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Abstract

We summarize existing theoretical claims linking poverty to rates of deforestation and then examine this linkage empirically for Costa Rica during the 20th century using an econometric approach that addresses the irreversibilities in deforestation. Our data facilitate an empirical analysis of the implications for deforestation of where the poor live. Without controlling for this, impacts of poverty per se are confounded by richer areas being different from the areas inhabited by the poor, who we expect to find on more marginal lands, for instance less profitable lands. Controlling for locations' characteristics, we find that poorer areas are cleared more rapidly. This result suggests that poverty reduction aids forest conservation.

Key Words: Land Use, Deforestation, Poverty, Climate Change, Development, Costa Rica.
JEL: I32, O13, Q51, Q54, Q56.

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1. Introduction

Pro-environment/resource/nature groups care about the details of forest degradation because of its implications for species habitat, carbon storage, erosion, and flooding. Whether poorer people degrade or conserve forest more, an understanding of their role in clearing is crucial, from this point view, for informing the design of policies to best conserve valued ecological services.

Pro-poor/equity/justice groups may not care about deforestation *per se*, viewing it as just a consequence, and perhaps a temporary one, of agricultural expansion yielding valued increases in consumption. However, in light of the possibilities for conservation-based transfers from richer parties, including from the Annex I countries, these actors may wish to demonstrate the scale of the benefits achievable through payments to the poor to promote conservation of forest.

Those in favor of ecological services *and* human equity desire such analysis to identify how to reduce tradeoffs between forests and food. For any of these issues, it is important to note that much of the world's forest resides where do the poor. Thus, examination of the relationship between poverty and deforestation can inform policies, be they bribing the poor to save forests or subsidizing forest for the poor, that matter for large areas of forest and large numbers of people.

Empirical examination of this relationship is important given the lack of a unidirectional theoretical prediction about how changing levels of income will affect forest outcomes. In a comprehensive review of evidence on links between macroeconomic growth and deforestation, Wunder 2001 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 the forest outcome, given income growth, is dependent upon the relative strengths of the growth of capital endowments, which enable deforestation, and incentive effects, which make deforestation less attractive due to the higher potential returns from other activities. He says their relative strength depends on the resource endowment and the type of growth path.

Likewise at a micro level, theoretical predictions concerning income and deforestation lack a unique direction, given many potential links. Increased income may relax constraints due to capital, raising capacity to clear and clearing. On the other hand, increased poverty may link with low wages, lessening disincentives to and thus increasing labor-intensive clearing of forests. We consider in more detail below a number of potential causal linkages from poverty to clearing.

Examining this relationship empirically also raises a another issue, a confounding factor for studying the clearing effects of poverty *per se*. In the data, outcomes for poor households or generally poor areas might differ from those for the rich not only because the poor may choose differently given an identical parcel of land, but also because the poor are likely to be on parcels of land with different characteristics. If the poor are in fact marginalized, in the sense of being on parcels with lower productivity and less access to markets, their returns and clearing will differ for that reason, complicating inference from cross-sectional data on poverty and deforestation.

This paper uses perhaps unique data for tropical forest to permit the analysis of the role of rich/poor locational differences within our study of effects of poverty on clearing. As the data fall between that for macro studies, i.e. good temporal coverage but little spatial detail, and micro studies, e.g. household-level detail but often one point in time, we can identify if the poor are on different quality land then control for that in testing poverty's impacts. We use forest data for Costa Rica for five years (1963, 1979, 1986, 1997, and 2000), and a partition of the country into 436 districts (with the ability to differentiate over 1000 sub-districts), along with a poverty index created from census data at the district level in each of four years (1963, 1973, 1984, and 2000).

Controlling for both observed and unobserved characteristics of locations, we find that the poorer areas are deforested more rapidly than richer areas, suggesting that poverty increases deforestation. Without such controls, estimating the impact of poverty on clearing is confounded by richer areas being significantly different from areas inhabited by the poor, as we document. We would expect the poor to be found on more marginal land, e.g. less profitable land. We find evidence of such marginalization of the poor along some although not all of the observable dimensions or characteristics of land parcels, and also along dimensions that we can not observe.

The rest of this paper proceeds as follows. Section 2 presents a formal model of dynamic land-use choice motivating our empirical approach (following Kerr, Pfaff and Sanchez 2003) and then reviews theory on the effects of poverty on land use and deforestation. Section 3 presents our data while Section 4 presents our results on effects of poverty and location on deforestation.

2. General Dynamic Model Of Land Use & Adding Poverty

This section draws heavily on Kerr et al. 2003, an economic analysis of deforestation over time in Costa Rica. Like others (e.g., Stavins and Jaffe 1990), we use a dynamic theoretical model, but we emphasize irreversibilities and the dynamics of development in our empirical approach. We feel this is important for understanding and projecting land use in a developing country, including projecting the effects of providing carbon sequestration credits to developing countries.

2.1 Dynamic Model Of Deforestation

The manager[1] of each hectare j, risk neutral by assumption, selects T, the time when land is cleared, to maximize the expected present discounted value of returns from use of hectare j:

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

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. However, even if 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[2] this necessary condition is also sufficient for clearing.

Following our model, we separate deforestation from reforestation because deforestation has irreversibilities, since trees take time to grow and incurring the costs of development changes marginal returns. Thus, we distinguish and focus upon deforestation transitions (in contrast to the forest-share equations that explain how much forest is present regardless of past deforestation).

Deforestation transitions for parcels occur when condition (2) is satisfied but have not been so previously. When this occur differs across space due to different returns, from variation in exogenous land quality and access to markets, and across time for exogenous and endogenous reasons. These individual decisions determine the aggregate patterns of deforestation over time. However, we observe not discrete clearing of individual parcels but continuous rates of loss in larger areas. Aggregating the model's predictions for these areas yields our empirical approach.

For such aggregated data, it is clear that we do not perfectly observe the variables in (2). Forest outcomes and explanatory returns and costs are measured for larger areas ((sub-)districts),

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[1] In assuming full ownership of the land by the manager, we are consciously not laying out a forest frontier model.
[2] For land-use change in a developing country, population and economic growth along with improved infrastructure may lead this to be true. But it may be violated as development proceeds, environmental protection becomes more stringent, returns to ecotourism rise, and capital intensive agriculture requires less land. Given that, note that our reduced form empirical specification can also be interpreted in terms of the profit conditions (see Kerr et al. 2003).

while actual returns and changes in costs vary across parcels for which the observable measures (X_{it}, i = (sub-)district) yield the same estimated net benefits from clearing for the entire district. Thus, X_{it} imperfectly measure parcels' net benefits from clearing as given by the variables in (2). We explicitly acknowledge that we do not measure returns perfectly, such that clearing occurs if:

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

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:

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

Since the X_{it} are the same for each parcel in a subdistrict, the predictions from the model are effectively for subdistricts' rates of deforestation during any given observed time interval. The predicted clearing rates depend upon the X_{it} as well as on the assumed distribution of the ε_{ijt}. If the cumulative distribution of ε_{ijt} is logistic, then we have a logit model for each parcel:

$$\mathrm{F}(X_{it}\beta) \;=\; \frac{1}{1+\exp(X_{it}\beta)} \tag{5}$$

For our grouped data, we estimate this model using the minimum logit chi-square method also known as "grouped logit".[3] If $\hat{h}_{it}$ is an area's measured rate of forest loss, then we estimate:

$$\log \frac{\hat{h}_{it}}{1-\hat{h}_{it}} = X_{it}\beta + \mu_{it} \tag{6}$$

The variance of the μ_{it} (referring to areas, not parcels) can be estimated by $\frac{1}{I_{it}\hat{h}_{it}(1-h_{it})}$, where I_{it} represents the number of forested parcels within area i at the beginning of interval t, and the estimator is consistent and asymptotically normal.[4] This is estimated by weighted least squares.

[3] Berkson 1953, cited in Maddala 1983. See also Green 1990 for explicit discussion of heteroskedasticity.

2.2 Poverty, Location and Land Use

Below, in Section 2.3, we will review arguments in the literature for why poverty should itself be one of the X_{it} explanatory variables within (6), i.e. whether poverty affects behavior conditional on the values of all of the other X_{it}. But first we consider a different reason for a correlation between poverty and land use or rates of deforestation. Poverty may systematically lead land users to face 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 quality agricultural land. Further, if they could borrow to purchase it, due to lower skill levels and perhaps less ability to purchase other inputs they might get lower returns and thus be willing to pay less than a better educated person with more assets. We might expect poorer people to end up on less productive land or migrate to frontiers farther from markets or, if very poor, to 'squat' on land with very low tenure security. Barbier (1996) claims, for instance, that almost three quarters of the poorest 20% within Latin America live on 'low potential' or marginal lands. Thus even if they would make the same clearing decisions on identical land, the poor are likely to face land characteristics X_{it} that lower the returns from clearing and hence discourage deforestation.

There are conditions under which this location effect is of ambiguous sign (see Rudel and Roper 1997, e.g.). If the poor are very poor and are literally subsistence producers who consume all their output instead of selling to the market, then low yield per hectare due to discouraging X_{it} might lead to more hectares being cleared to meet a fixed subsistence requirement for food. If poor lands also degrade faster, e.g. if they are sloped, ongoing clearing for food is promoted. Or if inability to compete for choice lands implies migration to frontiers far from markets, a farmer may choose transportable output such as cattle which can take as an input extensive areas of poor

[4] Maddala 1983, p. 30.

quality land (this requires some investments, and thus differs from the subsistence situation). Finally, if far from markets the poor might also be in locations with fewer off-farm opportunities.

2.3 Poverty and Land-Use Behavior

Since the UNCED summit in Rio de Janeiro in 1992, many have argued that poverty is a driver of land degradation and deforestation. Poor people have fewer assets and options and less security and may make different decisions. Rudel and Roper 1997 identify poverty-driven clearing as a main cause of rain-forest destruction. They argue that poor households in a given location may be more likely to degrade or clear forest because of: a) lower opportunity cost of clearing activities, i.e. lower off-farm economic opportunities due to fewer skills; b) a need to insure, in light of commodity-market swings, family emergencies and other shocks; and c) with low consumption, less preference on the margin for (at least luxury-type) environmental services. Others stress that low assets and access to credit lower ability to invest in capital (e.g., a tractor) or inputs (e.g., fertilizer) to raise yields. Poor people may also have less tenure security. These effects are discussed below, and along with location-based effects are summarized in Figure 1.

2.3.1 Income And Asset Levels

Many have claimed that poor households clear more land to maintain crop yields because they cannot afford investments to prevent soil degradation (and, therefore, decreasing harvests) on existing agricultural land. Thus, increasing capital for poor landowners, lowering poverty, would allow them to intensify their crop production and reduce their need to clear more forest.

However, this appears to assume a fixed need for production, versus profit maximization, perhaps implicitly assuming a subsistence setting. If that is not the case then relaxing capital constraints, lowering poverty, could instead lead a household to clear more, to invest the capital not in improving the existing land but in new clearing for a cash crop beyond subsistence needs.

Zwane 2002 provides evidence from a longitudinal household survey in Peru of the poor using additional income for land clearing, and Angelsen and Kaimowitz 1999 reviewed farm and regional empirical evidence from Latin America linking increased credit to greater deforestation.

Zwane 2002 does find, though, a non-linear relationship between income and clearing, i.e. the effect of increasing income on deforestation depends on the initial income level. For poor households, Zwane 2002 does not find that increased income increases purchases of farm inputs such as fertilizers and pesticides. At higher incomes, though, the relationship between income and fertilizer becomes positive and significant. Thus initially farmers might clear more land as income rises (so lowered poverty raises deforestation) but above a certain income level they may react to more income by intensifying production. In that case, lowering poverty further can lower deforestation, although intensification can also be consistent with using more land in production.

Thinking in terms of development-environment policies, simply increasing income may not be an effective way to combat deforestation. Zwane suggests that supporting the purchasing of capital inputs and 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). Opportunities may be limited by low skill levels or by a lack of well-functioning off-farm labor markets. Their absence makes poor households willing to undertake activities even with very low marginal returns to labor, 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 suggests that greater off-farm employment opportunities reduce deforestation by competing with agricultural activities. From this rationale, 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, allowing agricultural households to cope with unexpected events within market settings. On the income side, these could be a recession, being fired, or sickness of a wage earner. On the consumption side, these could include high food prices. Poor households are unlikely to have significant savings or ability to borrow in bad years. For many poor rural households, meeting at least their minimal food requirements on their own provides a degree of protection from risk.

As discussed in Rodriguez-Meza et al. 2003, this could lead greater levels of income (i.e., lower levels of poverty) to yield greater clearing, but this effect too can depend on initial levels of income. Eventually being richer reduces these precautionary demands for clearing altogether. A final twist within this discussion of risk is that if households can sell wood itself when income or prices shift disadvantageously, they might keep plots in forest as a store of natural capital.

In sum, the interactions between poverty and deforestation are complex, not yielding a simple unambiguous prior for the relationship. Figure 1 summarizes the links we have discussed. What do they imply for our empirical analysis? Our data has reasonable geographic detail, for both poverty (at district level) and land characteristics (some down to sub-district level), though not household detail such as individual economic opportunities or capital access. However, we have data over a long period of time, permitting us to contribute by identifying and controlling for locational effects in examining poverty's direct effect on deforestation choices and then also examining both the magnitude of and some of the nature of the impact of location upon clearing.

3. Data

3.1 Deforestation Variable

We observe forest cover at five points in time (1963, 1979, 1986, 1997, 2000). We use the separation of the country into 436 political districts, and can use as unit of observation a form of sub-district. Specifically, in each district we can distinguish each 'lifezone' that is present (the Holdridge Life Zone System (Holdridge 1967) divides Costa Rica into twelve ecological 'lifezones' reflecting levels of precipitation and temperature). On average there are about three lifezones present in a district and thus we can in principle use up to 1229 observations per year. Because the poverty index described below is for districts, though, we will focus upon districts. Our dependent variable (more below) is the annual percentage loss during a given time interval from the area of forest present within a given district-lifezone at the beginning of the interval. As some district-lifezones become fully deforested, over time the observations per time interval fall.

The data used to create the dependent variable come from several different sources (see Kerr et al. 2003 for more detail). The 1963 data are from aerial photos (translated into maps) digitized by the University of Alberta to distinguish forest and non-forest. The 1979 data were 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 (see FONAFIFO 1998) and distinguish forest, non-forest, and mangroves, while also indicating secondary forest (land classified as 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-lifezone 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.[5] If the measured gross deforestation is negative, since we are analyzing deforestation we use a value of zero. After 1986, we know the gross deforestation.

Our dependent variable, the deforestation rate, is the area deforested during an interval divided by the area within the district-lifezone of the forest "at risk" at the start of the interval. Areas with no forest at the start of an interval are dropped, as there is no risk of deforestation. We assume that forest in national parks and biological reserves is not at risk of deforestation (it was not in fact cleared[6]). We also drop areas for which we do not have poverty data (see below). Finally, because our time intervals are of varying lengths, for comparison we use annual rates of deforestation. If λ_{it} is the deforestation rate (area deforested over area at risk) for a given interval and n is the number of years in that interval, our annual deforestation rate dependent variable is:

$$\hat{h}_{it} = 1 - (1 - \lambda_{it})^{\frac{1}{n}} \tag{7}$$

Thus we implicitly assume that this annual deforestation rate was constant during each interval.

3.2 <u>Explanatory Variables</u>

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.

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[5] Anecdotes suggest reforestation was not widespread before 1986, so that this is probably not a major problem.

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 variables. Some examples are the percentage of dwellings without heaters, or without bathrooms, or without electricity. Others are the average number of occupants per bedroom and percent of people receiving 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[7]:

$$\textit{Marginality (or Poverty) Index}_j = W_1*(a_{j1}-a_1)/(s_1) + \ldots\ldots + W_n*(a_{jn}-a_n)/(s_n) \qquad (8)$$

where W is the weight for a variable (among variables 1 to n in (8)), a_j is the jth district's value for that variable and a and s are the mean and standard deviation of the variable across the districts.

This method is first used 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. In other words, the indices' units vary, precluding a comparison between years. Thus, as a second step, Cavatassi et al. 2003 also pool all years' data to estimate a single PCA for 1973-2000 using the seventeen variables and one for 1963-2000 using the twelve variables. For these pooled PCA estimations, a change in the marginality index arises only from changes in the levels of variables over time, not changes in the relative importance of each variable in the index.

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[6] For discussion of the parks and their forest outcomes see Sanchez et al. (2003).

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.

Finally, we make use of these indices in our regressions in a number of ways. First, we do work with both the 1963-2000 and the 1973-2000 indices to explore the tradeoff between more years of data and more observations per year. We match this data to our intervals as follows. For the 1963-2000 measure, 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 also try using the 1984 values for the 1997-2000 interval so that we are 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 (some data are spatially specific, so that they can be parsed into any district structure within a GIS). 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 directly, in their continuous form, but also create variables to reflect possible non-linear relationships (e.g., logarithms, quartiles) between poverty and deforestations since some of the theory concerning poverty's effect concerns extreme poverty, e.g. subsistence.

3.2.2 Returns Proxies

Given the difficulty of perfectly measuring returns, we also consider proxies for returns to clearing. Lacking a dollar measure of transport costs, we use the minimum linear distance in

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

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 market size, we 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 use lagged population densities.

Our ecological variables proxy for agricultural productivity. More productive land should have higher clearing rates. We create dummies 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); BADLZ includes very humid areas with high temperatures (tropical), very dry hot areas, and rainy lifezones, all of which are less productive. We also have data on seven different soil types for land outside national parks, another proxy for agricultural productivity.[8] We create a BADSOIL measure, i.e. the proportion of a district-lifezone with low-productivity entisol soil.

Finally, as discussed in Kerr et al. 2003, we include a polynomial for the total previous clearing in a district-lifezone (%CLEARED) as well as dummies for time periods. These proxy for unobservable changes within net returns over time resulting from exogenous improvements in infrastructure and the general development process. The discussions of Costa Rican history above suggest a trend of increasing returns but also a shift in trajectory over time, motivating the polynomial. The polynomial for %CLEARED is motivated by the existence of at least two priors for this proxy. A selection dynamic, in which the parcels with the highest unobservable returns to clearing are the first to be cleared, suggests a negative effect. Endogenous local development, where clearing raises future returns, suggests a positive one.

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

4. Empirical Results – Effects of Poverty and Location on Deforestation

Table 1 provides descriptive statistics for the 25% poorest districts and the other, richer districts. The first three variables do not change with time. The next two do but were pooled for the 1963 - 2000 time period in order to generate these averages, while deforestation is provided by period.

Poorer areas differ from those with richer people. The poorer areas are more rural, further from markets and much less densely populated. Perhaps surprisingly, a lower proportion of their area has poor climatic conditions, though a higher proportion has poor soil. Interestingly, they have if anything higher deforestation rates, suggesting that poverty might have a positive effect on clearing which overcomes distance to markets and poor soil (though again, climate is better).

4.1 Poverty & Clearing Choices

Table 2 presents our regression results, starting with a focus on poverty measures alone. In column I, poverty is not significant. In all columns of Table 2, the poverty measure is 1963-2000 with 1963, 1973, 1984 and 2000 values in the time intervals. The continuous index is used in columns I, II and III. While Table 1's deforestation rates suggested higher clearing in poorer areas, they were not on the whole greatly different, and not even always higher, and we find that this insignificance result for column I is consistent across the range of our poverty measures.

However, column II suggests that this result masks two significant but opposing effects. Using district fixed effects to control for the characteristics of the locations where the poor live, we find that the poorer areas feature higher clearing rates (we find the same using the subdistrict observations). A crucial point is that the fixed effects control for not only the characteristics of locations that we can observe but also whatever fixed differences exist that we can not observe. An example of the latter is a dimension of soil quality known to local land users but not to us. Our behavioral result, then, is that conditional on characteristics poor areas are deforested at a higher rate. This is consistent across poverty measures, though not for poorest-quartile dummies for all of the measures we tried. Column III shows that controlling further, with a variable that is significant in Kerr et al. 2003 and varies over time (% cleared), does not change this result.

4.2 Location & Deforestation

The first evidence on the effects of the differing locations of the poorer and richer comes from comparing columns I and II. The insignificance of poverty when no controls for differences between districts are used, juxtaposed with a significant positive effect of poverty on the rate of clearing if using fixed-effects controls for characteristics of districts (observed and unobserved), suggests that a negative effect of being in the poorer districts is part of the result in column I. Thus, a significant negative impact of the characteristics of poor locations is shown implicitly. This supports the prior that the poor will be unable to compete for the more productive parcels.

Pursuing this further, we can examine the estimated fixed effects to explore whether the characteristics of locations that we do observe are correlated with these district-specific results. While we have not presented this in a table, regressing the fixed effects on observable features of parcels shows, for instance, that the former are lower (i.e., indicate lower rates of deforestation) for districts with more area in poor climatic conditions and higher for districts with more area in good climatic conditions, though neither effect is very strong. This supports the interpretation of the fixed effects in column II as controlling for the differences between poorer and richer areas. The weak effects suggest that a set of differences we do not observe significantly affect clearing.

The fixed effects are also higher when distances to markets are higher, though this merits some discussion. The prior on market access, and the proxy of distance to markets, is negative. Deforestation should be lower when markets are more distant. Kerr et al. 2003 find this for their pooled regression including the 1900-1963 time period (for which we do not have poverty data), and for the 1900-1963 and later cross-sections as well. But for 1963-1979 the reverse is found, as though a frontier development push occurred at that time, perhaps linked to subsidies for cattle in areas far from cities. That result can dominate when 1900-1963 is dropped. Thus, we will not assume a single distance result and will not formally use distance in calculating the effects of observable differences between richer and poorer locations on clearing. However, recall from Table 1 that poorer locations are further from markets, often thought to discourage deforestation.

Finally, column IV drops the fixed effects and directly adds observable characteristics of district locations to the time-trend controls and poverty measure (here we use the poorest quartile version of the same poverty measure, for a reason given below). Ideally this would both permit estimation of the poverty effect and reveal the effects of measurable characteristics, permitting a decomposition of the insignificant net poverty effect in column I. However not surprisingly, given that the observable characteristics had only low explanatory power for fixed effects above, the poverty effect is confounded by differences in where richer and poorer live, as in column I. In column IV, the poorest-quartile dummy is not significant (neither is the continuous measure).

This dummy measure was chosen to focus on the relatively most poor, because in this regression we can include fixed characteristics of districts and thus interactions of poverty with those characteristics. For instance, we see a strong negative effect of bad climatic conditions, though good climatic conditions are not seen to differ greatly from medium climate (the omitted category). One theory concerning poverty is that the poor can not respond as well either to good opportunities or to challenging conditions. This suggests an interaction of being relatively quite poor with effects of climatic conditions. While the results are not extremely strong, column IV finds interactions that, for both of the climate variables, lessen the estimated effects of climate. This is at least consistent with the theory of less ability to adjust to positive or negative settings.

As noted, distance is not a focus here and thus we include distance as a control variable and permit its effect to vary by time period. We also use time dummies to absorb time trends. Given these, we also find that having more area with poor soil leads to lower rates of clearing. Finally, consistent with column III and Kerr et al. 2003, previous clearing has significant effects and is thus a useful control variable. For effects of observable characteristics that can be linked to Table 1, in sum poor climate has a negative effect and poor soil also has a negative effect. In light of Table 1, this yields an ambiguous prediction about the effects of differences between the poorer and richer districts, since the poorer districts have less bad climate but more bad soil. This ambiguity based on limited observable characteristics highlights the value of our data over time in permitting the fixed effects which control for and indicate the net effects of unobservables too.

5. Conclusion

This paper used perhaps unique data for tropical forest to analyze the effects of location differences between rich and poor in a study of the effects of poverty on the rate of deforestation. As the forest data fall between those typical for macro studies, with good temporal coverage but little spatial detail, and micro studies, with household detail often for only one point in time, we identify if the poor are on different quality land then control for that 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 controls for the characteristics of where the poor live, the impact of poverty on clearing that we have estimated would be underestimated (in this case it would be estimated to be zero) because richer areas are significantly different from areas inhabited by the poor, as we document; specifically, the poor are on more marginal lands, e.g. lands less profitable within agriculture.

We find evidence of marginalization of the poor along some although not all of our observable dimensions or characteristics of land parcels, and also along dimensions that we can not observe.

One might like to explore further empirically the effect of the observed differences between the poorer and richer areas. One difference that stands out is that poorer areas are more distant from major markets. Asserting what effects this has had on forest clearing is a challenge given previous findings (see Kerr et al. 2003) of structural change along the development path of in the effects of factors that affect rates of clearing. If clearing is sometimes slower and other times faster far from markets, it is difficult to assert the effects of the location of the poor. This issue raises more generally the issue of structural change. The effects of poverty on clearing may not be the same over time or may differ across settings, an issue that can be further explored.

A final important point, one indicating a natural path for future research concerning the effects of poverty, is about land ownership. Here, with district (not household) level poverty, and matching aggregated data on deforestation, we can make statements only about *poorer areas* and not necessarily *poorer land owners*. It is possible that even in poor areas, where most people are quite poor, most of the land could be owned by non-poor people. While our results add insight, including on controlling for location in testing behavior, that they are not incredibly strong would be predicted if those doing the forest clearing in poorer areas are not poorer. That this is possible in our data indicates the value, going forward, of household-level data on both poverty and deforestation.

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<u>Table 1</u> 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)	0.086 (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' Characteristics [a]

	I	II	III	IV
Dependent Variable [b]	annualized def. prob.	annualized def. prob.	annualized def. prob.	annualized def. prob.
POVERTY [c]	0.016 (0.82)	0.15 (3.2)	0.16 (3.3)	0.090 (0.41)
POVERTY * GOODLZ				-0.55 (-2.0)
POVERTY * BADLZ				0.44 (1.5)
%CLEARED			1.2 (1.3)	3.9 (7.7)
%CLEARED SQUARED			-3.4 (-3.5)	-2.6 (-4.6)
GOODLZ				0.078 (0.43)
BADLZ				-1.8 (-9.6)
BADSOIL				-0.43 (-2.9)
TIMEDUMMIES[d]	(these are always	Significant as our	Controls for	time trends)
DISTCITY				0.0011 (0.30)
DISTCITY * 63-79 DUMMY				0.0056 (1.4)
DISTCITY * 79-86 DUMMY				0.0038 (0.92)
DISTCITY * 86-97 DUMMY				-0.0053 (-1.2)
CONSTANT	-2.8 (-30)	-3.7 (-18)	-3.6 (-16)	-5.7 (-15)
FIXED EFFECTS		F = 7.8 (P = 0.00)	F = 6.3 (P = 0.00)	
ADJUSTED R^2	0.22	0.74	0.76	0.53
N	961	973	973	958

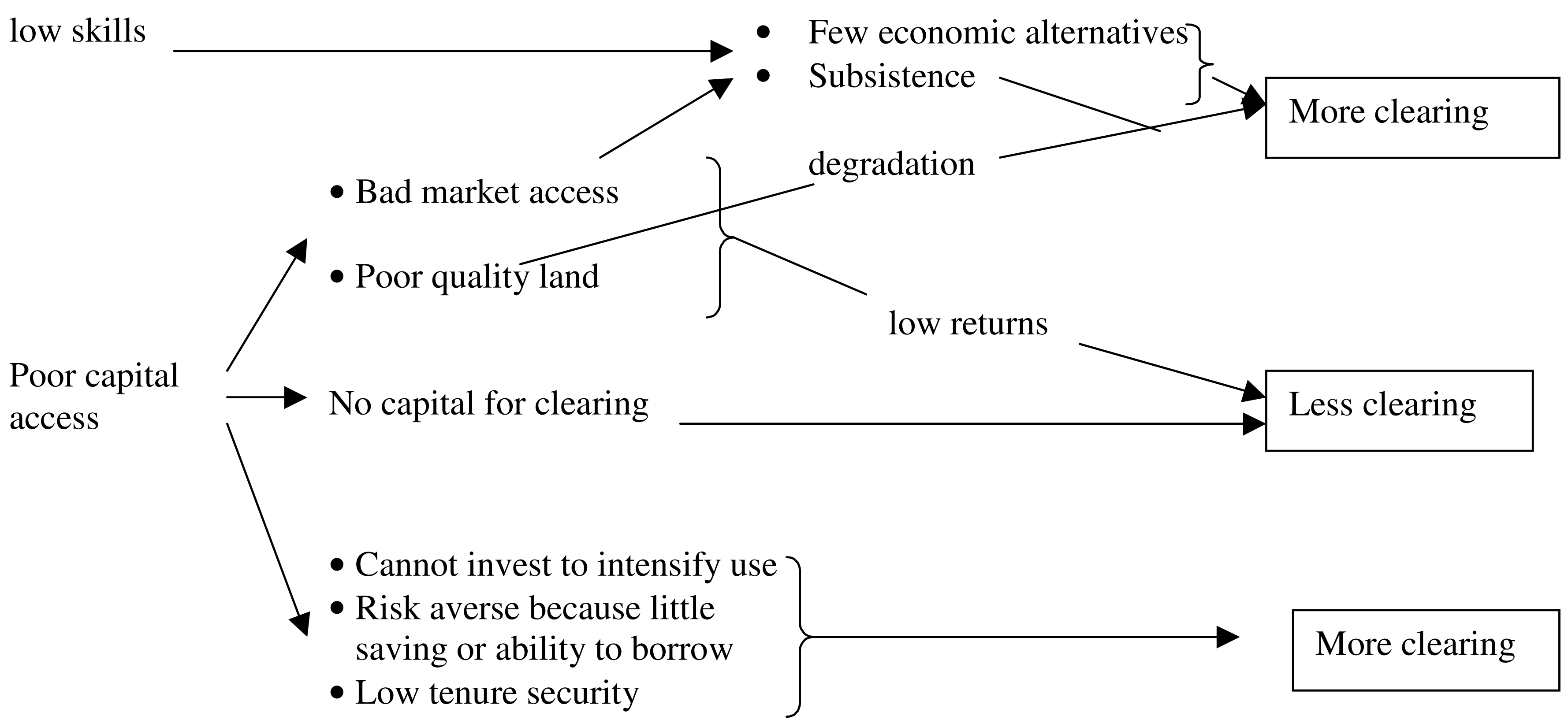
[a]: All regressions reported above are Grouped Logit regressions, following (6) above.

[b]: Coefficients reported above with t statistics below them in parentheses (except for fixed effects, where F reported above with P value below).

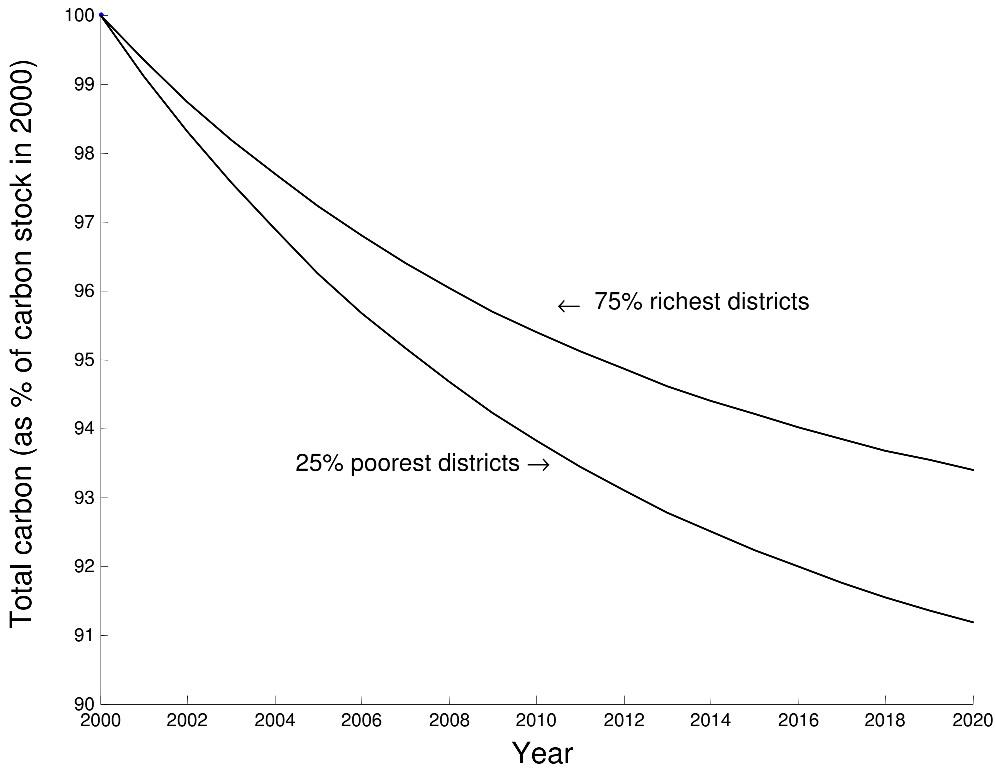
[c]: In all columns this is the 1963-2000 pooled index. In column IV, to focus on the relatively poor in particular, use dummy for poorest quartile.

[d]: Coefficients for time dummies not reported as not a focus here and would crowd the table (see Kerr et al. 2003 for discussion of time trends).

<u>Figure 1</u> Poverty and Deforestation



<u>Figure 2</u> Behavioral Difference between the richest and poorest post-2000 [a]



[a]: this follows from the coefficient on poverty in column II of Table 2

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