Spatial Interactions in Forest Clearing: Deforestation and Fragmentation in Costa Rica

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Abstract

We estimate local interaction effects in forest clearing in Costa Rica. To address the issues of simultaneity and spatially correlated unobservable factors, we instrument for neighboring forest clearing decisions using characteristics of neighboring land parcels. We explore a set of possible instruments. Neighboring ecological characteristics provide robust evidence that neighboring decisions reinforce one another. This finding should be taken into account in forest projections and in the design of conservation policies.

1 Introduction

In 1987, a group of small farmers in a village 100km east of the capital in Costa Rica received 190 hectares of primary forest designated for coffee and sugar cane production. Jointly, these farmers agreed instead to maintain forest and profit from tourism (and more than 50 communities followed their example (La Nacion 1/18/04)). While such choices could be explained by the farmers individual characteristics, the coordinated actions suggest externalities large enough to change land-use decisions and even community land-use outcomes. Whether interactions between such decisions are a significant factor in land use, however, is another matter. If they are, they will affect both the quantity and the spatial pattern of forest. Such effects on land use will also of course affect agricultural activities and the benefits they provide

The presence of such externalities can affect the efficiency and optimality of market outcomes (see Moffitt 2001, Cooper and Johns 1988, Brock and Durlauff 1999). Exogenous changes in the determinants of individual choice affect other individuals (Moffitt, 2001). The way these effects propagate in the population can be an important tool for policy implementation (Durlauff, 2001). For instance, as forested land and services that it provides become increasingly scarce, these issues may become important for agricultural development and forest conservation.

Spatial patterns and location of deforestation have been studied with greater ease since the use of Geographical Information Systems (GIS) has facilitated measurement of key spatial attributes (see, e.g., Serneels and Lambin 2001, Walsh et al. 2001, Kok and Veldkamp 2001, Chomitz and Gray 1996, Geist and Lambin 2001). Important issues related to deforestation behavior (Pfaff 1999, Chomitz and Gray 1996) and residential development (Irwin and Bockstael 2002, Irwin and Geoghegan 2001) can now be better addressed. An important contribution in this area, for example, was empirically finding negative effects of particular neighboring land-use choices on residential development (Irwin and Bosckstael 2002). Neighbors' interactions have also been shown to exist within agricultural technology adoption (Case 1992, Conley and Udry 2001).

We analyze neighbors' effects on tropical deforestation decisions in a developing country. We construct a spatially explicit land-use model with spatial interactions following literatures on social interaction (Brock and Durlauf 2001, Young 1999, Cooper and John 1988) and forest clearing (Kerr, Pfaff and Sanchez 2004, Pfaff 1999, Chomitz and Gray 1996). Our focus is the empirical implementation of Brock and Durlauf (2001) using the exogeneity of neighbors' characteristics to identify the presence of interactions in forest degradation.

Econometric research on social interactions has focused on whether neighbor's interactions can be measured (Manski 1993, Brock and Durlauf 2001, Beyer and Timmins 2003, Conley and Topa 2002, Glaeser and Scheinkman 2001, Moffitt 2001). A challenge for identification arises from other reasons why individuals behave similarly within a given region: spatial similarities among the unobservable characteristics of individuals; and direct effects of neighborhood and neighbors' characteristics (Manski 1993 and discussed below). That neighbors' and individuals' choices affect each other, known as simultaneity, can bias the estimates. Alternative approaches to identification have been proposed. The conditions in which they can be applied vary. Some applications have focused on: education (Crane 1991, Evans et al. 1992); employment (Conley and Topa 2002, Topa 2001); crime (Glazer, Sacerdote and Scheinkman 1996); and technology adoption (Conley and Udry 2001, Case 1992). Instrumenting neighbors' actions with neighbors' characteristics, the strategy of our choice, addresses most of these issues (Moffit

2001, Evans et al. 1992). However, the selection of the instrument becomes crucial in the procedure (Moffit 2001, Beyer and Timmins 2003).

For deforestation, neighboring outcome effects may exist for both agricultural and environmental reasons. Each set of reasons can be further classified into those that induce individuals to take the same action, i.e. exhibit "strategic complementarity", and those that induce individuals to take the opposite actions, i.e. exhibit "strategic substitutability" (Cooper and John, 1988). Agricultural strategic complementarities include farmers who as a group working cleared lands can improve their bargaining positions for buying inputs and selling outputs. Expected neighbor clearing will affect profit expectations. Environmental amenities can also feature strategic complementarities. As suggested by our first story above, an example is one locale's decision to maintain forest for tourist activities, such as hiking or sight seeing, which may be affected by neighboring locales also maintaining forest. Environmental amenities can also feature strategic substitutability. Tourism firms have incentives to use some land near forest for installations such as hotels, golf courses and other facilities, e.g. 185 condominiums next to a well known ecologically fragile tourist site, Playa Grande (Prensa Libre, September 28, 2002). Agriculture processes with strategic substitutability include reduced local incentives to clear resulting from neighbors' clearing and production of agricultural goods which reduced expected local output prices.

We empirically search for the net effects of any of these processes on the individual's decision. Costa Rica, is a good case for empirical exploration due to its ecological and topographic variation, even across relatively small areas, and the availability of spatially explicit social and economic information. Deforestation in Costa Rica has been extensively studied (Kerr Pfaff and Sanchez 2004, Pontius et al. 2001, Bulte et al. 2002). We use deforestation data analyzed in Kerr, Pfaff and Sanchez 2004. They study deforestation along the development path, finding not only that agricultural productivity and transport costs matter, in keeping with the literature, but also that controlling for those factors past clearing behavior and development proxies are significant.

We use instrumental variable techniques to estimate spatial interactions. In seeking neighbors' characteristics uncorrelated to the individual's decision, we try a variety of instruments for robustness. We also control for local fixed effects to absorb some spatial correlation. Finally, we also examine the results from other approaches.

As noted above challenges to identification exist, and these motivate the instrumental approach. To start, if neighbors' choices affect the individual then the individual's choices affect neighbors'. This simultaneity problem is avoided by using neighbor characteristics as an instrument for neighbors' behavior, one that is not affected by the individuals' choices (Moffitt 2001).

An important constraint on this approach is that the neighbors' characteristics must not have a direct effect on the individual's actions (Moffitt 2001). Neighbor's income, for instance, might explain in part not only the neighbor's choice but also the local demand for agricultural products and thus the individual's choices. A useful neighboring characteristic for use as an instrument might be the neighbor's land quality, which affects the behavior of the neighbor but does not directly affect the individual's decision.

The issue of unobservable spatially correlated characteristics of individuals must also be considered. Again, using neighbor characteristics is a good solution to identifying interaction effects (Moffitt 2001, Evans et al. 1992). The reason is that while spatially correlated unobservable characteristics may lead neighbor and individual decisions to be correlated, these unobservable characteristics do not affect neighbors' exogenous observed characteristics.

Independence of the instrument and spatially correlated unobservable variables is a key issue in instrument choice. If correlation exists, then we could be capturing the effects not only of neighboring decisions, as desired, but also the effects of spatially correlated unobservable characteristics. Consider the average of the neighbors' minimum distance to a local road as an instrument. This may well proxy successfully for the neighbor's clearing action. However, it may also reflect the unobservable abundance of roads in the neighborhood, which by itself may lead the individual to clearing. Using this as an instrument could represent as an interaction the effect of spatially correlated but unobservable driving factors that two deforestation decisions have in common. In some cases, this issue motivates our choice of how to measure a key variable and our inclusion of spatial fixed effects in order to control for the effects of unobserved factors.

Our estimates of how neighbors' decisions affect actions are significant. The biased Ordinary Least Square estimates show a larger and more significant effect than the other techniques, as expected. The second technique used for measuring interactions is Anselin (1988) Spatial Auto-Regressive model (Roe et al. 2002) which is widely cited and used. This approach yields lower estimates due to its close link to the spatial error correlation. Smaller and significant spatial correlation of the errors can affect the level of the interactions estimated. As we add spatial controls the estimates of the Spatial Auto-Regressive model even become negative and significant.

The instrumental variable results vary according to the instrument. When using the slope of the forest parcel that belongs to the neighbors as instrument, the results are positive and significant even when controlling for parcel's life zones and parcel's characteristics, such as distances to national and local roads, distance to San Jose and the main ports, distances to main towns, schools and sawmills, proximity to cleared areas, precipitation, elevation and parcel's slope. More controls reduced coefficient magnitude and significance, though. Alternatively, when using neighboring ecological characteristics as instruments, estimates of the local interaction coefficient are significant, even when possible downward biases are introduced by controlling for districts and the effect of the closest life zone.

These results suggest that interactions should be considered in, e.g., predicting deforestation over space and time, for instance when considering the effects of infrastructure investments on frontiers or developing spatially specific baselines for deforestation within international treaties. Potential multiple equilibria affect the probabilities of deforestation outcomes. Socially inefficient forest outcomes are possible. Small policy interventions could, then, "tip the balance" towards forest (or non-forest) equilibria when that would be individually and socially preferred.

Below we present our approach to the identification of interactions. In Section 2 we present a model that combines simple land-use theory and social interactions. In Section 3, we present our empirical strategy, while in Section 4 we describe the data. In Section 5, we present our results.

2 A spatial deforestation model with local interactions

We consider an endowment of land $L \subset \mathbf{R}^2$ covered by forest. This endowment is composed by n parcels. We assume that forest land has well defined property rights and it is in private hands. Each parcel is managed by a profit maximizing agent. Each agent chooses discretely between possible actions that lead to alternative land uses in the parcel. We denote the action taken by agent i as a_i. Agent i decides between: keeping forest, $a_i = 0$, or adopting an alternative land use, $a_i = 1$. Deforestation in region L is, then, described by the action profile $a = \{a_1, a_2, ..., a_n\}$.

Agent i's profits $\pi_i(a)$ can be divided in three elements: private characteristics' effects; neighbors' effects; and a random profit shock. Agent i's private characteristics are contained in the vector x_i. Private characteristics' effects on profits are linear and depend on the action taken by the individual. The vector of coefficients β_0 maps private characteristics to profits when $a_i = 0$ and β_1 maps private characteristics to profits when $a_i = 1$. It is necessary to make the distinction between private characteristics effects when clearing and when keeping forest. Rainy local climate conditions, for instance, affect private profits positively when the land is used for agricultural production and negatively when the land is covered by forest and used for recreation.

The random profit shock $\epsilon_i(a_i)$ represents unobservable characteristics only known by the agent. The shock varies according to the action. Individuals' knowledge of agriculture, for instance, has a positive effect on profits if i decides clearing and producing. However, this characteristic has no effect if i decides to maintain forest.

Neighbors' decisions also affect profits. There are four different effects of neighbors' actions on profits: the effect of neighbors clearing when agent i is clearing, b; the effect of neighbors keeping forest when i is clearing, d; the effect of neighbors clearing when i is keeping forest, c; and the effect of neighbors keeping forest when i is keeping forest, f. Table 1 describe situations generating these type of externalities.

We defined agent i's neighborhood, $B_i \subset \mathbf{R}^2$, as:

$$B_i = \{x \in L : x \notin L_i \text{ and } d(x, x_i) < r \text{ for any } x_i \in L_i\}$$

where d denotes the euclidian distance operator. The set of agent i's neighbors is:

$$N_i = \{j \in N : L_j \cap B_i \neq \emptyset\}.$$

Neighbors' externalities, when entering the profit function, are normalized by the amount of land each neighbor owns in agent i's neighborhood. The percentage of j's land inside B_i is described by

$$w_{ij} = \frac{|L_j \cap B_i|}{|B_i|}.$$

We denote w_{-i} as $(w_{i1}, w_{i2}, ..., w_{i,i-1}, w_{i,i+1}, ..., w_{in})$. Then the fraction of

i's neighborhood being cleared is expressed by $w_{-i}a'_{-i}$ and the fraction of i's neighborhood with forest is expressed by $(1 - w_{-i}a'_{-i})$, where a_{-i} as usual represents the vector of actions of all agents but i.

We can express profits when agent i chooses to maintain forest as:

$$\pi_i(0, a_{-i}) = x_i\beta_0 + cw_{-i}a'_{-i} + f(1 - w_{-i}a'_{-i}) + \epsilon_i(0)$$

and when i chooses to clear as:

$$\pi_i(1, a_{-i}) = x_i\beta_1 + bw_{-i}a'_{-i} + d(1 - w_{-i}a'_{-i}) + \epsilon_i(1).$$

Actions are taken simultaneously. Hence, agents form beliefs about each others' actions. Agent i's expectation of agent j's action is denoted by $\alpha_{i,j}$.

Agent i clears if expected profits of clearing are larger than the expected profits of maintaining forest:

$$\pi_i(1, \alpha_{-i}) - \pi_i(0, \alpha_{-i}) > 0. \tag{1}$$

where α_{-i} is the vector $(\alpha_{i,1}, \alpha_{i,2}, ...\alpha_{i,i-1}, \alpha_{i,i+1}, ..., \alpha_{i,n})$. We can rewrite Condition 1 as:

$$x_i\beta + (\rho_1 + \rho_0)w_{-i}\alpha'_{-i} - \rho_0 + \epsilon_i > 0,$$

where $\rho_1 = b - c$, $\rho_0 = f - d$, $\beta = \beta_1 - \beta_0$ and $\epsilon_i = \epsilon_i(1) - \epsilon_i(0)$. The difference of the shocks, ϵ_i, is assumed independent and identically distributed for each i.

The probability that agent i takes action $a_i = 1$ can be expressed by:

$$Prob\{a_i = 1|\alpha_{-i}\} = Prob\{x_i\beta + (\rho_1 + \rho_0)w_{-i}\alpha'_{-i} - \rho_0 > \epsilon_i\}$$

where the probability function depends on the assumption of the distribution of ϵ_i. We let F be the continuous cumulative distribution function of ϵ_i so that,

$$Prob\{a_i = 1|\alpha_{-i}\} = F(x_i\beta + (\rho_1 + \rho_0)w_{-i}\alpha'_{-i} - \rho_0).$$

We can now define the expected action of agent i as:

$$E(a_i) = F(x_i\beta + (\rho_1 + \rho_0)w_{-i}\alpha'_{-i} - \rho_0).$$

Following Brock and Durlauf (2000), we impose rational expectations. This implies that agent i's beliefs about agent j's action equals j's expected action. Formally,

$$\alpha_{i,j} = E(a_j) \ \forall j \text{ and } \forall i \neq j.$$

The equilibrium can be find then by solving the set of equations:

$$E(a_i) = F(x_i\beta + (\rho_1 + \rho_0)\sum_{j\neq i} w_{ij}E(a_j) - \rho_0) \ \forall i$$

which form a continuous mapping from $[0, 1]^n$ to $[0, 1]^n$. By Brouwer's fixed point theorem, there exists a solution to the system of equations, which proves Proposition 1.

Proposition 1 *There exists a set of self-consistent expectations in the spa-*

tial deforestation model with local interaction. □

Specifying the functional form of F is crucial for the empirical implementation of the model. Brock and Durlauf (2000) assumes that ϵ_i has an extreme-value distribution, which implies that the probability function is logistic.

When the system is in equilibrium, all individuals' beliefs about neighbors' actions generate the mathematical expectation of their neighborhood deforestation. This allows us to use actual neighborhood deforestation to estimate interactions.

3 Empirical Strategy

The identification of interaction effects has been widely discussed in economics (e.g., Brock and Durlauf 2001, Glaeser and Scheinkman 2001, Maskin 1993, Moffitt 2001, Beyer and Timmins 2003) and to some extent in land use in particular (Irwin and Bockstael 2002). A number of alternatives have been proposed, but consensus is that the best solution depends on the application (Moffit 2001, Glaeser and Scheinkman 2001). We are especially concerned with simultaneity and correlated unobservable variables. The implementation of an instrumental variable approach addresses these issues.

Simultaneity, an issue present in the estimation of interaction coefficients in any application cannot be ignored. If agent i is affected by agent j, then agent i also affects j's decision,

$$j \in N_i \Rightarrow i \in N_j.$$

This two-directional process biases the estimation. Without this potential bias being addressed, the estimate of the interaction coefficient would reflect not only the effect of agent j's action on i's decision, but also the effect of i's decision on j's action.

That the econometric analyst observes only limited information in terms of individual and parcel characteristics, such that many other driving factors must be in the errors of regressions equations, is crucial. In this case, it is especially important since some of those other factors are spatially correlated. The estimation, then, of the interaction term ρ by only using neighborhood deforestation rate $w_{-i}\alpha'_{-i}$ is inconsistent. What appear to be effects of neighboring choices on individuals' choices could be the result of spatially correlation between unobserved drivers.

Further, the factors that drive an individual's choice could include characteristics of the neighborhood. The estimate of ρ could capture, e.g., the direct effect of neighboring income if richer neighborhoods demand more output and clear more. That is, neighboring income may lead the neighbors to clear more and also directly lead individuals to clear, so that there might appear to be an effect of neighbor clearing on the individual's clearing when there is only a common effect of neighbor's income.

3.1 Instrumental Variable Approach

The Instrumental Variable (IV) approach addresses these problems (Moffitt 2001, Evans et al. 1992). We seek neighbors' characteristics uncorrelated to the individual's decision as instruments. Further, we control for local fixed effects, districts or counties, to absorb some spatial correlation in the estimation.

Recall that if neighbor choices affect a given individual then also the individual's choices affect the neighbors. Individuals' choices to clear do not, though, affect neighbors' characteristics. Further, these proxy for neighbor behavior and can be good instruments.

Another criterion, however, is that neighborhood characteristics must not have a direct effect on individuals' actions. Here, the ecological and topographic variation in Costa Rica is useful, as those neighboring characteristics vary over space, and affect the behavior of neighbors, but do not directly affect the decisions on neighboring parcels.

A third criterion is of course that the instruments not be correlated with the unobservable factors that drive individuals' decisions. Neighboring behaviors fail this test as they are driven in part by unobserved factors themselves, and those are likely to be spatially correlated with the unobserved factors driving individuals' choices. Neighboring characteristics may not be correlated with the errors in the deforestation equation, though.

That said, this is important to check. Average of the neighbors' minimum distance to a local road, for instance, could reflect unobservable abundance of roads in the area, something which while unobserved also may directly lead the individual to clear. The neighboring ecological characteristics and topography at first glance seem to satisfy this, however it is important to consider measurement error (more in subsection 4.4 below). For instance, it is possible that the neighboring ecological characteristics are correlated with measurement error in a parcel's ecological characteristics, i.e. with the parcel error.

One response to such potential issues is to absorb as much of the parcel spatially correlated error as possible in the deforestation equation itself. For instance, following the minimum distance issue just above, we might calculate the length of local roads in the neighborhood and add that into the equation as a control. We can control further by adding local fixed effects, i.e. county or district dummies. As noted above, these may bias against our estimation of spatial interactions.

3.2 Spatial Econometric Approach

Anselin's spatial econometrics models have also been used for the estimation of local interactions (e.g., Roe et al. 2002). The Spatial Autoregressive Model (SAR) designed to correctly estimate β, in our context, specifically models the interaction between neighbors' decisions. The SAR model deals with simultaneity by solving the econometric equation for the dependent variable present in the right and left hand sides of the equation, and then estimating the non-linear resulting functional form of the parameter via maximization of a likelihood function. However, this specification does not distinguish between effects arising from interactions and those arising from spatially correlated unobservable variables. A larger interaction coefficient, for instance, increases the value of the likelihood function in the presence of spatially correlated errors. The opposite is also true. In the presence of negative spatial correlation of unobservable variables, a smaller estimate of the interaction coefficient increases the value of the likelihood function.

The general specification of Anselin's spatial model considers spatial correlation in the errors and spatial correlation on the dependent variable.

However, the lack of knowledge of the specific spatial structure of these unobservable variables forces the researcher to make assumptions. If the spatial structure of the unobservable variables is wrongly specified, the identification of any spatially correlated variable is biased.

3.3 Discrete Dependent Variable

For a given location, deforestation is a discrete choice, either forest or not. Both of the empirical approaches discussed above though, IV and SAR, relate linearly the dependent variable and the regressors. They would be appropriate only for the linear probability model. A probability model that bounds the expected dependent variable values between 0 and 1 is more adequate, and would satisfy the model requirement of F allowing for existence of multiple equilibrium. However, the implementation of the instrumental variable approach requires additional considerations (e.g. Evans et al. 1992).

Discrete spatial econometric models have also been developed (Case 1992, Pinkse and Slade 1998, McMillan 1992, Beron and Vijverberg 2000, LeSage 2000). Fleming (2003) presents an extensive survey of these techniques. These approaches bring with them the strengths and the weaknesses of Anselin's linear spatial models. They can potentially solve the simultaneity problem but do not clearly differentiate between spatial unobservable errors and interaction effects. Additionally, however, these approaches constrain the number of observations that can be used due to highly demanding computational processes used during the estimation.

Fleming presents a far less computationally intensive alternative to the discrete spatial econometric models, the application of Non-Linear Least Squares models using a probit functional form. This application is based on Kelejian and Prucha (1998)'s IV approach to the Linear Spatial Econometric Model[1].

3.4 Land, Neighborhoods and Points

Due to the lack of individual land property information at a national level, we face a problem when trying to measure the interaction effects. We have a precise spatially disaggregated description of forest dynamics, population, transport costs and biological factors. However we lack individual behavioral information. Thus we don't know exactly where one person's property and actions stop and another's starts.

Many literatures use aggregated data. The economic growth literature, e.g., uses representative individual models and runs regressions based on aggregates. Research on deforestation and research on social interactions are not the exceptions. Some alternatives for estimating social interactions in the absence of individual data are spatial correlation techniques (Topa 2001, Conley and Topa 2000 on unemployment) and techniques based on differences on the variances across aggregate spatial observations (Gleazer, Sacerdote and Scheinkman 1996, on crime, and Gleazer and Scheiman 2001, on female household headship).

While we could resort to those techniques for estimating the interaction,

[1] Based on this idea, we will estimate the interaction parameter using the Non-Linear Least Squares Approach later on. By using the Non-Linear Instrumental Variable approach, we avoid computational heavy procedures, we satisfy the theoretical requirement of values being bounded, avoid simultaneity, and differentiate between neighborhood's unobservable characteristic effects and neighboring decision effects.

here we address this issue by using information from random point locations and applying average farm size information (around those point locations) to estimate where one property stops and another one starts. Our strategy is: first, randomly draw points across L; second, associate land and socioeconomic characteristics to each point; and finally, use these points as observations assuming that they represent a parcel of land. This is a valid strategy as long as:

$$Prob\{a_i = 1 | w_{-i}\alpha'_{-i}, X_i\} = Prob\{y_{l_i} = 1 | l_i \in L_i, w_{-i}a'_{-i}, \overline{X}_i\}, \forall l_i, \forall i \quad (2)$$

where l_i is a randomly drawn location, y_{l_i} represents the action taken in location l_i.

There are three important issues that we need to verify for concluding that equation (2) holds. First, we need,

$$a_i = 1 \Leftrightarrow y_{l_i} = 1.$$

This holds trivially by the assumptions of the model stating that the land manager faces a discrete decision between clearing or maintaining forest in the whole parcel (which is reasonable when a parcel is small enough). Second we assume that we can approximate individual characteristics by calculating ecological and socioeconomic point characteristics, $X_i = \overline{X}_i$. As we mentioned, there are unobservable characteristics unfeasible to obtain. However, our estimation technique addresses that issue.

Third, we need to make sure that the expected neighboring mean action can be approximated by $w_{-i}a_{-i}$. Under the rational expectation assumption, in equilibrium we have that,

$$E(w_{-i}\alpha'_{-i}) = w_{-i}a'_{-i}.$$

This means that what we observed as deforestation is what landowners expected by the time of their decision. It follows that by finding the fraction of the neighborhood deforested we can proceed with the estimation.

However, the lack of information of property borders also implies lack of information of the borders of the set B_i (Neighborhood). We can only approximate this set by generating a circle of radius r around each point.

This issue has two consequences. Individual i's own deforestation within properties larger than our neighborhood circle could be accounted as neighboring deforestation, which biases upward the local interaction estimate. Second, the probability of two points falling in the same parcel is strictly positive. Then, the instrument would be affected by the individual's own characteristics. We may be biasing estimated interactions downward, though, by potentially eliminating deforested areas that actually belong to the neighboring parcel that are very close to the chosen point.

4 Data

We collect the information from censuses and maps The combination of this information allows us to estimate the parameters of the model considering a large variety of social, economic and geographical variables.

4.1 Maps

We use GIS information on forest dynamics in Costa Rica from 1986 to 1997. These maps were specially developed to measure changes from forest to non-forest during this time period [2]. The information was created by The Tropical Scientific Center of Costa Rica and the Research Center for sustainable Development of the University of Costa Rica. With an image resolution of $30m^2$, we can precisely calculate location and quantity of deforested areas, location and quantity of forest persistence, and the distance from each location to the closest cleared area. The creators of the maps also pointed out locations where the classification of the pixel between forest and non-forest are dubious due to the image. We omit these locations of the analysis to reduce measurement error.

The Public Works and Transport Ministry in charge of the construction and maintenance of the roads in Costa Rica, developed road maps for 1985. We have two maps, one with the National roads, which shows the location of National roads, and the second map with local roads. There is no exact information when the roads were built, however they were already constructed by 1985.

As a proxy for yields and for costs of clearing, we use a Life Zone map, which divides the country in areas based on the type of vegetation, weather conditions and soil. We employed the Holdridge Life Zone System, which

[2]Given the length of the time spell, interactions could reflect reactions to past clearing within the time interval. Thus, the interaction coefficient estimate can reflect both, simultaneous interactions and interactions produced by changes in the state, for instance learning behavior in which information is inferred from others' past choices and outcomes given those choices

divides the country into 12 ecological zones (see Table 2). The most profitable areas for agricultural use in Costa Rica are the humid life zones, where conditions are especially good for coffee plantations. Very humid and montane life zones are related to less productive areas. However, the worst zones are the pluvial very humid life zones and tropical dry zones, due to bad agricultural yields and unfriendly vegetation (Kerr, Pfaff and Sanchez 2004).

Location of sawmills, towns and educational centers as well as elevation and rain maps are, also, available. The School of Forestal Engineering at the Instituto Tecnologico de Costa Rica created these maps. Town and sawmill locations represent the demand for agricultural products as well as forest products. Distance to educational centers is a proxy for residential land value. We also have a map of Protected Areas and clouds at the time any of the forest pictures were taken. We eliminate protected areas of the analysis since the government, instead of profit maximizing landowners, manages these locations. Clouds also made impossible to tell the presence of forest, which forces us to leave these areas out of the analysis.

4.2 Census Variables

We obtained two important variables from the 1984 Agricultural and the Population censuses, District Population and District Average Farm Size. Population serves as a local demand indicator for forest and agricultural products. It also approximates demand for land for housing and related infrastructure.

The 1984 Agricultural Census defines farm as an extension of land in which one person or many people dedicate full or part time to the production of one or many agricultural goods. The census reports the total extension of the farms and the number of farms by district. We find the average farm size by dividing the total extension of land in farms by the total quantity of farms in each district.

4.3 Point data, Parcel Area Estimates and Neighborhood

We randomly draw ten thousand points across Costa Rica's total area 51000 km^2. On average we have a sampled point every $5.1 km^2$ (see Figure 2). Point coordinates are plots in this highly precise forest map. Each point is classified as forest or non-forest for 1986 and 1997.

For each sampled point, we found the distance to the closest local road and the distance to the closest national road. We also calculated elevation and distances to the closest sawmill and county main city as well as the distances to San Jose and the main ports.

We classified the points by district, to which variables such as population and farm average size are associated. The district classification will also permit some control for unobservable factors including policy implementation, using dummies. After points were omitted for being inside Protected Areas or covered by clouds at the time or where the classification was said to be dubious, we are left with 7754 observations.

For estimating interactions, we define neighborhoods as the area inside a 10 km radius from the parcel. We then calculate neighborhood variables such as density of national and local road networks, density of educational centers, county capitals and sawmills for each point. Additionally, we calculate the amount of forest in each point's neighborhood.

We artificially create parcel areas based on district average farm size. We generate a circle around the sampled point in which deforestation is not considered as neighbors' deforestation but as own, and in which points are not used as instruments since they can reflect individual's own characteristics. We map district average farm size area to a radius of a circle that defines our artificial parcel. This radius length is found by calculating the maximum possible distance between any two points in a parcel. This parcel is assumed to be rectangular with a length four times its width with an area equal to the average farm size[3]. The distribution of the resulting cutoff distance for all points is shown in Figure 3 as well as the distribution of the average number of neighboring points. As it can be seen, the number of neighboring points inside these areas is relatively small.

Neighboring deforestation, $w_{-i}a_{-i}$, is the percentage of forest deforested in the area between the 10 km neighborhood and the artificially created parcel area. Instruments were also generated only from neighbor's characteristics located in this region. A summary of the statistics of all the variables and instruments is presented in Table 3.

4.4 Choosing the adequate instrument

Table 4 presents descriptive statistics of the possible instruments and the coefficient of determination, R^2, between each candidate and neighboring

[3]So, $A = 4l^2$, where A is the area and l is the length of the rectangle. The maximum distance between all points inside the farm is greater if we assume a rectangular farm than if we assume a circular farm given the same area. In fact, maximum distance between all points inside the farm increases as the difference between the length and the width of the rectangle increases.

deforestation. The first desirable property of a good instrument is high correlation to the variable being instrumented. We find four strong candidates: mean slope of neighboring sampled points, fraction of life zones in the neighborhood, lag deforestation in the neighborhood and mean distance to cleared areas of neighboring sample points.

The second desirable property is that the instrument would be independent of the dependent variable. Neighboring Life Zones do not have an effect on deforestation given the life zone of the parcel itself. Life Zones are a completely exogenous variable that are not affected by human decisions of deforestation or any other variable that might also cause deforestation. Neighboring slopes are also exogenous, since deforestation of the parcel itself does not affect the slope of the neighbors in any way and in general slopes are hardly affected by any human action.[4] Proximity to cleared areas is subjected to human decisions but there is not a clear link between neighbors' distance to cleared areas and deforestation. Past deforestation, however, could affect present deforestation for example by making available deforestation technologies and resources.

The third desirable property is that the variable would be uncorrelated to the errors. An important issue here is measurement error within the original deforestation equation and whether the instruments could be correlated with that error, which would be a problem. Errors in measurement in slope, for

[4]We ran regressions using neighboring decisions and neighboring slopes and found that slopes are not significant when controlled by neighboring behavior, which is evidence of independence between individual's decision and neighboring slopes. We also ran such regressions for neighboring Life Zones and only one of them was significant, but we believe that this is a consequence of ecological variation within life zones. We expect that by controlling additionally with closest life zone, this effect will disappear.

example, are said to rise with the slope, but it is not clear that neighboring slopes should be correlated with that measurement error.

Neighboring life zones might be a different story, however, given that within our discrete categorization of life zones surely parcels are heterogeneous. Parcels within the life zone tropical humid, for example, might have significantly different characteristics when close to another humid life zone than when close to a dry life zone. Thus the neighboring ecological characteristics could be correlated with the error in measurement implied by the discrete categorization of the ecological characteristics of the parcel of interest. We will attempt to address this issue by adding dummies for the closest life zone besides parcel's life zone dummies to our controls, thereby making an effort to reduce the mismeasurement that could end up in the error and be correlated with the instrument.

Neighbor's proximity to clear areas and past deforestation might also reflect unobservable spatially correlated information that directly affects the parcel's deforestation decision. Somewhat fixed variables such as relative land fertility, which is not perfectly measured and thus to some extent is in the error, affected deforestation within the neighborhood in the past as well as in the present. With spatial correlation of such unmeasured factors, past neighbor clearing may be correlated with current local clearing through this alone. Proximity to cleared areas may also reflect factors that are potentially durable over time and spatially correlated. This reduces the appeal of these two variables as instruments. However, if this is what drives the estimated interaction coefficient, then as we add individual spatially correlated characteristics and neighborhood controls into the initial deforestation equation, the empirical association with the instruments should be reduced.

5 Results and discussion

We present the OLS, SAR and IV estimates of the interaction parameter in Table 5. We use four instruments: mean slope of neighboring sampled points (NSL), fraction of life zones in the neighborhood (NLZ), lag deforestation in the neighborhood (D79) and mean distance to cleared areas of neighboring sample points (NPTC). We also estimate the parameter using both neighboring slope and neighboring life zones as instruments.

The estimates in the first row are calculated without any controls. We, then, progressively add variables to eliminate possible unobservable variation that can bias the estimates. We add parcel's life zones, then parcel's characteristics and neighborhood variables (see Table 3 for the complete list of parcel's characteristics and neighborhood characteristics). We then controlled for unobservable factors associated to second- or third-order political division by adding county or district dummies.

The OLS estimates of the parameter shown in the first column are large and highly significant. As argued before, the OLS estimates are biased due to simultaneity and spatial correlation of unobservable variables. By adding controls the estimates decrease, however they are still large, and highly significant, suggesting that simultaneity is a key problem here.

The estimates of the Spatial Auto-Regressive Model are in general lower than OLS estimates because it addresses the simultaneity issue. While we include these because of the popularity of the spatial econometric approach, it is worth emphasizing that we feel we cannot conclude anything about interactions from those estimates due to the close link between spatial error correlation and the interactions estimate. These estimates are in general smaller than the other estimates, yet this could result from positive but small spatial error correlation. See, for instance, that as we add controls, the estimate of the local interaction coefficient using the SAR model becomes negative and significant.

The estimates when instrumenting with neighboring slope are significant when life zones and parcel characteristics are used as controls. However, the coefficient becomes insignificant by adding neighborhood characteristics and regional effects at county level. It is possible that some of the controls we have introduced are correlated to neighboring slopes such as distance to roads or distance to towns.

Life zones remain highly significant when adding parcel's life zone, parcel's characteristics, neighborhood characteristics, county dummies as well as district dummies. We add another set of dummies to eliminate possible biases as consequence of unobservable variation of parcel quality within the life zone due to proximity to other life zone and the results remain highly significant.

Past deforestation shows evidence of existence of local interaction only under Life Zone controls. By adding more controls the significance disappears. Similar results are obtained using neighbor's proximity to cleared areas as instrument. This instrument also reflects past behavior as well as unobservable spatial elements.

In sum, at least using neighboring life zones, there is statistical evidence that proves the existence of local interactions. This holds even when controlling for parcel's characteristics, neighborhood variables, regional dummies and even closest life zone. We draw important conclusions from this result. First, forest and deforestation projections done without interactions might not be reliable. We can obtain outcomes unexpected under fairly robust models that ignore interactions. This is true not only in terms of quantities but also in terms of forest patterns. Forest patterns in the presence of positive local interactions have a greater tendency to be clustered.

We can also identify regions in which deforestation levels and forest patterns significantly change under different equilibriums. We can find stable equilibria by using location characteristics and the interaction coefficient. We can then map equilibrium outcomes and find places in which there are significant changes between equilibrium outcomes. These regions can be subjects of further research into policy intervention for efficiency in land use (given multiple equilibria) and for conservation. Policies could tip the balance towards forest or non-forest equilibria preferred in light of all tradeoffs.

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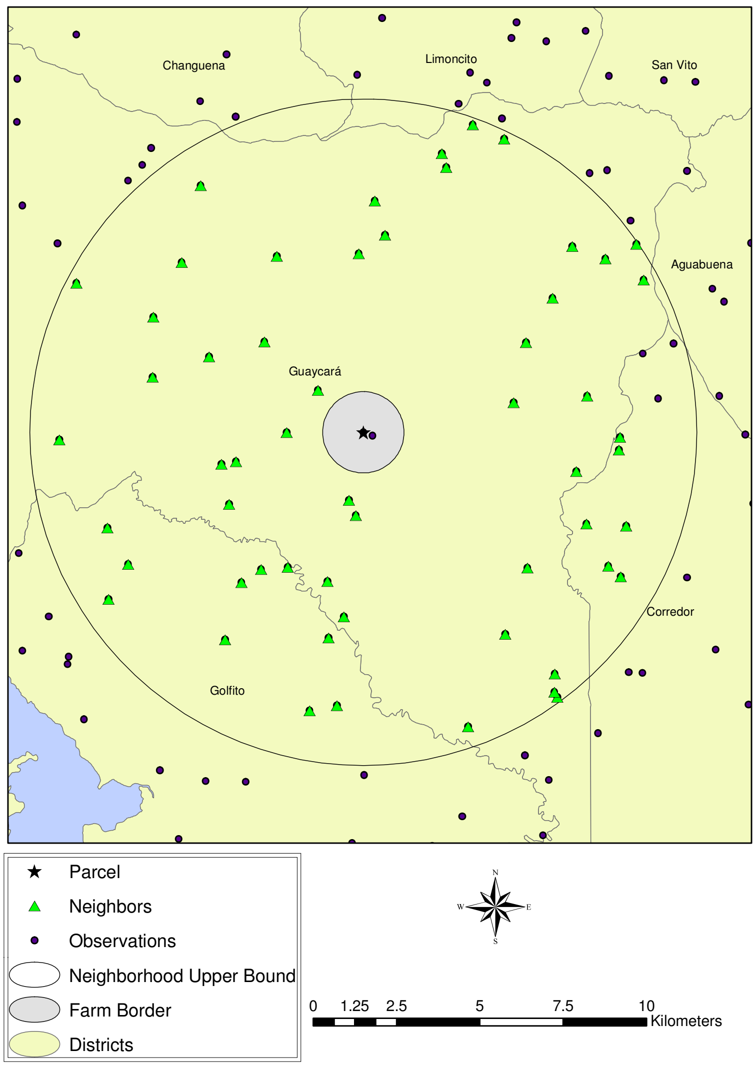

Figure 1: Empirical Neighbors

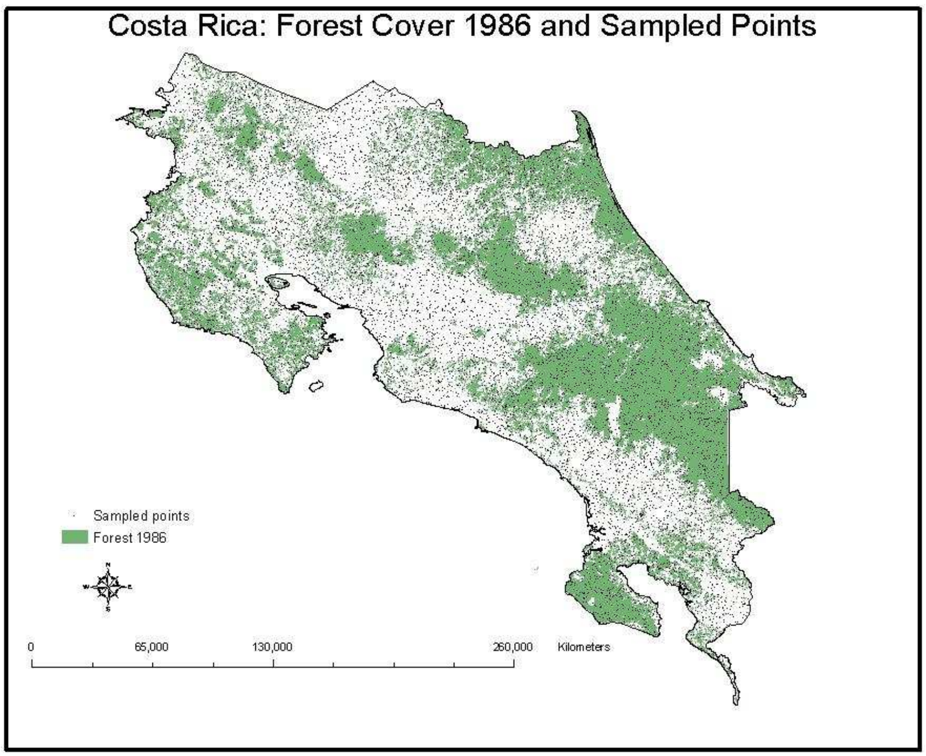

Figure 2: Costa Rica: Forest and Points

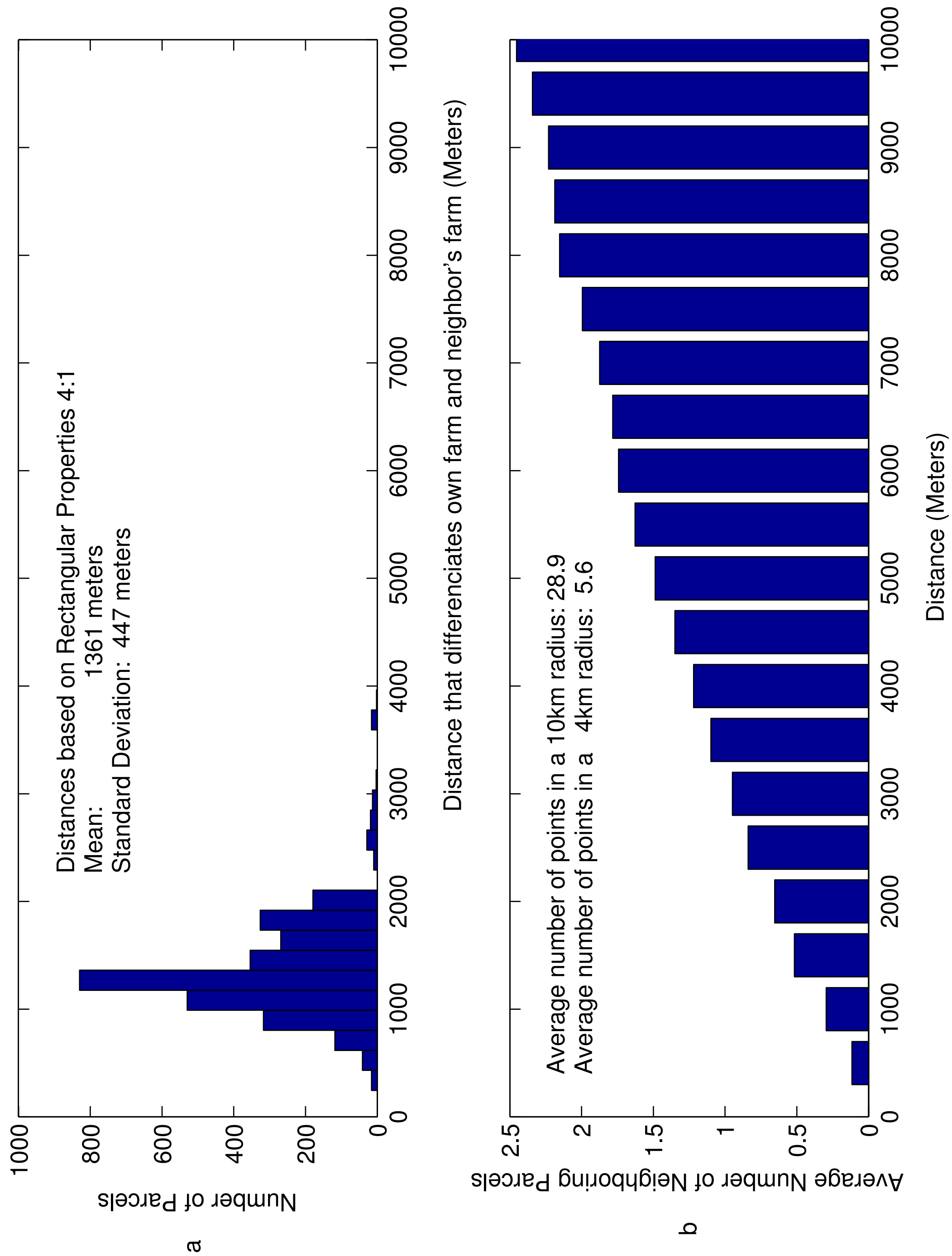

Figure 3: Neighbors and Cutoff Distances

Strategy	Neighbor's	Payoff	Agriculture	Environmental
Forest	Forest	f	Later development reduces clearing costs when neighbors also delay clearing	Forest for hiking worthwhile when others are keeping forest
Clearing	Clearing	b	Clearing based on expectations of enough neighbors clearing who will lobby for roads	Conglomeration of tourist infraestructure
Clearing	Forest	d	Agriculture when neighbors are keeping forest and local Ag. prices high	Tourist infrastructure when neighbors maintain forest
Forest	Clearing	c	Forest when neighbors are clearing and local Ag. prices low	Expectations of local forest scarcity

Table 1: Local Interaction Processes

Life Zone	Quality	Number
Humid Pre-Montane	Good	LZ1
Humid Lower Montane	Good	LZ2
Tropical Humid	Good	LZ3
Very Humid Pre Montane	Medium	LZ4
Very Humid Lower Montane	Medium	LZ5
Very Humid Montane	Medium	LZ6
Tropical Very Humid	Bad	LZ7
Tropical Dry	Bad	LZ8
Pluvial Pre Montane	Bad	LZ9
Pluvial Lower Montane	Bad	LZ10
Pluvial Montane	Bad	LZ11
Paramo	Bad	LZ12

Table 2: Holdrige Life Zone Classification

Variable		Group	SUM	Mean	STD	SE	MAX	MIN
Parcel Deforestation	Y	Dependent Var.	314	0.0959	0.2945	0.0051	1	0
Cleared Percentage	CPN	Neighborhood Ch.	1239.1	0.4033	0.2405	0.0043	0.9848	0.0002
Distance to San Jose	DSJ	Parcel Char.	2.7295e+5	88.85	47.604	0.8588	205.86	0
Distance to Caldera	DCA	Parcel Char.	3.7205e+5	121.11	52.264	0.9429	256.39	8.951
Distance to Limon	DLI	Parcel Char.	4.0122e+5	130.61	74.783	1.3493	305.15	0
Distance to L. Roads	DLR	Parcel Char.	13698	4.4589	4.9443	0.0892	37.973	0.0014
Distance to N. Roads	DNR	Parcel Char.	18698	6.0867	5.4836	0.0989	33.094	0.0111
Distance to Sawmills	DTS	Parcel Char.	69584	22.651	13.613	0.2456	71.463	0.5759
Distance to M Towns	DMT	Parcel Char.	74135	24.132	14.986	0.2703	78.449	0.5759
Distance to frontier	PTC	Parcel Char.	2022.4	0.6583	1.1316	0.0204	10.74	9.3e-6
Length National Roads	LNR	Neighborhood Ch.	85464	27.82	27.231	0.4913	284.92	0
Length Local Roads	LLR	Neighborhood Ch.	1.1669e+5	37.985	35.153	0.6342	248.91	0
# of Sawmills	NSM	Neighborhood Ch.	1080	0.3515	1.2049	0.0217	16	0
# of M Towns	NMT	Neighborhood Ch.	623	0.2028	0.60462	0.0109	9	0
# of Towns	NUT	Neighborhood Ch.	29886	9.7285	10.05	0.1813	78	0
# of Schools	NHS	Neighborhood Ch.	1977	0.6435	2.3546	0.0424	66	0
Altitude	REL	Parcel Char.	1.9063e+6	620.54	691.56	12.477	3250	0
Precipitation	RAI	Parcel Char.	1.1646e+7	3791	1056.2	19.057	8500	1400
Slope	SDA	Parcel Char.	25624	8.3413	8.3582	0.1508	36.87	0
Local Deforestation	$w_{-i}a_{-i}$	Interaction	324.15	0.0990	0.1114	0.0019	0.8833	0
Sample L. Deforestation	WY	Interaction	298.38	0.0971	0.1246	0.0022	1	0

Table 3: Statistics

Instrument	Mean	MAX	MIN	R^2 with $w_{-i}a_{-i}$
Neighbors' Distance to San Jose	89.7	217.0	0.75	0.0294
Neighbors' Distance to Caldera	124.8	273.1	15.19	0.0007
Neighbors' Distance to Limon	126.2	301.8	4.64	0.0238
Neighbors' Distance to L. Roads	4.56	34.1	0.17	0.0298
Neighbors' Distance to N. Roads	6.39	31.6	0.01	0.0013
Neighbors' Distance to Sawmills	23.1	66.0	3.40	0.0330
Neighbors' Distance to Main Towns	24.5	73.6	3.40	0.0019
Neighbors' Distance to Cleared Area	0.68	5.87	0	0.1121
Neighbors' Altitude	632.2	2638.4	0	0.0878
Neighbors' Precipitation	3784	6043.1	1400	0.0081
Neighbors' Slope	8.72	25.7	0	0.1745
Neighbors' LZ1	0.04	1	0	
Neighbors' LZ2	0.00	0.5	0	
Neighbors' LZ3	0.15	1	0	
Neighbors' LZ4	0.18	1	0	
Neighbors' LZ5	0.03	0.88	0	
Neighbors' LZ6	0	0	0	
Neighbors' LZ7	0.34	1	0	
Neighbors' LZ8	0.01	1	0	
Neighbors' LZ9	0.11	1	0	
Neighbors' LZ10	0.09	0.7796	0	
Neighbors' LZ11	0.03	0.7567	0	
Neighbors' LZ12	0	0	0	
Neighbors' LZ				0.1404
Neighborhood deforestation 79-86	0.10	0.9642	0	0.1396

Table 4: Statistics: Instruments

Controls	OLS	IV NSL	IV NLZ	IV D79	IV NSL-NLZ	IV NPTC	SAR
No Controls							
ρ	0.96	0.96	1.14	0.71	1.05	0.96	0.53
t-stat	22.38	8.83	11.86	5.85	13.27	7.06	15.52
LZ							
ρ	0.92	0.92	1.12	0.66	0.98	0.86	0.48
t-stat	20.00	7.53	7.21	4.84	9.32	5.21	13.25
LZ and Parcel Char.							
ρ	0.87	0.62	0.85	0.41	0.78	0.34	0.30
t-stat	13.69	1.76	4.01	0.77	4.11	1.10	7.04
LZ, Parcel and Neighborhood Characteristics							
ρ	0.85	0.53	0.77	0.03	0.71	0.02	0.28
t-stat	12.96	1.38	3.72	0.04	3.69	0.05	6.50
LZ, Parcel and Neighborhood Char. and Counties							
ρ	0.88	0.49	0.79	0.49	0.69	0.30	0.17
t-stat	10.99	1.09	2.88	0.76	2.77	0.65	3.62
LZ, Parcel and Neighborhood Char. Counties and Closest LZ							
ρ	0.87	0.22	0.74	0.45	0.62	0.20	-0.15
t-stat	10.72	0.41	2.37	0.72	2.21	0.39	-2.73
LZ, Parcel and Neighborhood Char. and Districts							
ρ	0.80	0.67	0.51	0.65	0.56	-0.07	-0.34
t-stat	7.68	1.47	1.61	1.14	2.04	-0.12	-5.99
LZ, Parcel and Neighborhood Char. Districts and Closest LZ							
ρ	0.80	0.44	0.44	0.61	0.48	-0.62	-0.38
t-stat	7.49	0.87	1.23	1.14	1.56	-0.72	-6.56

Table 5: Linear Probability Model: Estimates of ρ