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Abstract

We review theory linking poverty to deforestation and examine this link using multiple observations of Costa Rica after 1960. Country-wide disaggregate data facilitate empirical analysis of poverty's location and its impact on deforestation. If where the poor live is not controlled for, poverty's impact is confounded with differences between richer and poorer areas. Without controls for location there is no apparent effect of poverty. Using our data over time to implement controls for location, however, we find that the poor are marginalized, on less profitable land. With our controls for location, the poorer areas appear to be cleared more rapidly. This suggests that poverty reduction aids forest conservation. For the very poorest areas, this result is weaker and another effect is found: deforestation in the poorest areas responds less to productivity, i.e. the poorest people appear to have less ability to expand on productive or to reduce on unproductive land.

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1. Introduction

Pro-environment groups should care whether the poor degrade forests more or less than others. An understanding of the role(s) of poverty should inform policies for conserving species habitat, storing carbon and preventing erosion. Pro-poor groups may not care about such outcomes but still favor ecological-service (or any) payments to the poor. Understanding the effects of poverty generally helps to demonstrate the benefits of programs targeted at or simply affecting the poor.

Whatever one's motivation, much of the world's forests reside in poor areas. Policies that address links between ecological services and poverty can affect a lot of forest and many people.

Empirical examination of the poverty/deforestation relationship is particularly important given ambiguous theoretical predictions about how changing incomes will affect forest clearing. Concerning links between macroeconomic growth and deforestation, Wunder 2001's review of the evidence concludes that income levels have an ambiguous link to land degradation. In some countries, higher incomes are associated with higher deforestation. In others, the opposite is true. Wunder concludes that as income growth occurs, forest outcomes will depend upon the strength of capital-endowment growth relative to the change in incentives due to higher potential returns in other activities. The former enables deforestation while the latter makes it less attractive. Their relative strengths, Wunder says, depend on the resource endowment and the type of growth path.

At the individual scale, theoretical predictions concerning income and deforestation again lack a unique direction. Increased wealth may relax capital constraints, raising capacity to clear. However a rising wage, which decreases poverty, will discourage labor-intensive forest clearing. We consider in more detail below a number of potential causal linkages from poverty to clearing.

While in light of these many linkages empirical analysis can identify poverty's net effect, estimating that effect raises a complication. Outcomes for poorer areas may differ from those in richer areas due to not only a behavioral effect, i.e. the poor may use identical land differently, but also the possibility that the poor's land is not identical. If the poor are marginalized, i.e. they have less profitable land, that confounds cross-sectional inference concerning a behavioral effect.

This paper uses panel data for tropical forest to control for differences between poorer and richer locations in studying the effect of poverty on clearing. Forest data for all of Costa Rica in 1963, 1979, 1986, 1997 and 2000 are partitioned into over 400 districts. A poverty index has been created from census district data for 1963, 1973, 1984, and 2000. These district data offer greater spatial detail than typical "macro" data over time, such that the location of the poor can be distinguished, but also greater temporal coverage than typical "micro" (e.g., household) data, such that if the poor are on different land we can control for that in testing for poverty's impact.

Without controls for location, we find no effect of poverty upon the rate of deforestation. However if including location explicitly by controlling for unobserved characteristics of districts, we find evidence that the poor are marginalized, i.e. they are on land that is worse along some observable and unobservable dimensions. Controlling for this, poorer areas are seen to be cleared more rapidly than richer areas. This result suggests that poverty reduction lowers deforestation.

Comparing the poorest with all other areas tempers that conclusion, as the effect (with controls for location) of being in the lowest quartile of the poverty index is less significant. Yet this focus provides additional evidence of poverty's impacts. Clearing in poorest areas responds less to the productivity of the land, i.e. is expanded less on better and reduced less on worse land.

The rest of the paper proceeds as follows. Section 2 provides a model of land-use choice motivating our empirical approach and reviews existing theory concerning the direct and indirect

effects of poverty on land use. Section 3 presents our data while Section 4 presents results on the

deforestation effects of poverty's location and of poverty itself. Finally, Section 5 concludes.

2. Land Use, Location & Poverty

2.1 Land Use

We use a dynamic theoretical model, like others (Stavins and Jaffe 1990), but empirically

emphasize key irreversibilities and the dynamics of development.[1] We feel both are important

for understanding deforestation within a developing country, including the effects of payments.

Each forested hectare j has a risk-neutral manager who selects T, the time when that land

will be cleared of forest, in order to maximize the expected present discounted value of returns[2]:

$$\text{Max}_T \int_0^T S_{jt}\, e^{-rt}\, dt\ + \int_T^\infty R_{jt}\, e^{-rt}\, dt - C_T\, e^{-rt} \tag{1}$$

where:

S_{jt} = expected return to forest uses of the land

R_{jt} = expected return to non-forest land uses

C_T = cost of clearing net of obtainable timber value and including lost option value

r = the interest rate

Two conditions are necessary for clearing to occur at time T. First, clearing must be profitable.

Second, even if that is so, it may be more profitable to wait and clear at $t+1$, so (2) must hold:

$$R_{jt} - S_{jt} - r_t\, C_t + \frac{dC_T}{dt}\ > 0 \tag{2}$$

and if a second-order condition holds this necessary condition is also sufficient for clearing.[3]

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[1] For more discussion of the model and of structural change over time, see Kerr et al. 2005 for underlying research.

[2] In assuming full ownership of the land by the manager, we are consciously not laying out a forest frontier model.

[3] Population and economic growth along much of the development path may well lead the second-order condition to hold for land-use change in a developing country. However, the condition may be violated as development proceeds further, for instance if environmental protection becomes more stringent, returns to ecotourism rise, and capital-

Consistent with this model, we assume that deforestation has irreversibilities, since trees take time to grow and incurring the costs of development changes marginal returns to land uses. We separate deforestation from (still rare) reforestation and empirically examine deforestation, i.e. examine where forest present at the beginning of a period is cleared by the end of the period.[4]

In the model, deforestation occurs when (2) is satisfied for the first time. When it occurs differs due to variation across space in exogenous land quality and access to markets and due to both exogenous and endogenous temporal shifts. The model's individual decisions are discrete, while we observe continuous rates of loss in districts, so we aggregate the model's predictions.

Specifically, in our aggregated data we do not perfectly observe the variables in (2) since deforestation and the factors that explain it (X_{it}, i = district, t = time) are measured for districts. The X_{it} vector generates a single estimated net clearing benefit for an entire district, though the actual returns and changes in costs of course vary across the parcels within each district. Thus, we imperfectly measure parcels' net benefits from clearing in (2), such that clearing occurs if:

$$R_{ijt} - S_{ijt} - r_t\, C_t + \frac{dC_T}{dt} \;=\; X_{it}\beta \;-\; \varepsilon_{ijt} \;>\; 0 \qquad (3)$$

where again i refers to an area, j to a specific parcel, ij to a specific parcel j known to be in area i, and ε_{ijt} is a parcel-year-specific term for the unobserved relative returns to forested land uses, so:

Probability (satisfying (3) so that cleared if currently in forest) = Prob ($\varepsilon_{ijt} < X_{it}\beta$) (4)

The predicted district-level clearing rates depend upon X_{it} and the distribution of the ε_{ijt}. If the cumulative distribution of the ε_{ijt} is logistic, then we have a logit model for each parcel:

$$F(X_{ijt}\beta) \;=\; 1 \,/\, (\,1 + \exp(X_{ijt}\beta)\,) \qquad (5)$$

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intensive agriculture requires less land. For the case in which it is violated, note that our reduced form empirical specification can also be interpreted in terms of the combination of expression (2) and the profitability condition.
[4] Unlike common regressions for how much forest is present at a point without regard for the previous deforestation.

For our grouped data, we estimate this model using the minimum logit chi-square method also known as "grouped logit".[5] If h_{it} is an area's measured rate of forest loss, then we estimate:

$$\log (h_{it} / (1- h_{it})) = X_{it}\beta + \mu_{it} \qquad (6)$$

The variance of the μ_{it} (referring to areas, not parcels) can be estimated by $(1 / I_{it} h_{it} (1- h_{it}))$, where I_{it} represents the number of forested parcels in area i at the beginning of interval t and the estimator is consistent and asymptotically normal.[6] This is estimated by weighted least squares.

2.2 Poverty & Location

In Section 2.3 below we will review arguments in the literature for why poverty should itself be one of the X_{it} explanatory variables within (6), i.e. for why poverty affects behavior conditional on the values of all of the other X_{it}. But first we consider here a different reason for a correlation between poverty and rates of deforestation. Specifically, poverty may systematically cause land users to have higher or lower values of the other X_{it} and thus make different decisions.

Lacking assets and access to capital, poor households may not compete effectively for the most profitable land. Even if they could put forward the money to purchase, they might get lower returns due to low levels of skill and other complementary inputs and thus be willing to pay less. We might expect poorer people to: have less productive land; to migrate to frontiers farther from markets; and if very poor, to 'squat' on land with low tenure security. Concerning productivity, Barbier (1996) claims almost 75% of the poorest 20% in Latin America live on 'low potential', marginal lands. Even if they would make the same clearing decisions on identical land, the poor are more likely to have land characteristics X_{it} that dictate low returns and discourage clearing.

Marginalization could in principle, though, have the opposite effect (Rudel and Roper 1997). In subsistence settings with all output consumed, low yield due to poor X_{it} could raise the

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[5] Maddala 1983. See also Green 1990 for an explicit discussion of the heteroskedasticity.
[6] Maddala 1983, p. 30.

area cleared, to meet the minimum consumption requirement. Also, if poor lands degrade faster, e.g. are sloped, again further clearing would be promoted. In the case of migration to frontiers far from markets, farmers may shift to transportable outputs such as cattle, which degrade extensive areas of poor quality land. Finally, far from markets there may be fewer off-farm opportunities.

2.3   Poverty & Land-Use

Many have argued that poverty is a driver of deforestation. Rudel and Roper 1997 argue that poor households may be more likely to clear a given parcel due to: a) lower skills and lower off-farm economic opportunities; b) a need to insure, in light of commodity and other shocks; and c) less preference on the margin for some environmental services. Others stress lesser ability to raise yields by investing in capital (e.g., a tractor) or other inputs (e.g., fertilizer). The poor may have less tenure security. These effects are all discussed below and summarized in Figure 1.

2.3.1 Income And Asset Levels

Poor households may not be able to invest to prevent soil degradation and lower harvests. Thus they may have to clear more if their goal is to maintain their level of output. Increased assets and access to capital for poor landowners could then reduce the need to clear more forest.

However, if the setting does not feature fixed outputs as a goal, e.g. it is not a subsistence setting, then relaxing capital constraints could lead to more clearing. Increases in capital may then support additional clearing for production of cash crops beyond consumption needs. Zwane 2002 provides evidence, from a longitudinal household survey in Peru, that the poor were using additional income for land clearing. Angelsen and Kaimowitz 1999 review farm and regional empirical evidence from Latin America that links increased credit to greater deforestation rates.

Zwane 2002 does find a non-linear relationship between income and clearing. For poor households more income does not increase purchases of fertilizers but at higher incomes it does.

Thus farmers may initially clear more land as income rises but, above a certain income level, instead intensify production. In the latter setting, lowering poverty could lower deforestation too.

However, intensification can also be consistent with using more land in production. And more generally, increasing income may not be the most effective way to combat deforestation. Zwane suggests that increasing off-farm opportunities would enable poor households to improve their financial position while reducing their need to conduct further agricultural expansion.

2.3.2 Off-farm Economic Opportunities

Several authors attribute most deforestation, especially in countries with small forests, to expanding peasant and shifting cultivator populations with few other economic opportunities (Geist and Lambin 2001 and Zwane above). Low skills or weak off-farm labor markets can lead poor households to undertake activities with low returns, such as exploitation of marginal lands.

Deininger and Minten 1996 link poverty and deforestation through the presence and absence of alternative opportunities (as well as the access to markets and poor quality land discussed above). Their find low levels of poverty were associated with reduced deforestation. Household-level analyses reviewed by Angelsen and Kaimowitz 1999 suggest that greater off-farm employment opportunities reduce deforestation by competing with agricultural activities. Along these lines, policies that could lower poverty could also help to lower deforestation.

2.3.3 Security Given Income And Price Risk

Agricultural production involving forest clearing can also provide some degree of income security, given shocks (such as recessions, sickness, and price changes) and little savings or ability to borrow. Meeting minimal food requirements on one's own lowers one's effective risk.

As discussed in Rodriguez-Meza et al. 2003, this could mean that lowered poverty will yield greater clearing. Yet as in Zwane, this effect too can depend on the initial level of income.

Further, if households can sell wood itself when income or prices shift disadvantageously, then they might keep plots of land in forest as a store of natural capital to exploit in the worst times. Eventually, though, being richer will reduce such precautionary demands for clearing altogether.

3. DATA

3.1 Deforestation Variable

We observe forest cover at five points (1963, 1979, 1986, 1997, 2000). The country has 436 political districts. Our smallest unit of observation is a form of sub-district, distinguishing different 'lifezones'. The Holdridge Life Zone System (Holdridge 1967) assigns each location in Costa Rica to one of twelve lifezone categories. These reflect precipitation and temperature. On average there are about three lifezones present in a district so we can use up to 1229 observations per year. Yet as the poverty index described below is generated for districts, we focus on district results (Table 2) while also providing supporting results for sub-district observations (Table 3). In either case, our dependent variable is annual percentage loss of forest during a time interval.

Data for the dependent variable come from several sources (Kerr et al. 2005 for details). The 1963 data are from aerial photos digitized by University of Alberta to distinguish forest and non-forest. 1979 data are produced from Landsat satellite images by the National Meteorological Institute of Costa Rica (IMN 1994). The 1986 and 1997 data were also derived from Landsat satellite images (FONAFIFO 1998) and distinguish forest, non-forest, and mangroves, while also indicating secondary forest (i.e., forest in 1997 but not 1986). The 2000 Landsat images were processed by the University of Alberta EOSL to be consistent with the 1986 and 1997 data sets.

For each district for each time interval, we calculate the area deforested. The 1986, 1997 and 2000 maps all have clouds so we calculate these areas deforested (and thus also rates of loss)

from the visible portions of each observation, using pairs of images with consistent clouds. For intervals before 1986-1997 we cannot distinguish the gross from net transitions, and assume gross deforestation equals net.[7] If the measured gross deforestation is negative, we assign a zero.

Our dependent variable is the area deforested divided by the area of forest "at risk" at the start of the interval. We assume national parks and biological reserves are not at risk (note they were not in fact cleared[8]). We also drop areas for which we do not have poverty data (see below). Because our time intervals are of varying lengths, we use annualized rates of deforestation. If λ_{it} is the area deforested over a given interval divided by the area at risk and n is the number of years in that interval, our annualized dependent variable (assume constant during the interval) is:

$$h_{it} = 1 - (1-\lambda_{it})^{1/n} \tag{7}$$

3.2 Explanatory Variables

3.2.1 Poverty Index

Here we summarize Cavatassi et al. 2003's poverty index estimation for Costa Rica. Without sufficient household-level data for a 'small area estimation' approach, they chose to use 'principal components analysis' (PCA). The necessary data are available from the census over four decades, permitting a poverty index that can be matched with the deforestation observations.

The data are variables common to multiple censi, at district level. Seventeen variables are common to 1973, 1984 and 2000, of which twelve are common to the 1963 census as well. See Cavatassi et al. 2003 for discussion of judgments about variables' economic meanings and roles in explaining the overall variance in these data. Variables chosen include demographic, labor, education, housing, infrastructure and consumer durable measures. Some examples are the

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[7] Anecdotes suggest reforestation was not widespread before 1986, so that this is probably not a major problem.
[8] For discussion of the parks and their forest outcomes see Sanchez et al. (2003).

percentage of dwellings without: heaters; bathrooms; and electricity. Others include the average number of occupants per bedroom and the fraction of people who receive job remuneration.

In PCA, eigenvectors of the correlation matrix for these variables indicate the direction and weight of variables in the index. Cavatassi et al. 2003 find that greater values of variables that should be positive correlated with poverty (% with dirt floor, % without refrigerators) have positive signs in the poverty index, as expected, while the wage remuneration and education variables have negative signs, as makes sense. The weights are used to create a poverty index[9]:

$$\textit{Marginality (or Poverty) Value}_i = W_1*(a_{i1}-a_1)/(s_1) + \ldots\ldots + W_n*(a_{in}-a_n)/(s_n) \qquad (8)$$

where W is the weight for a variable (among variables $j = 1$ to n in (8)), a_{ij} is the ith district's value for variable j and a_j and s_j are its mean and standard deviation across all of the districts.

This method is used first to create year-specific poverty indices for 1963, 1973, 1984 and 2000. Such indices, however, are not comparable over time. Each is based on a scale relevant only to that year. Thus, as a second step, Cavatassi et al. 2003 pool all years' data to estimate a PCA for 1973-2000 using the seventeen common variables and a PCA for 1963-2000 using the twelve common variables. For these pooled PCA estimations, changes in marginality value arise only from changes over time in measured variables, not from changes in their relative weights.

As noted above, some observations must be dropped because of a lack of poverty data. The reason is that the number of districts changes each census year (from 334 in 1963 to 406 in 1973, to 459 in 2000) as older larger districts are split to form newer smaller districts. When they knew how such a split has occurred, Cavatassi et al. 2003 are able to use the poverty values for older larger districts for each of the smaller newer districts into which they split. However, for some districts they were unable to track these changes over time, and thus districts are dropped.

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[9] This formula is based upon Filmer and Pritchett 1998.

We use the 1963-2000 and the 1973-2000 indices to explore the tradeoff between more years of data and more observations per year. We match to intervals as follows. For the 1963-2000 index, for 1963-1979 we use the 1963 values, while for 1979-1986 we use the 1973 values, for 1986-1997 we use the 1984 values and for 1997-2000 we use the 2000 values. We try using the 1984 values for the 1997-2000 interval also, to have the option of using lagged values. For the 1973-2000 measure the difference is that for 1963-1979 we have only the 1973 values.

A final matching step is to the 436-district structure used by the University of Alberta to organize the forest data and some explanatory data. For years before 2000 we must match the smaller number of census districts to these 436 while for 2000 we match the 459 districts to 436.

We use the indices in continuous form. To focus on greater poverty, e.g. subsistence, we also use quartiles, e.g., to allow for non-linearities within the poverty-deforestation relationship.

3.2.2 Returns Proxies

Given the difficulty of perfectly measuring returns, we consider proxies for the returns to clearing. Lacking a dollar measure of transport costs, we use the minimum linear distance in kilometers to a major market, DISTCITY, i.e. the shortest of the distances from an observation's center to San José, Puntarenas and Limon. To control for local markets, we can include district-level population density POPDEN. The measure is from census data at the district level, for 1950 and 1984, and is simply divided by the area of the district. Because population is potentially endogenous to other factors that lead to deforestation, we can use lagged population densities.

Our ecological variables proxy for agricultural productivity. More productive land should have higher clearing rates. We create dummies at sub-district level for three groups of lifezones: GOODLZ includes all humid (medium precipitation) areas, which have moderate temperatures; MEDLZ includes very humid areas (higher precipitation) in moderate to mountain elevations

(and hence moderate temperature); and then BADLZ includes the very humid areas with high temperatures (tropical), very dry hot areas, and rainy lifezones, all of which are less productive. The district values are area-weighted averages of these dummies for the lifezone sub-districts.

We also have data on seven different soil types outside national parks.[10] We create a BADSOIL measure, i.e. the proportion of a district-lifezone with low-productivity entisol soil.

We include a polynomial for the total previous clearing in a district-lifezone (%CLEARED) as well as dummies for time periods. These variables proxy for unobservable changes in the net returns to clearing over time which resulted from exogenous improvements in infrastructure and more generally from development. Costa Rican history suggests a trend of increasing returns as well as a shift in the trajectory over time (see Kerr et al. 2005). A polynomial for the previous forest clearing, e.g. our quadratic term (%CLEARED^2), is motivated by at least two types of priors. Selection, in which those parcels with the highest (observable and to us unobservable) returns to clearing are the first to be cleared, would suggest a negative coefficient for the quadratic term. Endogenous local development, in which clearing raises future returns, suggests a positive one.

4. Results

Table 1 provides descriptive statistics for the 25% poorest districts and the other, richer districts. The first three rows do not change with time. The next two do change but were pooled for the 1963 - 2000 time periods to generate these averages. Deforestation rates are provided by period.

Poorer areas are further from markets and less densely populated. Perhaps surprisingly, a lower proportion of their area has poor climatic conditions; but a higher proportion has poor soil. In a crude first cut, they seem to have if anything higher deforestation rates but not significantly.

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[10] This comes from the Ministry of Agriculture of Costa Rica. It resulted from a joint project with the UN FAO.

Table 2 presents results from regressions using district observations, starting with poverty alone and focusing on poverty all through. In all columns, the poverty measure used is a pooled 1963-2000 index, with 1963, 1973, 1984 and 2000 values matched to the 1963-1979, 1979-1986, 1986-1997 and 1997-2000 intervals in which deforestation is observed. In columns I - III, the (A) regression uses the continuous index while the (B) uses a dummy for the poorest quartile. In column IV, to focus upon the interaction stories that apply to the most poor, only the (B) is run. Table 3 has the exact same format. It provides supporting results using sub-district observations.

Poverty without & with controls

In Table 2's column I, poverty is not significant. That is the case both for the (A) run with the continuous poverty index and for the (B) run with the poorest-quartile dummy. It is also the case in Table 3. While the existence of unobserved variation in poverty across sub-districts given our district-level index could in principle complicate such regressions, in the column I regression there are no other sub-district varying explanatory variables to absorb its effects. If anything, then, Table 3 supports Table 2's conclusion that column I's estimated effect is zero.

However, column II suggests that this could mask two significant but opposing effects. Table 2's column II uses district-level fixed effects to control for the fixed characteristics of each location. It also includes the only time-varying explanatory variable we have, the prior clearing (to facilitate comparison below of the unobservable with only observable fixed characteristics).

With these controls for unobserved differences between the poorer and richer areas, our (A) regression finds that the poorer areas feature higher deforestation rates. The (B) result for the poorest quartile is not significant. However, Table 3's column II is significant for both measures.

Thus while the poorest-quartile results must be said to be less significant, overall it appears that when conditioning on their other characteristics, the poorer areas are deforested at a higher rate.[11]

Comparing columns I and II in Tables 2 and 3 juxtaposes a lack of effect without controls against a significant positive effect of poverty on rates of clearing when using location controls. This comparison provides evidence that poorer districts are marginalized in unobserved ways.

Observable characteristics only

Table 2's column III replaces the district fixed effects (or sub-district effects in Table 3) with the fixed location characteristics that we can measure, retaining the prior clearing variable. Now poverty is again insignificant, in both the (A) and (B) regressions in both Tables 2 and 3. Apparently our ability to observe the important differences across locations is somewhat limited.

That observable differences across locations do not clearly explain the marginalization revealed in column II is further suggested by the coefficients in column III and values in Table 1. While bad soil and bad climate both reduce deforestation in column III, recall that the poorer districts have more bad soil but less bad climate. Also, while those districts are quite a bit farther from markets on average, and the prior on distance is negative (and supported in Kerr et al. 2005 pooled regressions including pre-1963 deforestation as well as recent cross-sections), we note that for 1963-1979 the reverse is found. It may be that the frontier development push, perhaps linked to subsidies for cattle in areas far from cities, dominates in that period and also overall when pre-1963 is dropped, as it is here necessarily since we do not have pre-1963 poverty data.

Poverty & response to land productivity

Columns IV of Tables 2 and 3 use the poorest-quartile dummy only to focus on an effect of significant poverty, specifically evidence of an inability to adjust to opportunities or their lack.

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[11] That the continuous-index results is stronger suggests that differences in income above the poorest quartile matter. This could be viewed, like Zwane 2002, as changes in income for the most poor not permitting much response.

In a subsistence setting, one might not be able to reduce (and might even increase) clearing when land is bad, to meet a fixed need for food or revenue. More generally, inability to invest might mean less clearing on good land. Both directions suggest an interaction between being quite poor and land productivity, i.e. high or low productivity should have less impact upon deforestation.

The results in column IV of Table 2 support the idea that the poor decrease clearing less when conditions are bad. The poverty-bad lifezone interaction is positive. Column IV in Table 3 has an insignificant interaction with the low or bad productivity indicator but features a positive and significant effect of high productivity alongside a negative and significant interaction of that indicator with the poorest quartile of the sub-districts. Thus, poorer areas appear to respond less.

5. Discussion

This paper used a rare panel data set for tropical forest to identify the effect of differences between the poorer and the richer areas within a study of the effects of poverty on deforestation. The district (or sub-district) data have greater spatial detail than macro or country data, so that the location of the poor can be distinguished, but greater temporal coverage than many micro or household data, helping to control for characteristics of locations in testing poverty's impacts.

Controlling for both observed and unobserved characteristics of locations, we find that poorer areas are cleared more rapidly than richer, suggesting that poverty increases deforestation. Without controlling for locations' characteristics, the impact of poverty on clearing would be underestimated (in this case at zero) because, as we show, poorer areas have more marginal land, i.e. land that appears to be less profitable within agriculture. For the poorest areas, the impact of poverty is weaker, yet we find that in these areas clearing responds less to productivity of land.

Thus we provide evidence that poverty does indeed affect deforestation rates. Yet it is not clear that changing the incomes of the very poorest areas will affect deforestation greatly. As

others have observed more generally, raising the poor's income may be better justified by a focus on income than by a focus on deforestation. Further, as others have observed, exactly how the poor's income is changed (e.g., transfers versus higher off-farm wages) should affect its impact.

A final key point concerns land ownership. With district poverty and deforestation data, we can make statements only about *poorer areas* and not necessarily about *poorer land owners*. It is possible that in areas where most people are poor, most of the land is owned by non-poor. While our results already provide insight, they might be stronger and clearer if we possessed data permitting us to distinguish the less poor within the more poor areas and so forth. This possibility indicates the value, going forward, of household-level data on both poverty and deforestation.
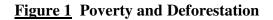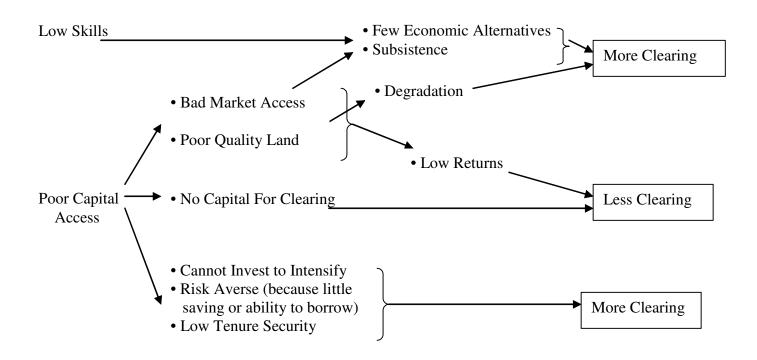
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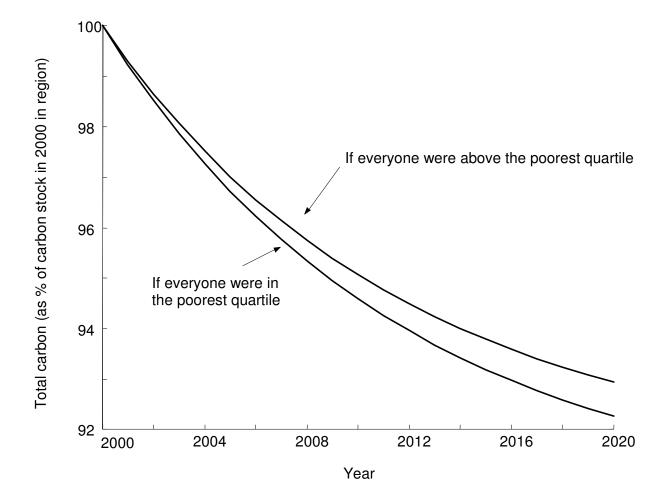
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Figure 1 Poverty and Deforestation

Low Skills   ⟶   • Few Economic Alternatives   • Subsistence   → More Clearing

• Bad Market Access

• Poor Quality Land

Poor Capital Access   ⟶   • No Capital For Clearing

• Degradation

• Low Returns   → Less Clearing

• Cannot Invest to Intensify
• Risk Averse (because little saving or ability to borrow)
• Low Tenure Security   → More Clearing

Figure 2   Behavioral Difference between the poorest and others post-2000

If everyone were above the poorest quartile

If everyone were in the poorest quartile

Total carbon (as % of carbon stock in 2000 in region)

Year

Table 1 Summary statistics for Costa Rican districts [a]

	Poor Districts	**Rich Districts**
Bad Climate (%)	0.47 (0.50)	0.63 (0.48)
Bad Soil (%)	0.14 (0.26)	0.09 (0.19)
Distance to Market (km)	87 (43)	56 (35)
Population Density	0.16 (0.80)	0.79 (4.5)
Per Capita Forest Cover (ha)	4.5 (6.6)	3.7 (6.2)
Deforestation Rate (%)		
1963 – 1979	0.033 (0.044)	0.025 (0.047)
1979 – 1986	0.046 (0.047)	0.018 (0.036)
1986 – 1997	0.0067 (0 .0083)	0.0091 (0.0096)
1997 – 2000	0.0015 (0.0041)	0.00062 (0.0016)

[a]: For greatest relevant to the regressions, weights for these averages are the initial forest in each period.

[b]: Standard deviations for these measures within these groups of districts are given in brackets.

[c]: "Bad Climate" = percentage of district identified as a poor productivity or "bad" lifezone.

[d]: "Bad Soil" = percentage of district identified as a poor performing or "bad" soil.

Table 2 Deforestation, Poverty and Locations – District Level [i]

	I		II		III		IV
	A [ii]	B [ii]	A	B	A	B	B
POVERTY [ii]	.02 (0.8)	.04 (0.6)	.16 (3.3)	.12 (0.9)	.004 (0.2)	.05 (0.8)	.09 (0.4)
FIXED EFFECTS			F = 6.3 (P=.00)	F = 6.1 (P=.00)			
CONSTANT	-2.8 (30)	-2.8 (46)	-3.6 (16)	-3.2 (17)	-3.9 (21)	-3.9 (23)	-3.7 (18)
%CLEARED			1.2 (1.3)	2.0 (2.3)	3.7 (7.2)	3.7 (7.2)	3.9 (7.7)
%CLEARED^2			-3.4 (3.5)	-4.1 (4.4)	-2.2 (3.9)	-2.1 (3.9)	-2.6 (4.6)
BADSOIL					-0.3 (2.4)	-0.4 (2.5)	-0.4 (2.9)
BADLZ					-1.2 (11)	-1.2 (12)	-1.8 (9.6)
POV $_*$ BADLZ							0.4 (1.5)
GOODLZ							.08 (0.4)
POV $_*$ GOODLZ							-0.6 (2.0)
DISTCITY					.01 (7.8)	.01 (8.0)	.01 (7.6)
DIST $_*$ 79-86					-.00 (0.9)	-.00 (1.0)	-.00 (1.1)
DIST $_*$ 86-97					-.01 (4.2)	-.01 (4.4)	-.01 (4.5)
DIST $_*$ 97-00					-.00 (1.1)	-.00 (1.2)	-.01 (1.4)
TIME DUMMIES	[these are always		significant as		controls for		time trends [iii]]
ADJUSTED R^2	0.22	0.22	0.76	0.75	0.51	0.51	0.53
N	961	961	961	961	958	958	958

[i]: All regressions are Grouped Logit explaining annualized deforestation probabilities, following expression (6), using district observations. Coefficient is reported, with t statistic below it, except for the fixed-effects component within II where F statistic is reported with P value below.

[ii]: 1963-2000 pooled index in all columns. Column IV focuses solely on the poorest quartile as an interaction effect is motivated by the very poor. Within the other three columns (I – III) the A regression uses the continuous poverty index while the B regression uses a poorest quartile dummy.

[iii]: Coefficients for time dummies not reported as not a focus here and would crowd the table (see Kerr et al. 2005 for discussion of time trends).

Table 3 Deforestation, Poverty and Locations – Subdistrict Level [i]

	I		II		III		IV
	A [ii]	B [ii]	A	B	A	B	B
POVERTY [ii]	.01 (0.5)	.01 (0.2)	.12 (4.0)	.21 (2.5)	-.002 (0.1)	.02 (0.5)	.10 (1.4)
FIXED EFFECTS			F = 8.4 (P=.00)	F = 8.3 (P=.00)			
CONSTANT	-2.5 (41)	-2.5 (63)	-3.3 (26)	-3.0 (36)	-3.5 (31)	-3.6 (35)	-3.7 (34)
%CLEARED			0.5 (1.3)	0.9 (2.4)	1.8 (6.1)	1.8 (6.1)	1.9 (6.5)
%CLEARED^2			-1.5 (4.0)	-1.8 (5.0)	-0.3 (1.1)	-0.3 (1.0)	-0.5 (1.6)
BADSOIL					-0.1 (1.6)	-0.2 (1.6)	-0.2 (2.5)
BADLZ					-0.6 (11)	-0.6 (11)	-0.5 (6.5)
POV $_*$ BADLZ							0.1 (0.9)
GOODLZ							0.4 (5.2)
POV $_*$ GOODLZ							-0.3 (3.1)
DISTCITY					.01 (10)	.01 (10)	.01 (11)
DIST $_*$ 79-86					-.003 (2.0)	-.003 (2.3)	-.003 (2.7)
DIST $_*$ 86-97					-.01 (5.9)	-.01 (6.2)	-.01 (6.5)
DIST $_*$ 97-00					-.01 (2.6)	-.01 (2.7)	-.01 (2.9)
TIME DUMMIES	[these are always		significant as		controls for		time trends [iii]]
ADJUSTED R^2	0.20	0.20	0.79	0.79	0.37	0.37	0.38
N	2604	2604	2604	2604	2421	2421	2421

[i]: All regressions are Grouped Logit explaining annualized deforestation probabilities, following expression (6), using subdistrict observations. Coefficient is reported, with t statistic below it, except for the fixed-effects component within II where F statistic is reported with P value below.

[ii]: 1963-2000 pooled index in all columns. Column IV focuses solely on the poorest quartile as an interaction effect is motivated by the very poor. Within the other three columns (I – III) the A regression uses the continuous poverty index while the B regression uses a poorest quartile dummy.

[iii]: Coefficients for time dummies not reported as not a focus here and would crowd the table (see Kerr et al. 2005 for discussion of time trends).

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