estimated to have a positive and significant impact on changes in the "richness gap index" (RGI) when the lower poverty lines (one or 1.5 times official lines) are used. When our baseline is used (two times official poverty lines), we estimate positive and weakly significant impacts of our biomass measure – NDVI changes and initial levels – on the change in the RGI, but statistically insignificant impacts of our forest measure, *Δz-NDVI*. Moreover, in models of change in the squared richness gap (*ΔSRG*) – the richness measure that weights the "very rich" more heavily – we find no significant impacts of environmental change.[27]

(3) *Comparing effects on the poor and non-poor*. There is no clear-cut way to evaluate relative magnitudes of environmental effects on the poor and the non-poor. To gain a rough sense of these relative impacts, we consider two thought experiments, both designed to compare impacts on the "poor," defined as below-median expenditure, and the "non-poor," defined as above-median. First, we compare the marginal effects of environmental change on, respectively, median expenditures and the 75th percentiles. The difference provides a loose gauge for how much more the penultimate upper quadrant of the expenditure distribution (50th to 75th) benefits from environmental change, vis-à-vis the bottom half. When using our biomass environmental measure, a one standard deviation increase in environmental change (*ΔNDVI*) is estimated to raise

real median expenditures by 44.3 Rupees, or 13.6 percent of the initial mean (of 50th Percentile), and to raise the real 75th percentile value by 62.6 Rupees, or 13.9 percent of the initial mean (of 75th Percentile). Similarly, when using our forest measure (z-NDVI), a one standard deviation increase in the environmental change is estimated to raise real median expenditures by 45.5 Rupees, or 13.9 percent of the initial mean (325.6 Rupees), and to raise the real 75th percentile by 65.2 Rupees, or 14.5 percent of initial mean (450.3 Rupees). In sum, point estimates of environmental impacts on expenditures are greater for the higher expenditure-class cutoff (75th vs. 50th) in absolute terms (Rupees), but approximately the same as a proportion of initial expenditures.

Second, to exploit our FGT-based estimations, consider the following: Environmental change alters expenditures of well-defined "poor" and "non-poor," respectively, without altering the composition of the two groups. (In our sample, of course, we cannot control the composition of the two expenditure classes.) For this purpose, we consider the intermediate (1.5 times official) poverty line which, on average, almost exactly equals average median expenditures in our sample. Our estimates (in the Poverty Gap change and Richness Gap change equations of table 10B) then imply marginal effects of the environmental variables on poverty-line-deflated incomes of poor and non-poor, respectively, equal to our coefficient estimates divided by the headcount ratio HCR (for the poor) and divided by one minus the HCR (for the non-poor).[28] We will want to compare these marginal effects both directly (the absolute magnitude comparison) and as a share of the respective average poverty-line-deflated incomes of the two groups. In our sample, the initial (1994-95) average poverty-line-deflated income of "the non-poor" (district-level sample averages, averaged across our sample districts) is 1.56, and for the poor, .76. Using the Poverty Gap and Richness Gap models (of table 10B) to gauge the impacts of a positive NDVI (z-NDVI) change, we estimate a marginal effect of -.019 (-.258) on deflated incomes of the poor, that is, an 11.7 (11.9) percent (of .76) expenditure improvement due to a one-standard-deviation increase in *ΔNDVI* (4.64) (*Δz-NDVI*, .35). For the non-poor, the estimated marginal effects are .055 (.684); these estimates imply that a one-standard-deviation increase in *ΔNDVI* (*Δz-NDVI*) raises expenditures of the non-poor by 16.3 (15.3) percent of their initial average deflated expenditure (1.56). Again, *we estimate that the non-poor benefit more from an improvement in environmental conditions than the poor*.

Our results support one part of Hypothesis 2 – that all income groups dependent on the environment will enjoy enhanced incomes when the environment improves – but contradict another part of Hypothesis 2 – that environmental change has more acute effects on the poor than on the non-poor. The "poor," as we define them empirically, include the extreme poor whose health and social status can limit any resource extraction. And the "rich" may be able to expand their legal entitlements and employ more low cost labor for resource exploitation when the environment improves. In addition, the types of resource collection activities in which the rich engage may yield benefits that are more sensitive to environmental change.

(4) *There are positive urban income and population share spillovers on rural incomes*. Higher urban population shares have positive and significant estimated effects on rural expenditures of all income groups except the very poor and the very rich.[29] From tables 8 and 9, urban per capita consumption expenditures are estimated to have

positive and significant effects on changes in all expenditure percentiles except the highest (Δ90th Percentile).

The "Poverty Trap"

Does environmental degradation fuel income reductions that spur further degradation (the poverty trap)? We find that degradation fuels income reductions, but that these reductions drive environmental improvement, contradicting the "poverty trap." However, there are negative effects of increased headcount poverty on the environment, and deleterious effects of environmental degradation on headcount poverty (table 10C), consistent with the poverty trap. Which effects dominate?

Consider the one-cycle feedbacks of an exogenous negative shock to the environment (ΔE<0). Using our table 8 (Models 2 and 4) and table 10C (Model 5) estimations to gauge income distribution effects (of an exogenous change in the NDVI on changes in 25th Percentile, 75th Percentile, and HCR) and, in turn, Model 2 of table 5 to gauge the environmental feedback (of the induced changes in 25th Percentile, 75th Percentile, and HCR on *ΔNDVI*), we find that the feedback offsets 3.4 percent of the initial NDVI shock; the 95 percent confidence interval for this proportional net feedback (corresponding to the mean estimate -.034) is (-.196,.128). Using analogs for the z-NDVI,[30] the estimated feedback offsets 2.7 percent of the initial z-NDVI shock, with a 95 percent confidence interval (-.224,.170). If we instead use Models 1, 3 and 5 of table 10C to gauge income distribution effects (of an exogenous change in the NDVI on changes in Poverty Gap, Richness Gap, and HCR) and, in turn, Model 3 of table 6 to gauge the environmental feedback (of the induced changes in HCR, Poverty Gap and Richness Gap on *ΔNDVI*), we find that the feedback offsets 4 percent of the initial NDVI shock, with 95 percent confidence interval (-.205,.125). Using analogs for the z-NDVI, the estimated feedback offsets 3.5 percent of the initial z-NDVI shock, with 95 percent confidence interval (-.194,.125).[31]

On net, feedbacks are estimated to be offsetting in all cases – evidence *against* the poverty trap conjecture (Hypothesis 3). However, these estimates are imprecise. For example, we cannot reject the null hypothesis of a zero one-cycle net feedback. Of course, a zero effect is also the natural null against which the (alternative) poverty trap hypothesis of positive net feedback would be tested. Moreover, even the positive upper bounds of our 95 percent confidence intervals are much smaller than the corresponding estimated feedbacks of a worsened natural environment, and lagged reduction in environmental health, in promoting subsequent environmental improvement (the Simon/Boserup conjecture). Overall, therefore, our results do not support the conjecture of a vicious cycle between poverty and environmental degradation, at least in the context of our Indian sample region.

Summary and Conclusion

Using a district level dataset from South, West and Central India, this paper investigates the relationships between income distribution, measured using consumption expenditure data, and changes in rural environmental conditions as measured by two satellite based indices, one an index of a district's overall biomass and the other an index of forest cover. Our consumption expenditure indicators encompass poverty, median levels of consumption expenditures, and "richness" (expenditures of higher income households). We investigate both directions of effect: how the consumption expenditure distribution affects environmental change and how environmental change affects the expenditure distribution. In doing so, we account for the joint endogeneity of environmental change.

While prior work studies the extent to which different households (and income groups) depend upon natural resources for their livelihood, this paper instead investigates the effect of environmental conditions on income status. For example, the poor may depend heavily on natural resources, but this in itself need not imply that their economic welfare suffers when the environment degrades, or conversely, that their economic welfare improves when the environment improves; benefits of environmental improvement could be captured by wealthier groups, and environmental degradation could reduce competition for the degraded resources to the advantage of the poor. Conversely, greater resource dependence need not translate into greater negative impacts on the environment, as the poor may engage in less harmful resource collection activities and may have less opportunity to expand these activities.

On the environment-to-income side, we find that the economic well-being of the poor rises when the environment improves. Intermediate expenditure groups (those between the poor and the "very" rich) also benefit from environmental improvement, indeed to a greater absolute extent than do the poor. However, we do not find statistical evidence that the "very rich" benefit from environmental improvements. What we call "intermediate expenditure" households are actually quite poor, with per-capita expenditures in the neighborhood of US$15 per month in 2000-01. Our results suggest that enhancing the rural natural environment in India can serve poverty alleviation objectives, but that environmental improvement is likely to benefit the borderline poor –

in the middle of the consumption expenditure distribution – more than the extreme poor at the bottom.

On the environmental side, we find that higher median consumption expenditures and "richness" (measured either with the expenditure cutoff for the top 10 percent of households or the average poverty-line deflated gap between expenditures of the non-poor and the poverty line) have a significant negative impact on environmental health. Although higher poverty counts promote environmental degradation, neither counts of the extreme poor (measured using official poverty lines) nor measure of income poverty (measured using either the expenditure cutoff for the bottom 10 percent of households or the Foster-Greer-Thorbecke poverty gap index) have significant effects on changes in our environmental indicators.

These results suggest that environmental degradation is driven less by the very poor and more by higher income classes in rural economies who increase their exploitation of environmental resources as their incomes rise. We cannot distinguish effects of greater rural "richness" in driving demand for marketed products from natural resources (that in turn drives environmental exploitation, perhaps by the poor) and in increasing the exploitation of natural resources by the relatively rich themselves. The work of Narain, et al. (2008) suggests that it may well be the latter, as the relatively rich in their study villages depend quite heavily on natural resources for their welfare. Regardless, our results suggest reason for concern about the middle tier of the rural income distribution when environmental preservation is desired.

We began the paper by discussing the "poverty trap" – the conjectured spiral between poverty-fueled environmental degradation and degradation-fueled increases in poverty.

In our models, environmental degradation worsens the economic status of the poor, but also has an even greater adverse impact on the relatively rich, intermediate expenditure households. However, reduced expenditures of the poor have a *positive* (but insignificant) impact on subsequent forestation and improvement in the biomass environment. Moreover, lowered expenditures of the relatively rich promote environmental improvement. Hence, the predicted channel of effect *contradicts the poverty trap conjecture*; environmental degradation fuels subsequent environmental gains, not further degradation.

This conclusion must be qualified. A greater extent of poverty, as measured by the population share of the poor and as contrasted with the income deprivation of the poor (the poverty gap or bottom decile expenditure cuttoff), is found to promote environmental degradation in our models. Hence, the border-line poor have adverse effects on the environment, consistent with "poverty trap" logic. However, these impacts are more than offset by the other environment-to-income-to-environment linkages. Moreover, we find large and significant environment-to-environment feedbacks. Consonant with the Simon / Boserup conjecture, a worsened initial environment spurs subsequent environmental improvement due to both natural growth logic and dampened incentives to exploit degraded resources. Overall, for rural India, our results provide qualified evidence that income-environment feedbacks need not reinforce environmental decline and thereby weaken the Simon / Boserup effect.

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Table 1. Variable Definitions and Summary Statistics

Variable	Description	Mean	Std.Dev.
Environmental Variables			
ΔNDVI (1994-2001)	Change in average NDVI from 1994-95 to 2000-01	-10.29	4.64
ΔzNDVI (1994-2001)	Change in z-NDVI from 1994-95 to 2000-01	-0.57	0.35
NDVI (1994)	NDVI 1994-95	174.41	10.97
z-NDVI (1994)	z-NDVI 1995-95	-0.15	0.85
ΔNDVI (1990-94)	Change in average NDVI from 1990-91 to1993-94	5.61	2.52
ΔzNDVI(1990-94)	Change in average z-NDVI from 1990-91 to1993-94	0.46	0.30
Avg Rain (1994-2000)	Average rainfall in centimeters from 1994 to 2000	111.56	82.09
Avg Temp (1994-2000)	Average temperature in Celcius from 1994 to 2000	26.48	1.06
Elevation	Average district elevation in meters	355.18	201.97
Rain Dev(+)(1994-2000)	Positive deviations in rainfall from normal 1994-2000 (total cm)	56.41	30.51
Rain Dev(-)(1994-2000)	Negative deviations in rainfall from normal 1994-2000 (total cm)	45.84	24.19
Net Sown Area (1991)	Net Sown Area as % of total district area 1991	0.52	0.15
Yield Growth (1994-2000)	Annual % change in value-weighted yield per hectare 1994-00	1.03513	0.0586
Socio-economic Variables			
Avg hh size(R) (1991)	Average household size 1991	5.40	0.71
Death rate (R) (1991)	Deaths per thousand population 1991	13.72	7.01
Inf death rt(R) (1991)	Infant deaths per thousand live births 1991	23.51	18.26
Fem work(R) (1991)	Females in workforce as percentage of working age female population 1991	28.41	13.03
Life Exp(R) (1991)	Life expectancy at birth 1991	60.49	7.44
Lit rate(R) (1991)	Literates per hundred population 1991	46.46	17.94
Muslims(R) (1991)	% of Muslims in population 1991	5.84	7.20
Popn dens(R) (1991)	Population (thousand) per square kilometer 1991	0.23	0.19
Sex ratio(R) (1991)	Females per thousand males 1991	960.05	55.70
Tribals(R) (1991)	% of Tribal population in total population 1991	12.36	16.92
Urban popn (1991)	% of urban population in a district 1991	24.72	14.41
Road density (1994)	Rural road density (km per thousand sq.km) 1994	4481.67	3985.82

Note - Sample size: 162; R denotes Rural; Urban (U) counterparts of socio-economic variables omitted here, but included in regressions.

Table 1. Variable Definitions and Summary Statistics (contd..)

Consumption Expenditure Distribution Variables			
Per-capita Cons Exp(R) (2pl) (1994)	Per-capita Consumption Expenditure (PCE) as proportion of 2*official poverty lines 1994-95	0.88	0.17
Head Count Ratio(R)(2pl) (1994)	Head Count Ratio (proportion of poor) using 2*official poverty lines 1994-95	0.73	0.13
Head Count Ratio(R)(1.5pl) (1994)	Head Count Ratio (proportion of poor) using 1.5*official poverty lines 1994-95	0.49	0.17
Head Count Ratio(R)(1pl) (1994)	Head Count Ratio (proportion of poor) using 1*official poverty lines 1994-95	0.15	0.12
Poverty Gap Index(R)(2pl) (1994)	Poverty Gap Index (PGI) using 2*official poverty lines 1994-95	0.25	0.08
Poverty Gap Index(R)(1pl) (1994)	Poverty Gap Index (PGI) using 1*official poverty lines 1994-95	0.03	0.03
Richness Gap Index(R)(2pl) (1994)	Richness Gap Index (RGI) using 2*official poverty lines 1994-95	0.13	0.11
Richness Gap Index(R)(1pl) (1994)	Richness Gap Index (RGI) using 1*official poverty lines 1994-95	0.79	0.33
Gini (R) (1994)	Gini index for consumption expenditure 1994-95	0.24	0.05
10th Percentile (R) (‘94)	!0th percentile of consumption expenditure ‘94-5	195.04	40.43
25th Percentile(R) (‘94)	25th percentile of consumption expenditure ‘94-5	246.52	48.38
50th Percentile(R) (‘94)	50th percentile of consumption expenditure ‘94-5	325.59	67.45
75th Percentile(R) (‘94)	75th percentile of consumption expenditure ‘94-5	450.52	109.43
90th Percentile(R) (‘94)	90th percentile of consumption expenditure ‘94-5	620.49	172.41
Δ10th Percentile(R) (1994-2001)	Real change in !0th percentile 1994-95 to 2000-01	-9.62	45.87
Δ25th Percentile(R) (1994-2001)	Real change in 25th percentile 1994-95 to 2000-01	-17.94	49.13
Δ50th Percentile(R) (1994-2001)	Real change in 50th percentile 1994-95 to 2000-01	-31.32	66.72
Δ75th Percentile(R) (1994-2001)	Real change in 75th percentile 1994-95 to 2000-01	-56.20	106.14
Δ90th Percentile(R) (1994-2001)	Real change in 90th percentile 1994-95 to 2000-01	-76.13	189.48
ΔPCE(R) (2pl) (1994-2001)	Change in PCE, 1994-5 to 2000-01 using 2*official poverty lines	-0.02	0.20
ΔHCR(R) (2pl) (1994-2001)	Change in HCR, 1994-5 to 2000-01 using 2*official poverty lines	0.03	0.15
ΔHCR(R) (1.5pl) (1994-2001)	Change in HCR, 1994-5 to 2000-01 using 1.5*official poverty lines	0.04	0.19
ΔHCR(R) (1pl) (1994-2001)	Change in HCR, 1994-5 to 2000-01 using 1*official poverty lines	0.03	0.16
ΔPGI(R) (2pl) (1994-2001)	Change in PGI, 1994-5 to 2000-01 using 2*official poverty lines	0.03	0.10
ΔPGI(R) (1pl) (1994-2001)	Change in PGI, 1994-5 to 2000-01 using 1*official poverty lines	0.005	0.04
ΔRGI(R) (2pl) (1994-2001)	Change in RGI, 1994-5 to 2000-01 using 2*official poverty lines	0.003	0.13
ΔRGI(R) (1pl) (1994-2001)	Change in RGI, 1994-5 to 2000-01 using 1*official poverty lines	-0.02	0.43

Note - Sample size: 162; R denotes Rural; pl denotes official poverty lines.

Table 2. State Averages of Selected District Data

	Average Rain (cm/yr)	NDVI (1994-95)	z-NDVI (1994-95)	NDVI Min-Max (1994-95)	Avg. Std. Dev. NDVI-pixels
Andhra Pradesh	60.16	178.06	.041	162-193	16.48
Gujarat	58.70	165.55	-.947	151-177	15.17
Karnataka	78.78	174.59	-.171	160-193	16.71
Kerala	185.02	191.76	.866	174-199	15.31
Madhya Pradesh	95.46	175.66	-.070	167-190	17.68
Maharashtra	94.41	172.21	-.271	163-192	19.20
Rajasthan	56.08	161.92	-1.105	140-172	15.06
Tamil Nadu	306.52	179.66	.145	165-198	13.30

	ΔNDVI	Δz-NDVI	Δ10th Percentile	Δ50th Percentile	Δ90th Percentile
Andhra Pradesh	-8.84	-.446	5.30	-4.59	-2.46
Gujarat	-10.80	-.609	-25.70	-70.29	-155.05
Karnataka	-7.42	-.316	-16.78	-20.46	-45.44
Kerala	-12.85	-.913	23.24	25.30	65.07
Madhya Pradesh	-14.03	-.744	-29.78	-76.69	-150.09
Maharashtra	-10.55	-.504	-19.78	-28.81	-92.28
Rajasthan	-10.24	-.633	1.49	-21.72	-122.60
Tamil Nadu	-3.03	-.257	1.93	-19.29	-9.29

Averages across sample districts in each State. The "NDVI Min-Max" gives the range of district values for the average NDVI in the State. The "Avg. Std. Dev." gives the cross-district average of within-district standard deviations of pixel-level NDVI.

Table 3. Official Poverty Lines (in Rupees per Month)

	Rural (1993-94)	Urban (1993-94)	Rural (2000-01)	Urban (2000-01)
Andhra Pradesh	163.02	278.14	262.94	457.4
Gujarat	202.11	297.22	318.94	474.41
Karnataka	186.63	302.89	309.59	511.44
Kerala	243.84	280.54	374.79	477.06
Madhya Pradesh	193.1	317.16	311.34	481.65
Maharashtra	194.94	328.56	318.63	539.71
Rajasthan	215.89	280.85	344.03	465.92
Tamil Nadu	196.53	296.63	307.64	475.6
India	205.84	281.35	327.56	454.11

Table 4. Agricultural Yield Growth Regressions

Panel A. Models Including Rain Deviations

	(1) Yield Growth (1994-2000)	(2) Yield Growth (1994-2000)	(3) Yield Growth (1994-2000)	(4) Yield Growth (1994-2000)	(5) Yield Growth (1994-2000)
Avg Rain (1994-2000)	-7.79e-05	-9.17e-05	-8.03e-05	-0.000118	-7.64e-05
	(0.696)	(0.645)	(0.599)	(0.428)	(0.606)
Net Sown Area (1991)	0.0958*	0.0952*	0.0766**	0.0626*	0.0776**
	(0.0604)	(0.0618)	(0.0368)	(0.0859)	(0.0213)
Rain Deviation(+) (1994-2000)	0.000517*	0.000517*	0.000582**	0.000597**	0.000564**
	(0.0845)	(0.0840)	(0.0236)	(0.0178)	(0.0245)
Rain Deviation(-) (1994-2000)	-6.28e-05	-0.000119	-7.93e-05	-0.000170	3.60e-05
	(0.901)	(0.812)	(0.855)	(0.685)	(0.929)
Urban popn (1991)	0.00109**	0.00107**		0.000829**	
	(0.0163)	(0.0181)		(0.0216)	
Socio-economic variables included	Yes	Yes	No	No	No
Rural expenditure distribution indices included	Yes	Yes	Yes	Yes	No
Initial environmental indices included	Yes	Yes	Yes	Yes	No
R-sq	0.276	0.271	0.105	0.134	0.084

Panel B. Models Without Rain Deviations

	(1) Yield Growth (1994-2000)	(2) Yield Growth (1994-2000)	(3) Yield Growth (1994-2000)	(4) Yield Growth (1994-2000)	(5) Yield Growth (1994-2000)
Avg Rain (1994-2000)	9.41e-05	9.33e-05	0.000106	9.14e-05	7.04e-05
	(0.369)	(0.373)	(0.137)	(0.196)	(0.263)
Net Sown Area (1991)	0.0928*	0.0929*	0.0769**	0.0636*	0.0804**
	(0.0682)	(0.0675)	(0.0370)	(0.0828)	(0.0183)
Urban popn (1991)	0.00113**	0.00111**		0.000845**	
	(0.0132)	(0.0143)		(0.0209)	
Socio-economic variables included	Yes	Yes	No	No	No
Rural expenditure distribution indices included	Yes	Yes	Yes	Yes	No
Initial environmental indices included	Yes	Yes	Yes	Yes	No
R-sq	0.256	0.251	0.068	0.096	0.043

Notes: p-value in parentheses, *** p<0.01, ** p<0.05, * p<0. Robust standard errors.
Yield growth refers to annualized geometric value-weighted agricultural yield growth from 1994 to 2000.
Socio-economic variables include (R=rural, U=Urban): Death rate (R,U), Life Exp (R,U), Lit Rate (R,U), Fem Work (R,U), Sex Ratio (R,U), Inf Death Rt (R,U), Popn Dens (R,U), Muslims (R,U), Tribals (R,U), Avg hh size (R,U), Per-capita Cons Exp (U). Environmental indices include: NDVI, z-NDVI. Rural expenditure distribution indices include (all using twice official poverty lines):
Models 1 and 3: Poverty Gap Index (R), Richness Gap Index (R), Head Count Ratio (R),.
Models 2 and 4: Head Count Ratio (R), Per-capita Cons Exp (R).
All models include Intercept, Avg Temperature (1994-2000), and Elevation.

Table 5. Environmental Change Regressions with Percentile Measures of the Consumption Expenditure Distribution

Dependent Variable →	(1) ΔNDVI (1994-2001)	(2) ΔNDVI (1994-2001)	(3) ΔNDVI (1994-2001)	(4) Δz-NDVI (1994-2001)	(5) Δz-NDVI (1994-2001)	(6) Δz-NDVI (1994-2001)
Consumption expenditure distribution indicators						
10th Percentile(R) (1994)	-0.00967			-0.00117		
	(0.340)			(0.144)		
90th Percentile(R) (1994)	-0.00929***			-0.00061***		
	(0.000532)			(0.00343)		
25th Percentile(R) (1994)		-0.0123			-0.00149*	
		(0.287)			(0.0989)	
75th Percentile(R) (1994)		-0.0168***			-0.00122***	
		(0.00360)			(0.00593)	
50th Percentile(R) (1994)			-0.0285**			-0.00245***
			(0.0114)			(0.00484)
Headcount Ratio (R) (2pl) (1994)	-8.162**	-12.22***	-11.66**	-0.526*	-0.937***	-0.906**
	(0.0217)	(0.00782)	(0.0229)	(0.0586)	(0.00787)	(0.0221)
Gini(R) (1994)			-14.39**			-1.025**
			(0.0134)			(0.0236)
Environmental indicators						
NDVI or z-NDVI (1994-95)	-0.293***	-0.295***	-0.295***	-0.323***	-0.328***	-0.319***
	(2.09e-10)	(2.71e-10)	(5.55e-10)	(5.88e-15)	(2.89e-15)	(1.15e-14)
ΔNDVI or Δz-NDVI (1990-94)	-0.278**	-0.310**	-0.244*	-0.314***	-0.315***	-0.294***
	(0.0399)	(0.0241)	(0.0734)	(0.000247)	(0.000224)	(0.000646)
Avg Rain (1994-2000)	0.0492***	0.0542***	0.0502***	0.00391***	0.00422***	0.00394***
	(2.94e-05)	(5.46e-06)	(2.38e-05)	(1.89e-05)	(3.49e-06)	(1.46e-05)
Elevation	0.00348	0.00376	0.00311	0.000547***	0.000555***	0.000501**
	(0.183)	(0.150)	(0.258)	(0.00917)	(0.00742)	(0.0229)
Avg Temp (1994-2000)	0.345	0.285	0.112	0.0970**	0.0910**	0.0782*
	(0.506)	(0.583)	(0.839)	(0.0180)	(0.0252)	(0.0693)
Socio-economic indicators						
Popn density (R) (1991)	3.376	3.567	3.518	0.0155	0.0252	0.00936
	(0.155)	(0.136)	(0.144)	(0.934)	(0.891)	(0.960)
Life Exp (R) (1991)	0.0797*	0.0877*	0.0686	0.00955**	0.0105***	0.00892**
	(0.0977)	(0.0748)	(0.156)	(0.0118)	(0.00613)	(0.0179)
Avg hh size (R) (1991)	-1.895**	-1.634*	-2.084**	-0.0344	-0.0190	-0.0503
	(0.0452)	(0.0834)	(0.0306)	(0.639)	(0.793)	(0.497)
Popn density (U) (1991)	-0.0121	-0.0403	-0.0101	-0.0143	-0.0167*	-0.0140
	(0.913)	(0.722)	(0.928)	(0.102)	(0.0567)	(0.106)

Notes: 162 obs. p-value in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors. R=rural, U=Urban. Head Count Ratio constructed using twice official poverty lines (2pl). Explanatory variables included in all models but not presented: Intercept, Net Sown Area, Rain Dev (+,-), Urban Popn, Per-capita Cons Exp(U), Life Exp (U), Avg hh size (U), Lit Rate (R,U), Fem Work (R,U), Sex Ratio (R,U), Muslims (R,U), Tribals (R,U), State per-capita consumption expenditure (R,U).

Table 6. Environmental Change Regressions with Poverty and Richness Gap Measures of the Consumption Expenditure Distribution

Dependent Variable →	(1) ΔNDVI (1994-2001)	(2) ΔNDVI (1994-2001)	(3) ΔNDVI (1994-2001)	(4) Δz-NDVI (1994-2001)	(5) Δz-NDVI (1994-2001)	(6) Δz-NDVI (1994-2001)
Consumption expenditure distribution indicators						
Headcount Ratio(R)(1pl) (1994)	-8.241			-0.109		
	(0.202)			(0.830)		
Poverty Gap Index (R) (1pl) (1994)	35.08			0.933		
	(0.211)			(0.670)		
Richness Gap Index (R) (1pl) (1994)	-2.261*			-0.142		
	(0.0539)			(0.122)		
Headcount Ratio (R) (1.5pl) (1994)		-9.062*			-0.639*	
		(0.0594)			(0.0923)	
Poverty Gap Index (R) (1.5pl) (1994)		13.48			1.164	
		(0.179)			(0.141)	
Richness Gap Index (R) (1.5pl) (1994)		-7.244***			-0.478**	
		(0.00349)			(0.0148)	
Headcount Ratio (R) (2pl) (1994)			-12.93**			-0.767*
			(0.0174)			(0.0748)
Poverty Gap Index (R) (2pl) (1994)			9.999			0.773
			(0.152)			(0.164)
Richness Gap Index (R) (2pl) (1994)			-14.27***			-0.847***
			(0.000289)			(0.00648)
Environmental indicators						
NDVI or z-NDVI (1994)	-0.269***	-0.263***	-0.272***	-0.304***	-0.302***	-0.307***
	(4.54e-09)	(6.76e-09)	(1.33e-09)	(2.89e-13)	(2.66e-13)	(8.79e-14)
ΔNDVI or Δz-NDVI (1990-94)	-0.252*	-0.274**	-0.285**	-0.320***	-0.335***	-0.330***
	(0.0693)	(0.0462)	(0.0347)	(0.000290)	(0.000139)	(0.000155)
Avg Rain (1994-2000)	0.0515***	0.0535***	0.0571***	0.00419***	0.00422***	0.00439***
	(2.90e-05)	(9.64e-06)	(2.07e-06)	(1.15e-05)	(6.65e-06)	(3.11e-06)
Elevation	0.00425	0.00468*	0.00550**	0.00065***	0.00066***	0.00071***
	(0.116)	(0.0760)	(0.0338)	(0.00262)	(0.00200)	(0.000876)
Avg Temp (1994-2000)	0.474	0.589	0.774	0.114***	0.120***	0.129***
	(0.370)	(0.259)	(0.137)	(0.00684)	(0.00420)	(0.00215)

Notes: 162 obs. p-value in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors. R=rural, U=Urban. '1pl' , '1.5pl' and '2pl' indicate that the expenditure distribution measure is constructed using official poverty lines, 1.5 times official poverty lines, and twice official poverty lines, respectively. Explanatory variables included in all models but not presented: Intercept, Net Sown Area, Rain Dev (+,-), Urban Popn, Per-capita Cons Exp (U), Population density (R,U), Life Exp (R,U), Avg hh size (R,U), Lit Rate (R,U), Fem Work (R,U), Sex Ratio (R,U), Muslims (R,U), Tribals (R,U), State per-capita consumption expenditure (R,U).

Table 7. Environmental Change Regressions with Consumption Expenditure Distribution Interactions with Road Density

	(1) ΔNDVI (1994-2001)	(2) ΔNDVI (1994-2001)	(3) Δz-NDVI (1994-2001)	(4) Δz-NDVI (1994-2001)
Consumption expenditure distribution indicators				
25th Percentile(R) (1994)	-0.0443*** (0.00877)		-0.00362*** (0.00677)	
75th Percentile(R) (1994)	0.000736 (0.923)		-0.000104 (0.862)	
50th Percentile(R) (1994)		-0.0303** (0.0116)		-0.00276*** (0.00315)
Head Count Ratio(R) (2pl) (1994)	-12.02** (0.0100)	-15.12*** (0.00368)	-0.907** (0.0131)	-1.115*** (0.00606)
Gini(R) (1994)		-2.201 (0.779)		-0.113 (0.854)
Road-density(R)*25th Percentile(R) (1994)	9.32e-06** (0.0115)		6.13e-07** (0.0342)	
Road-density(R)*75th Percentile(R) (1994)	-4.58e-06*** (0.00589)		-2.87e-07** (0.0280)	
Road-density(R)*50th Percentile(R) (1994)		8.22e-07 (0.419)		9.49e-08 (0.237)
Road-density(R)* Headcount Ratio(R) (2pl) (1994)	-5.37e-05 (0.902)	0.000939*** (0.00390)	-6.57e-06 (0.848)	5.66e-05** (0.0254)
Road-density(R)* Gini(R) (1994)		-0.00257* (0.0767)		-0.000192* (0.0922)
Environmental indicators				
NDVI or z-NDVI (1994)	-0.278*** (6.84e-10)	-0.280*** (1.71e-09)	-0.313*** (8.66e-15)	-0.308*** (3.9e-14)
ΔNDVI or Δz-NDVI (1990-94)	-0.267** (0.0441)	-0.199 (0.135)	-0.295*** (0.000460)	-0.283*** (0.000917)
Avg Rain (1994-2000)	0.0445*** (0.000777)	0.0370*** (0.00476)	0.00346*** (0.000710)	0.00300*** (0.00309)

Notes: 162 obs. p-value in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors. R=rural, U=Urban. Explanatory variables included in all models but not presented: Intercept, Net Sown Area, Rain Dev (+,-), Urban Popn, Percapita Cons Exp(U), Population density(R,U), Life Exp (R,U), Avg hh size (R,U), Lit Rate (R,U), Fem Work (R,U), Sex Ratio (R,U), Muslims (R,U), Tribals (R,U), State per capita consumption expenditure (R,U), Avg. temperature and Elevation. The headcount ratio of poverty is based on twice the official poverty lines.

Table 8. Consumption Expenditure Percentile Change Regressions with the NDVI

	(1) Δ10th Percentile (R) (1994-2001)	(2) Δ25th Percentile (R) (1994-2001)	(3) Δ50th Percentile (R) (1994-2001)	(4) Δ75th Percentile (R) (1994-2001)	(5) Δ90th Percentile (R) (1994-2001)
Environmental indicators					
ΔNDVI (1994-2001)	3.521	2.513	9.554***	13.49***	15.57
	(0.197)	(0.394)	(0.00755)	(0.00930)	(0.121)
NDVI (1994)	0.312	0.0649	1.845*	3.341*	5.055
	(0.709)	(0.941)	(0.0976)	(0.0507)	(0.143)
ΔNDVI (1990-94)	-0.206	-0.232	-0.325	2.680	-3.418
	(0.908)	(0.887)	(0.887)	(0.457)	(0.616)
Rain Deviation (+) (1994-2000)	0.0460	-0.00714	-0.446*	-0.779**	-0.775
	(0.828)	(0.973)	(0.0645)	(0.0383)	(0.301)
Rain Deviation (-) (1994-2000)	0.263	0.152	0.210	0.502	0.702
	(0.123)	(0.397)	(0.410)	(0.209)	(0.369)
Elevation	0.00430	0.0340	0.0739*	0.0741	0.149
	(0.883)	(0.181)	(0.0853)	(0.274)	(0.237)
Avg Temp (1994-2000)	-2.271	0.385	-1.046	-4.261	8.072
	(0.710)	(0.946)	(0.913)	(0.781)	(0.778)
Consumption expenditure distribution indicators					
Per capita Cons Exp (R) (2pl) (1994)	-7.837	-0.791	6.540	-93.34	-13.45
	(0.769)	(0.978)	(0.888)	(0.195)	(0.911)
10th Percentile(R) (1994)	-0.835***				
	(3.6e-14)				
25th Percentile(R) (1994)		-0.828***			
		(01.92e-12)			
50th Percentile(R) (1994)			-0.771***		
			(5.69e-07)		
75th Percentile(R) (1994)				-0.533***	
				(5.39e-05)	
90th Percentile(R) (1994)					-0.619***
					(0.000107)
Socio-economic indicators					
Urban popn (1991)	0.0948	0.164	0.865**	1.628**	1.033
	(0.710)	(0.507)	(0.0359)	(0.0130)	(0.366)
Death rate (R) (1991)	-1.856*	-1.911**	-3.889***	-3.781**	-4.560
	(0.0562)	(0.0500)	(0.000747)	(0.0340)	(0.167)
Life Exp(R) (1991)	4.933	6.608**	9.019*	15.35**	27.30**
	(0.112)	(0.0360)	(0.0575)	(0.0307)	(0.0342)
Per capita Cons Exp (U) (2pl) (1994)	55.14***	54.01**	86.07***	101.2**	24.93
	(0.00747)	(0.0117)	(0.00379)	(0.0289)	(0.795)
First stage F statistic	21.87	21.47	22.78	22.99	23.05
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Notes: 162 obs. p-value in parentheses. *** p<0.01, ** p<0.05, * p<0.1. R=rural, U=Urban. Two step GMM with robust standard errors. Identifying instrument: Avg Rain. Explanatory variables included but not presented: Intercept, Net Sown Area, Death rate (U), Life Exp (U), Lit Rate (R,U), Fem Work (R,U), Sex Ratio (R,U), Inf Death Rt (R,U), Popn Dens (R,U), Muslims (R,U), Tribals (R,U), Avg hh size (R,U).

Table 9. Consumption Expenditure Percentile Change Regressions with the z-NDVI

	(1) Δ10th Percentile (R) (1994-2001)	(2) Δ25th Percentile (R) (1994-2001)	(3) Δ50th Percentile (R) (1994-2001)	(4) Δ75th Percentile (R) (1994-2001)	(5) Δ90th Percentile (R) (1994-2001)
Environmental indicators					
Δz-NDVI (1994-2001)	42.56	32.91	129.9**	186.4**	197.8
	(0.249)	(0.400)	(0.0116)	(0.0104)	(0.171)
z-NDVI (1994)	4.518	3.952	20.10	39.56	37.71
	(0.697)	(0.750)	(0.237)	(0.119)	(0.453)
Δz-NDVI (1990-94)	10.57	5.527	8.926	36.75	-6.639
	(0.519)	(0.717)	(0.715)	(0.338)	(0.925)
Rain Deviation (+) (1994-2000)	0.0786	0.0125	-0.358	-0.638*	-0.658
	(0.676)	(0.946)	(0.117)	(0.0658)	(0.333)
Rain Deviation (-) (1994-2000)	0.226	0.144	0.0882	0.310	0.330
	(0.185)	(0.400)	(0.733)	(0.448)	(0.673)
Elevation	-0.00755	0.0255	0.0581	0.0364	0.121
	(0.812)	(0.368)	(0.227)	(0.609)	(0.354)
Avg Temp (1994-2000)	-5.149	-0.883	-6.959	-15.85	-7.710
	(0.413)	(0.882)	(0.490)	(0.315)	(0.775)
Consumption expenditure distribution indicators					
Per capita Cons Exp (R) (2pl) (1994)	-12.84	-10.35	-24.60	-128.2*	-24.04
	(0.629)	(0.694)	(0.596)	(0.0875)	(0.846)
10th Percentile(R) (1994)	-0.812***				
	(5.23e-14)				
25th Percentile(R) (1994)		-0.780***			
		(1.44e-12)			
50th Percentile(R) (1994)			-0.662***		
			(3.99e-05)		
75th Percentile(R) (1994)				-0.459***	
				(0.00203)	
90th Percentile(R) (1994)					-0.611***
					(0.000253)
Socio-economic indicators					
Urban popn (1991)	0.0920	0.169	0.809*	1.476**	0.775
	(0.709)	(0.492)	(0.0597)	(0.0225)	(0.495)
Death rate (R) (1991)	-1.880*	-1.951**	-4.004***	-3.859**	-4.563
	(0.0513)	(0.0447)	(0.000841)	(0.0343)	(0.184)
Life Exp(R) (1991)	6.059**	7.516***	11.58**	17.94**	32.50**
	(0.0349)	(0.00889)	(0.0156)	(0.0127)	(0.0143)
Per capita Cons Exp (U) (1994)	58.66***	56.47**	100.9***	130.9***	48.14
	(0.00712)	(0.0153)	(0.00124)	(0.00652)	(0.642)
First stage F statistic	17.32	16.88	16.87	16.87	15.64
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)

Notes: 162 obs. p-value in parentheses. *** p<0.01, ** p<0.05, * p<0.1. R=rural, U=Urban. Two step GMM with robust standard errors. Identifying instrument: Avg Rain. Explanatory variables included but not presented: Intercept, Net Sown Area, Death rate (U), Life Exp (U), Lit Rate (R,U), Fem Work (R,U), Sex Ratio (R,U), Inf Death Rt (R,U), Popn Dens (R,U), Muslims (R,U), Tribals (R,U), Avg hh size (R,U).

Table 10. Regression Results for Changes in FGT Consumption Expenditure Indices: Poverty Gaps, Richness Gaps, and Poverty Headcount Ratios

Panel A. Using official poverty lines (1pl)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable (Using 1pl) →	ΔPoverty Gap (1994-2001)	ΔPoverty Gap (1994-2001)	ΔRichness Gap (1994-2001)	ΔRichness Gap (1994-2001)	ΔHCR (1994-2001)	ΔHCR (1994-2001)
Environment Index →	NDVI	z-NDVI	NDVI	z-NDVI	NDVI	z-NDVI
ΔNDVI / Δz-NDVI (1994-2001)	-0.00436*	-0.0607*	0.0607**	0.858**	-0.0105	-0.134
	(0.0607)	(0.0644)	(0.0114)	(0.0143)	(0.258)	(0.297)
NDVI / z-NDVI (1994)	-0.00108	-0.0173	0.0251***	0.368***	-0.00407	-0.0459
	(0.148)	(0.108)	(0.00166)	(0.00182)	(0.177)	(0.284)
ΔNDVI / Δz-NDVI (1990-94)	-0.000963	-0.0180	0.0213	0.308**	0.00419	0.00752
	(0.477)	(0.197)	(0.147)	(0.0385)	(0.432)	(0.892)
First stage F stat	22.97	16.55	22.97	16.55	21.73	15.84
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0001)

Panel B. Using 1.5 times official poverty lines (1.5pl)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable (Using 1.5pl) →	ΔPoverty Gap (1994-2001)	ΔPoverty Gap (1994-2001)	ΔRichness Gap (1994-2001)	ΔRichness Gap (1994-2001)	ΔHCR (1994-2001)	ΔHCR (1994-2001)
Environment Index →	NDVI	z-NDVI	NDVI	z-NDVI	NDVI	z-NDVI
ΔNDVI / Δz-NDVI (1994-2001)	-0.00790*	-0.107*	0.0234**	0.292*	-0.0146*	-0.210*
	(0.0827)	(0.0976)	(0.0313)	(0.0568)	(0.0997)	(0.0891)
NDVI / z-NDVI (1994)	-0.00220	-0.0260	0.00885**	0.0834	-0.00291	-0.0339
	(0.132)	(0.227)	(0.0160)	(0.118)	(0.302)	(0.403)
ΔNDVI / Δz-NDVI (1990-94)	0.000564	-0.00912	-0.00238	0.0273	-0.00101	-0.0207
	(0.840)	(0.739)	(0.737)	(0.709)	(0.872)	(0.717)
First stage F stat	22.68	16.15	22.68	16.15	24.3	17.42
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0001)

Panel C. Using twice official poverty lines (2pl)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable (Using 2pl) →	ΔPoverty Gap (1994-2001)	ΔPoverty Gap (1994-2001)	ΔRichness Gap (1994-2001)	ΔRichness Gap (1994-2001)	ΔHCR (1994-2001)	ΔHCR (1994-2001)
Environment Index →	NDVI	z-NDVI	NDVI	z-NDVI	NDVI	z-NDVI
ΔNDVI / Δz-NDVI (1994-2001)	-0.0115**	-0.158**	0.0113*	0.138	-0.0183***	-0.266***
	(0.0263)	(0.0328)	(0.0667)	(0.121)	(0.00991)	(0.00878)
NDVI / z-NDVI (1994)	-0.00310*	-0.0361	0.00503**	0.0450	-0.00586**	-0.0617*
	(0.0605)	(0.142)	(0.0220)	(0.151)	(0.0141)	(0.0989)
ΔNDVI / Δz-NDVI (1990-94)	-0.000322	-0.0207	-0.00259	0.00590	-0.00316	-0.0361
	(0.924)	(0.534)	(0.540)	(0.892)	(0.519)	(0.446)
First stage F stat	24.02	16.83	24.02	16.83	26.86	18.04
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0001)

Notes: HCR = headcount ratio of poverty. 162 obs., p-value in parentheses, *** p<0.01, ** p<0.05, * p<0.1, Two step GMM with robust standard errors. Identifying instrument: Avg Rain. Explanatory variables included but not presented: Intercept, Net Sown Area, Rain Deviation(+,-),Death rate (R,U), Life Exp (R,U), Lit Rate (R,U), Fem Work (R,U), Sex Ratio (R,U), Inf Death Rt (R,U), Popn Dens (R,U), Muslims (R,U), Tribals (R,U), Avg hh size (R,U), Avg Temperature, Elevation, Urban popn, Per-capita Cons Exp(R,U) and the initial (1994) level of the expenditure distribution index corresponding to the dependent variable (poverty gap, richness gap, or HCR).

Endnotes

[1] JFM was started in the 1990's with the aim of reducing rural poverty and preserving forest resources by providing villagers with formal common property entitlements (see Rabindranath and Sudha, 2004).

[2] We apologize to authors of the many profound papers on this topic not cited here, including a large literature on environmental impacts of population growth (see Bhattacharya and Innes, 2008, for some references). Our focus on links between the environment and income distribution (vs. population growth) distinguishes the present paper from our earlier work. By examining links between income and the environment, the present paper is also related to an enormous literature on the Environmental Kuznets Curve (e.g., Stern, 2004). While this literature gives an unclear picture of empirical relationships between average incomes and environmental health, it also abstracts from effects of income distribution that are our central concern.

[3] See, for example, Narain, Gupta and van't Veld (2008) and Reddy and Chakravarty (1999) on rural India; Adhikari, Falco, and Lovett (2004) on rural Nepal; Dasgupta, Deichmann, Meisner, and Wheeler (2005) on Southeast Asia; and Cavendish (2000) on Zimbabwe.

[4] To our knowledge, the only extant study that directly attempts to gauge the impact of poverty on environmental change is Dasgupta, et al. (2005) who regress district-level forest changes on lagged levels of population and poverty in Cambodia. They find that only population is significant as a factor leading to deforestation. We build on their work by studying a more comprehensive district-level dataset that enables us to examine

income distribution (including, but not limited to poverty), environmental health, and their contemporaneous feedbacks.

[5] Substantial anecdotal evidence indicates that poorer households engage in more resource collection activities on "the commons," including those to which they do not have legal entitlements (e.g., Jodha, 2000; Reddy and Chakravarty, 1999). Drawing upon the household production literature (e.g., Renkow (1990), Singh, Squire and Strauss (1986)), our supplementary appendix contains a model and analysis of household level resource exploitation, with expected sanction costs that change with income endowments.

[6] There are a number of other mechanisms that can give rise to Hypothesis 4. As open access environmental resources become increasingly scarce – and hence increasingly valuable and costly to exploit – governmental incentives to protect the resources grows, whether in terms of improved property law (Libecap and Smith, 2002; Demsetz, 1967) or increased enforcement of environmental protection laws. For privately owned environmental resources, scarcity spurs higher prices for environmental products and, hence, heightened incentives for the private supply of these resources.

[7] The eight states are selected due to availability of socio-economic data from Human Development Reports for India.

[8] Three all-urban districts are excluded (Mumbai, Hyderabad, and Chennai). Six new districts are combined to match district definitions at the start of our sample period. 11 districts are excluded due to small sample sizes of NSSO expenditure surveys. And a number of other districts were omitted due to missing data, primarily on birth and death rates from the Registrar General's office. These omissions reduced our sample from 199 to 162 districts.

[9] We use urban counterparts to our rural data to control for urban-rural spillovers. Per the Census of India, urban (vs. rural) areas are defined as all locations within a defined municipality and all other areas that have (a) a minimum population of 5000, (b) at least 75 percent of the male working population engaged in non-agricultural activities, and (c) a population density of at least 400 people per square kilometer.

[10] Calculation of the NDVI is based on the spectral bands of the photosynthetic output in a pixel from a satellite image. It measures the amount of green vegetation in an area and is based on the principle that green plants absorb radiation in the visible region of the spectrum (Photosynthetically Active Radiation, PAR) and reflect radiation in the Near Infrared region (NIR). Given these "spectral signatures," the NDVI for a pixel is calculated as follows: NDVI = (NIR – PAR) / (NIR + PAR). The NDVI can take a value between 0 and 256. NDVI data is obtained from the NOAA/NASA Pathfinder AVHRR Land dataset, http://daac.gsfc.nasa.gov/data/dataset/AVHRR/01_Data_Products/04_FTP_Products/index.html.

[11] The calculated critical N index value is 177. This is somewhat higher than the critical index value used by Foster and Rosenzweig (2003) to measure forest cover.

[12] Also potentially indicative of this conclusion is the lack of correlation between district size and pixel-level variation. Both the initial (1994-95) within-district standard deviations and their changes (from 1994-95 to 2000-01) are slightly negatively correlated with the size of a district's rural area (with correlation coefficients equal to -.197 for levels and -.273 for changes).

[13] Consumption expenditures reflect permanent incomes to the extent that consumption smoothing is possible using either explicit credit markets, asset trading, or informal credit markets. For example, see Townsend (1994) for discussion of consumption smoothing opportunities in rural India, despite an absence of formal credit markets. Without smoothing opportunities, consumption expenditures proxy for current incomes.

[14] If $\alpha = 2$, Y_α in equation (1) gives the Squared Poverty Gap index (SPG) which adds weight to larger shortfalls from the poverty line. Similarly, if $\alpha = 2$, Y_α in equation (2) gives the Squared Richness Gap index (SRG). Our supplementary appendix presents estimations using the SPG and SRG.

[15] The reductions in our rural per capita consumption expenditure measures appear to be at odds with widely cited statistics on growth in real per capita GDP in India over our sample period (1994-5 to 2000-01). For example, DeLong (2001) cites IMF statistics indicating overall real per capita GDP growth of 4.4 percent in India from 1990 to 2000. Similar numbers can be found from other sources. The Government of India's Planning Commission (2011, planningcommission.nic.in/data/datatable/1705/databook_dch_160511.pdf) indicates geometric average annual real GDP growth of 5.5 percent over 1991-2001; net of overall annual population growth of 1.989 percent over this period (Census of India, 2001), per capita real GDP growth was roughly 3.5 percent. There are three reasons for the differences with our data. First, our data reflects only the rural sector of India, which experienced much less economic growth than the urban sector. Second, we use poverty lines to gauge inflation in a basic basket of goods, rather than the overall inflation rate for India; over our sample period, poverty lines appreciated by more than inflation rates used

to measure real GDP changes. Finally, our unit of analysis is a district in India, rather than individuals or households. Consider the first two differences. From the Planning Commission (2011), real geometric average annual agricultural GDP growth over our sample period was 2.48 percent; net of 1.48 percent rural annual geometric average population growth over this period (indexmundi.com/facts/india/rural-population), rural sector GDP growth was roughly 1 percent. However, geometric average annual growth in poverty lines in our data was 6.98 percent, compared with an overall annual GDP deflator over this period of 5.43 percent. Netting out this difference in inflation leaves an estimate of real per capita rural GDP growth of -.55 percent. Similarly, using direct measures of real rural per capita consumption expenditures from 1993-4 and 1999-2000 (Planning Commission, 2011, p. 51), average annual growth (weighting States by district numbers in our data) was roughly 1.24 percent; again netting out the difference in our inflation measure leaves an estimated change in real rural per capita consumption expenditures of -.31 percent. In addition, by weighting each district equally, averages in our data weight smaller, less urban districts – which tend to have experienced less income growth (as seen in our regressions below) – by more than the population weights that are implicitly applied in aggregate statistics. Our cross-district average changes in per capita expenditure measures will therefore tend to be lower. By contrast, India's urban sector experienced much more income growth over our sample period. For example, geometric average annual growth in real industrial GDP was 7.4 percent from 1994-5 to 2000-01 (Planning Commission, 2011); netting out urban population growth of 3.48 percent per annum gives approximate per-capita urban GDP growth of almost 4 percent. Similarly, direct measures of urban real per capita consumption expenditures indicate annual growth in our sample states of over 2.9 percent (Planning Commission, 2011, p. 51).

[16] Recent literature focuses on aggregation in the dependent variable, with no aggregation in the right side data (e.g., Garrett, 2003; Cherry and List, 2002). Our case of two-sided aggregation voids many of the issues raised in this work.

[17] In earlier work, we used the following inverse indicators of health status to identify population growth and changes in the expenditure distribution (poverty and average expenditures): raw rural 1991 death rates, 1991 rural infant death rates, and square of the raw death rate. Additional instruments were also considered: squared infant death rates, rural household size (1991), and squared rural household size. Although a variety of instrument combinations were considered, in no estimation was a change in income distribution found to have a significant effect on environmental change (with p-values ranging from .174 to .904).

[18] A large empirical literature on population and the environment finds negative effects of population growth (e.g., Cropper and Griffiths, 1994; Cropper, Griffiths, and Mani, 1999; Pfaff, 1999; Bhattacharya and Innes, 2008).

[19] Extant theory argues that environmental deterioration can promote or inhibit migration and increase rural families' demand for children to manage livestock or to fetch water and fuelwood (Nerlove, 1991; Dasgupta, 1995) or, by worsening individual and public health (and thus raising child and adult mortality), to provide economic support to the household (Schultz, 1997). Empirical work confirms these links (e.g., Amacher, et al., 1998; Bhattacharya and Innes, 2008).

[20] Acemoglu, Johnson and Robinson (2002) document the correlation between income growth and both urbanization and population density. Intuitively, agglomeration can drive economic growth. This logic motivates inclusion of these indicators – initial (lagged) urban population share and urban / rural population density – as explanatory variables in our regression. Although causation may also potentially run in the opposite direction (income growth promotes agglomeration), two features of our empirical exercise tend to vitiate this concern. First is the temporal structure of our analysis, using lagged levels of urbanization / density to explain subsequent changes in the expenditure distribution. Second, our focus is on the rural sector only; agglomeration spillovers (urban to rural) plausibly run in one direction.

[21] The rainfall deviations also directly affect changes in forest cover, but this creates no problem for our analysis. The rain deviations are constructed as follows: with μ_j representing 20-year average rainfall for subdivision j, district i (of subdivision j) has the raw rainfall deviation for year t,

$$RD_{it} = (NDVI_i/NDVI_j)(Rain_{jt} - \mu_j).$$

The district rainfall deviations sum (respectively) the positive and negative R_{it} deviations over 1994-2001.

[22] In principle, another candidate channel for effect of normal rainfalls on expenditure changes is due a putative impact on population decisions that are "netted out" of our expenditure change equations; this could invalidate our instrument if our other explanatory variables fail to capture effects of systematic differences in agricultural productivity on population. However, we control for a wide range of cross-district differences in natural and economic conditions that capture precisely these impacts,

including the initial consumption expenditure distribution, initial environmental conditions, and percentage net sown area.

[23] To construct the yield growth measure in table 4, we use two year yield averages at the start and end of our sample period, and compute annual geometric growth rates. We have also estimated our expenditure change equations including yield growth on the right hand side (both lagged, 1987-94, and contemporaneous, 1994-2000). In these regressions, the yield growth coefficients are statistically insignificant and our main qualitative results persist.

[24] We are indebted to an anonymous referee for suggesting the inclusion of the inequality measure. Conceptual work on the commons indicates the potential importance of inequality to resource outcomes (Baland and Platteau, 1997. 1998, 1999).

[25] We are grateful to an anonymous referee for suggesting these interactions.

[26] This implication is obtained by summing coefficients on the initial NDVI (z-NDVI) and prior period change in the NDVI (z-NDVI).

[27] Results are available in our supplementary appendix.

[28] We calculate *average* marginal effects by taking the average values of these ratios. It might seem that we could get at these estimates more directly by estimating models of change in poverty and richness "intensity," which are the gap indices constructing using numbers of the poor and rich (respectively) as divisors, rather than the overall sample size. However, the latter estimations give a very distorted picture of environmental effects on income. Consider poverty intensity. Environmental improvement will shift the least impoverished out of the poverty group, thus raising poverty intensity, a clearly spurious effect. Likewise for "richness" intensity, environmental improvement adds

some of the impoverished population to the ranks of the rich and thereby reduces richness intensity, again a spurious effect. For this reason, we adhere to estimations of changes in the Foster-Greer-Thorbecke gap measures.

[29] Larger urban population shares are estimated to significantly reduce poverty, increase median expenditures, and increase expenditures of the non-poor. with significant coefficients on *Urban Popn* in: Models 3 and 4 of tables 8-9, the table 10 models of poverty change using all but the lowest (one times official) poverty lines, and the table 10 models of change in "richness gaps" using all but the highest (twice official) poverty lines.

[30] For the z-NDVI, we use Models 2 and 4 of table 9, and Model 6 of table 10C to gauge income distribution effects of the exogenous change in the z-NDVI (on 25th Percentile, 75th Percentile, and HCR), and Model 5 of table 5 to gauge the resulting feedback of the induced income changes to *Δz-NDVI*.

[31] For the z-NDVI, we use Models 2, 4 and 6 of table 10c to gauge income distribution effects of the exogenous change in the z-NDVI (on PGI, RGI and HCR), and Model 6 of table 6 to gauge the resulting feedback of the induced income changes to *Δz-NDVI*.