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Contagious development: Neighbor interactions in deforestation

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ABSTRACT

We estimate neighbor interactions in deforestation in Costa Rica. To address simultaneity and the presence of spatially correlated unobservables, we measure for neighbors' deforestation using the slopes of neighbors' and neighbors' neighbors' parcels. We find that neighboring deforestation significantly raises the probability of deforestation. Policies for agricultural development or forest conservation in one area will affect deforestation rates in non-targeted neighboring areas. Correct estimation of the interaction reverses the naive estimate's prediction of multiple equilibria.

1. Introduction

Rural areas of developing countries contain most of the world's tropical forest. The demand for the local, regional and global services that forests provide, alongside the poverty in these areas, indicates the need for policies that balance development with forest conservation. The provision of forest services depends upon both the extent and the spatial distribution of standing forest. One important determinant of both the rate and spatial pattern of tropical deforestation is interdependency among deforestation decisions.

In general, interdependencies affect the efficiency and optimality of the outcomes of individual choice (Brock and Durlauf, 2001; Cooper and Johns, 1988, and Moffitt, 2001). Exogenous shifts in the determinants of individual choices can have expansionary effects if interdependencies exist (Durlauf, 2001, and Moffitt, 2001). How such spillovers propagate within a population or across space needs to be considered in policy design (Durlauf, 2001). We find significant interdependencies among individuals' deforestation decisions in a developing country.

Measuring such interactions is difficult (Bayer and Timmins, 2003; Brock and Durlauf, 2001; Conley and Topa, 2002; Glaeser and Scheinkman, 2001; Manski, 1993, and Moffitt, 2001). One challenge for identifying whether individuals are influenced by their neighbors to take the same action, for instance, is that there are other reasons neighbors behave similarly. Neighbors can have similar unobservable characteristics and be affected by the same unobservable influences (Manski, 1993). Another challenge is that neighbors simultaneously affect each other when interactions exist (Manski, 1993 and Moffitt, 2001). To address these challenges we apply the instrumental variable approach (Moffitt, 2001), using exogenously varying topological instruments: the slopes of neighbors' and neighbors' neighbors' parcels.

The literature uses instrumental variables and other approaches to identify interactions in a range of settings such as: education (Crane, 1991; Evans et al., 1992, and Gaviria and Raphael, 2001); employment (Conley and Topa, 2002, and Topa, 2001); crime (Bayer et al., 2004, and Glaeser et al., 1996); and migration (Munshi, 2003). Land-use research has focused on spatial externalities in residential development (Irwin and Bockstael, 2002) and on information networks that may affect technology adoption in agriculture (Case, 1992, and Conley and Udry, 2001). We extend this approach to the study of development and tropical deforestation.

Deforestation decisions depend on expected profits that can be affected by neighborhood deforestation for a number of reasons. Local prices may fall if others deforest for agricultural production, reducing

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the incentives for further clearing (strategic substitutability in clearing). Local profitability of deforestation may rise, though, if others who clear for production arrange transport to market that features economies of scale in transport for others (strategic complementarity in clearing). On the other hand, farmers have been observed to band together to maintain contiguous blocks of forest for tourism, where the commitment to forest by one raises the returns from maintaining forest for others (strategic complementarity in conservation). In contrast, if enough others have conserved and have created a tourism destination, this may raise the returns to forest clearing to create a new hotel (strategic substitutability in conservation). These interactions can take place simultaneously.

We estimate the net effect of these interactions within a system of two simultaneous equations. The first equation explains neighborhood deforestation using the instruments while the second equation explains individuals' discrete deforestation decisions using instrumented neighborhood deforestation. The system is estimated using two stage least squares and probit two stage least squares (Maddala, 1983) and then we examine the equilibria that are implied using all of the information in the explanatory variables plus the parameter estimates.

We use neighbors' slopes and neighbors' neighbors' slopes as instruments for neighborhood deforestation. The use of adequate instruments addresses both simultaneity and spatially correlated unobservable effects (Moffitt, 2001). While spatially correlated unobservable characteristics, such as regional policies or unobservable local shocks, may lead neighbor and individual decisions to be correlated, these unobservable factors do not affect neighbors' slopes or neighbors' neighbors' slopes. The independence between the instrument and unobservable deforestation drivers is the key to the estimation.

We feature neighbors' slopes and neighbors' neighbors' slopes because these variables not only significantly affect deforestation decisions in the neighborhood but also do not affect individuals' deforestation directly. Consistent with this assertion, when controlling for important parcel and neighborhood characteristics using the over-identification restriction test, we find that there is no evidence of correlation between unobservable drivers of deforestation (errors) and the instruments that would bias our estimates. However, one could imagine unobserved variables correlated with neighbors' and neighbors' neighbors' slopes that are also correlated with one's own deforestation decisions. For example, unobserved variation in the quality of roads could depend on slopes in the area, and in turn influence the costs and benefits of deforestation. We discuss why we believe some of the unobserved variables that could affect the estimates are unlikely to have strong effects in the case of Costa Rica.

Costa Rica is a good case for empirical exploration of this issue due to its topographic variation, even across relatively small areas, and the availability of spatially explicit social and economic information. We use highly explicit spatial deforestation data. We also use maps with information about the location of towns, sawmills, schools, rivers, roads, cities and ports, slopes as well as Holdridge Life Zones. Finally, we obtained the direction in which the parcels' slope faces (aspect) and daily average amount of sunlight that the parcel receives to control for parcel characteristics that might also be correlated with neighbors' slopes.

Using the average of neighbors' slopes as an instrument for neighborhood deforestation, we find that the interaction coefficient is positive and significant, even after controlling for parcel and neighborhood characteristics. An increase of 1% in neighborhood deforestation increases the probability of deforestation between 0.4% (from the Probit indicated by the binary dependent variable) and 0.7% (from an OLS linear probability model). We find these results to be robust to changes in these specifications and to changes in the definition of neighborhood.

One potential implication of such interactions is that multiple equilibria in deforestation could arise and decentralized private choices would not assure that the socially preferred one would be realized. Interventions to "tip the balance" towards a preferred equilibrium might be worthwhile. In this case, we find that the biased or naive interaction parameter estimate implies multiple equilibria. Estimated correctly, however, the interaction parameter does not imply multiple equilibria in deforestation. This result shows the value of proper estimation while still indicating a significant interaction that will affect the impacts of policies.

These findings suggest that interactions should be considered in predicting deforestation over space and time, for instance when considering the effects of infrastructure investments on frontiers or when developing spatially specific baselines for deforestation within international treaties, or designing spatial incentive schemes. Laboratory evidence on choice in the presence of spatial interactions created by spatial incentive policies has shown their potential importance in habitat conservation (Parkhurst et al., 2002) and our results here support their relevance concerning land-use behavior and thus also policy design.

The rest of the paper is as follows. In Section 2, we discuss the deforestation context in Costa Rica and the main determinants of deforestation. In Section 3, we describe the data. We present our empirical strategy in Section 4. In Section 5, we present our results. Finally, we conclude in Section 6.

2. Background

2.1. Economic activities leading to deforestation

Land-use decisions have long been central to the Costa Rican economy. Agriculture played a critical role in the early stages of development and, as a consequence, in the seventies and early eighties the deforestation rate in Costa Rica was one of the highest in the world (Sanchez-Azofeifa et al., 2001). Market conditions such as beef price levels were important determinants but economic policies also contributed by encouraging crop production and cattle ranching (Gaupp, 1992 and Lutz et al., 1993).

The activities that drove deforestation differed across regions. Coffee was critical in mountain regions. Cattle played an important role in drier areas in the North Pacific. Deforestation in the Caribbean and South Pacific followed the expansion of banana production in the sixties and early seventies and cattle ranching in the seventies and early eighties (Roebeling and Ruben, 2001).

In the late nineties, deforestation slowed (Pfaff and Sanchez-Azofeifa, 2004). The reasons for this included a fall in beef prices, the reduction of agricultural subsidies, and the fact that there is only a small amount of productive land that is still covered by forest and where land use was not restricted by the increase in public conservations policies. Additionally, the opportunity costs of clearing increased as alongside public conservation the private sector increased eco-tourism activities as their perceived profit potential rose rapidly.

2.2. Micro determinants of deforestation decisions

As agriculture was the main land use competing with forest, here we discuss the factors that lead a landowner to choose agriculture or forest. We draw upon a large literature including empirical research that has evolved from explaining forest level in countries to using large polygons such as counties and now to analysis of highly disaggregated spatial data.[1] Such work has provided evidence for effects on deforestation of biophysical characteristics such as slope,

[1] For examples of all these types of analyses, see Anderson et al., 2002; Chomitz and Gray, 1996; Cropper and Griffiths, 1994, Geoghegan et al., 2001; Kaimowitz and Angelsen, 1998; Nelson and Hellerstein, 1997; Pfaff, 1999; Pfaff et al., 2007, 2009b; Sernels and Lambin, 2001; Stavins and Jaffe, 1990.

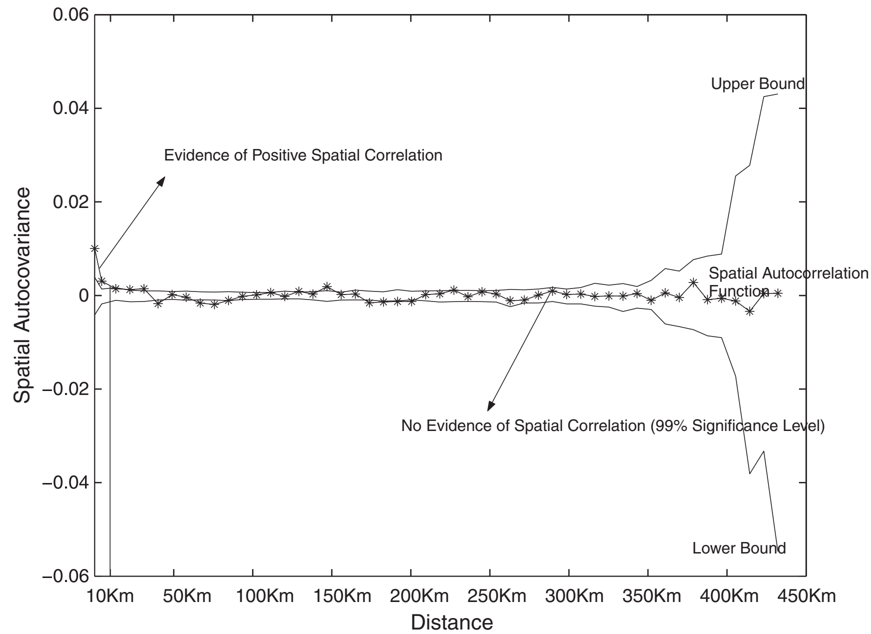

Fig. 1. Spatial autocorrelation function.

soil quality and rain as well as socioeconomic factors such as distance to roads and along roads to markets.

Examining these characteristics is sensible as they affect the net benefits of converting forested land for agricultural production. A simple model of the clearing decision, i.e. whether to conserve forest or clear for an alternative use, involves the land owner comparing the expected benefits and costs from each of the land uses. High slope, for instance, tends to lower the benefits of use in agricultural production as discussed below. Higher transport costs from high distances to markets to and along major roads will lower farm gate output prices and raise farm gate input prices. We expect land use to change with the variables that affect these net benefits.

2.2.1. Parcel's topographic and biological characteristics

Topographic and biological characteristics of the land play a key role in deforestation decisions. Slopes, soil, vegetation and precipitation are key constraints on land use, as they affect the costs and net benefits of agricultural development and therefore the likelihood of deforestation.

Steep slopes lower the net benefits of agricultural development, reducing deforestation. Cropper et al. 1999 find this in Thailand. Evidence that slopes discourage commercial farming was also found in Belize (Chomitz and Gray, 1996). Parcels with steeper slopes are also associated with lower deforestation rates in Southern Yucatan, Mexico (Vence and Geoghegan, 2002) and in Brazilian Amazon (Pfaff et al., 2007). In Costa Rica, steep slopes have also been associated with lower deforestation rates. This evidence is robust at different periods (see Sader and Joyce, 1988 for the period from 1940 to 1983, Pfaff et al., 2009b for the period from 1986 to 1997, and Sanchez-Azofeifa et al. 2007 for the period from 1997 to 2000) and at different scales (see Sanchez-Azofeifa et al. 2007 for 5 km by 5 km grids and see Andam et al., 2008 and Pfaff et al., 2009b for pixels).

Other biophysical characteristics also affect the net benefits agricultural development and thus also deforestation rates. Precipitation (Chomitz and Gray, 1996; Laurance et al., 2002; Pfaff et al., 2007, 2009b; Vence and Geoghegan, 2002), soil quality (Chomitz and Gray, 1996; Geoghegan et al., 2001; Laurance et al., 2002, and Pfaff and Sanchez-Azofeifa, 2004) and vegetation (Pfaff et al., 2007; Pfaff et al., 2009b and Sanchez-Azofeifa et al., 2001) are some of the most relevant determinants of deforestation decisions that consistently appear in the literature.

2.2.2. Access

Parcels with lower transport costs to markets are significantly more profitable for agricultural development and are consistently found in the literature to have higher deforestation rates. The distances to roads and distance to markets robustly and significantly affect deforestation rates in Belize (Chomitz and Gray, 1996), Mexico (Geoghegan et al., 2001; Vence and Geoghegan, 2002), Costa Rica (Pfaff et al., 2009b and Sanchez-Azofeifa et al., 2001) and Brazil (Pfaff et al., 2007; Pfaff et al., 2009a, 2010) and elsewhere (Kaimowitz and Angelsen, 1998). The infrastructure investments that affect land use in this way do not need to be in the immediate vicinity in the sense of the same political unit. The impacts of road investments in neighboring units are found across census tracts in the Brazilian Amazon (Pfaff et al., 2007) as well as across larger county units (Pfaff, 1999).

2.2.3. Interactions and deforestation

As noted previously, there are a number of reasons to expect neighbors' clearing decisions to affect an individual's clearing decision. They arise for both agriculture and forest conservation and can raise or lower deforestation. These effects can be classified into those that induce individuals to take the same action – "strategic complementarity" – and those that induce individuals to do the opposite — "strategic substitutability" (Cooper and John, 1988).

Agricultural strategic complementarities arise when farmers acting as a group can improve their bargaining positions for buying inputs and for selling outputs from cleared land. One example is a reduction in transport costs due to economies of scale in shipping goods to market. Farmers' cooperatives common in Costa Rica in coffee and milk have promoted such coordination.

Competitive crop markets, in contrast, can generate strategic substitutability in the agricultural decisions that generate deforestation. If neighbors engage in agriculture, with the attendant deforestation, their crop supply can drive local output prices down. This action, or expectations of such production, can certainly reduce the incentives to clear forest for the individual farmer.

Forest conservation can also feature strategic substitutability. Tourism firms have incentives to clear land near forest for installations such as hotels and golf courses. An example of this is the deforestation caused by the construction of 185 condominiums next to an eco-tourism site in the Pacific cost of Costa Rica (*Prensa Libre*, September 28, 2002).

The production of environmental amenities can also feature strategic complementarities, though, such as when one locale's decision to maintain forest for tourism helps to induce adjacent locales to also maintain forest. Such is the case of 50 communities in Costa Rica that have engaged in rural tourism activities conserving their forests (*La Nacion* January 18, 2004).

Such spillovers can be more direct, i.e. from one person to another, such as learning about the value of the forest from a neighbor when an individual decides to maintain forest. They can also be less direct, such as when an individual's decision affects another variable such as a price and that in turn affects neighborhood deforestation. Either form of spillover can be a critical factor in land use.

3. Data

3.1. Data sources and units of analysis

We empirically analyze deforestation in Costa Rica. Our data sources are: the 1984 Agricultural Census from the National Institute of Statistics and Censuses; satellite pictures of forest developed by the Tropical Scientific Center; and other geographic information from the Ministry of Transport and the Geographic Information Systems Laboratory at the Costa Rican Institute of Technology. These highly precise data are useful for measuring spatial interactions on deforestation.

Satellite pictures, taken in 1986 and 1997, describe the presence of forest in discrete fashion within 30 m^2 grids across Costa Rica.[2] The rest of the geographic information pinpoints the location of sawmills, towns, schools and roads, and characterizes the entire country by altitude, slope and ecological zones.

We randomly draw ten thousand locations from across the 51,000 km^2 that constitute Costa Rica's total area. These locations are treated as parcels in this analysis. In spite of its precision, information from satellite pictures has its disadvantages. Some parcels were covered by clouds when the images were recorded. Also, specialists pointed out areas in which forest pictures are inconclusive due to seasonal weather conditions. We omit these parcels from the analysis. Between cloud cover and potentially misspecified points, the sample decreases by less than 12% (1170 locations).

We focus on forest clearing.[3] Thus, we consider only parcels covered by forest at the start of the period. These parcels represent 47% of the total sample in 1986 (see Table 1).

We do not consider parcels in national parks or government conservation areas as they are protected from clearing. These areas constitute 32% of the entire country. Information about protected areas was obtained from the 1999 Conservation Area Map of the National System of Conservation Areas. In Table 1, we provide statistics for the presence of forest in 1986 and 1997 and the deforestation and reforestation during those years.

[2] From the information on average farm size by district, we estimate that the average farm size of the country is about 30 ha or 300,000 m^2. Each pixel has 784 m^2. Therefore, on average, a farm has around 380 pixels.

[3] We focus only on forest clearing because this action is irreversible in different environmental dimensions. In the best case scenario, forest will take decades to recover while deforestation takes months. Generally, the costs and benefits generated by maintaining forest and reforesting are different.

Table 1
Parcels' forest and neighborhoods descriptive statistics.

Variable	Source date	Man	Standard deviation
Full sample (Obs. 8830)	All parcels		
Forest 1986 (d)	1986	0.47	0.50
Deforested during 86–97 (d)	86–97	0.03	0.18
Reforested during 86–97 (d)	86–97	0.02	0.14
Forest 1997 (d)	1997	0.46	0.49
Within a National Park (d)	1999	0.32	0.46
Privately owned forest in 86 (d)	1986	0.21	0.40
Neighborhoods (Obs. 1882)	Private parcels in forest in 86		
Number of sampled neighbors (radius 10 km)		18.20	9.37
Number of sampled neighbors (radius 8 km)		12.54	6.58
Number of sampled neighbors (radius 12 km)		24.53	12.24
Number of sampled neighbors (radius 10 km, c)		17.68	9.13
Deforestation and slopes (Obs. 1877)			
Parcels deforested by 1997 (d)	86–97	0.13	0.33
Neighborhood deforestation^k	86–97	0.13	0.13
Neighbors' slope^k	S	6.31	5.57
Neighbors' neighbors' slope^k	S	6.20	5.15
Districts (Obs. 415)	Districts' characteristics		
Number of farms	1984	245.62	226.40
Land in farms (hectares)	1984	7398.50	11,500.09

(d) Dummy variable. S indicates static characteristics before the time of the analysis. (c) using district average farm size information, neighboring parcels too close to the parcel were not considered neighboring parcels as they might belong to the same farmer. (k) for these calculations the neighborhood chosen had a 10 km radius.

3.2. Defining neighborhoods and Neighbors

The definitions of neighborhoods and neighbors within the literature are as numerous as the type of interactions that have been studied. It is common to define neighborhoods using political divisions such as provinces, counties or districts. We focus on neighborhoods defined by distances, regardless of political boundaries. We define an empirical neighborhood as the area within a chosen distance.

In Table 1, we present the mean and the standard deviation of the number of neighbors for different neighborhoods (different chosen distances). We focus on 10 km to be consistent with results on the distance at which decisions appear to be spatially correlated.[4] Neighborhood size will also be tested for robustness using 8 km and 12 km radius.

In Table 1, we also present descriptive statistics of neighborhood deforestation and neighbors' slopes. Neighborhood deforestation was calculated for the entire 10 km-radius neighborhood. We then find the fraction of the neighborhood that has been deforested. Neighbors' slope, however, was calculated using neighbors' information based on the sample of locations that we have drawn.[5] To calculate neighbors' slope, we average neighboring parcel's slopes. To calculate neighbors' neighbors' slope, we average neighbors' neighboring parcel's slopes that are not defined as neighboring parcels. In our empirical strategy below, neighbors' slopes and neighbors' neighbors' slopes are used as instruments for neighborhood deforestation.

We finally present descriptive statistics of the total number of farms and the total amount of land in farms by district from the 1984 Agricultural Census in Table 1. Using this information, we can calculate that the average farm across the country has 30 ha. Given that each parcel we study has around 900 m^2,[6] the average farm has around 334 parcels.

[4] Based on Conley and Topa, 2002's Spatial Autocorrelation Function (see Fig. 1).

[5] We are forced to drop five observations without neighboring points in the sample.

[6] We also consider that each hectare has 10,000 m^2.

Table 2
Parcel characteristics descriptive statistics full sample and by neighbors' and neighbors' neighbors' slopes.

Variables	Full sample		Split sample by neighbors' slopes		Split sample by neighbors' neighbors' slopes	
	Mean	Standard error	High slopes	Low slopes	High slopes	Low slopes
Deforestation						
Parcels' deforestation (%)	13.05	0.78	8.94	17.18	8.89	17.25
Neighborhood deforestation (%)	12.57	0.30	7.82	17.33	7.69	17.45
Parcels' characteristics						
Distance to San José (km)	97.60	1.14	94.89	100.33	96.16	99.04
Distance to the Atlantic Port (km)	151.14	1.87	150.00	152.28	152.87	149.40
Distance to the Pacific Port (km)	114.37	1.25	111.68	117.06	111.54	117.19
Distance to local roads (km)	2.42	0.05	2.23	2.61	2.16	2.68
Distance to national roads (km)	4.15	0.09	3.58	4.73	3.32	4.99
Distance to sawmills (km)	18.75	0.25	15.96	21.55	16.06	21.43
Distance to schools (km)	15.34	0.23	12.20	18.50	11.65	19.03
Distance to cleared areas (km)	0.23	0.01	0.24	0.23	0.22	0.25
Distance to main towns (km)	20.80	0.30	15.04	26.57	14.81	26.78
Parcel's slope (degrees)	6.22	0.16	10.63	1.80	10.06	2.39
Altitude (meters from sea level)	410.78	11.13	660.57	160.20	648.73	173.09
Biological' characteristics						
Humid pre-montane (d)	0.07	0.01	0.04	0.11	0.05	0.09
Humid lower-montane (d)	0.00	0.00	0.01	0.00	0.01	0.00
Tropical humid (d)	0.23	0.01	0.28	0.18	0.28	0.18
Very humid pre-montane (d)	0.25	0.01	0.23	0.28	0.23	0.28
Very humid lower montane (d)	0.03	0.00	0.05	0.01	0.05	0.00
Very humid montane (d)	0.00	0.00	0.00	0.00	0.00	0.00
Tropical very humid (d)	0.30	0.01	0.21	0.39	0.18	0.42
Tropical dry (d)	0.02	0.00	0.00	0.04	0.01	0.03
Pluvial pre-montane (d)	0.07	0.01	0.13	0.00	0.13	0.01
Pluvial lower-montane (d)	0.02	0.00	0.04	0.00	0.04	0.00
Pluvial montane (d)	0.01	0.00	0.01	0.00	0.01	0.00
Paramo (d)	0.00	0.00	0.00	0.00	0.00	0.00
Characteristics of areas around the parcel[k]						
Length of national roads	0.26	0.02	0.37	0.14	0.39	0.12
Length of local roads	0.84	0.06	1.19	0.49	1.23	0.44
number of Sawmills	0.50	0.03	0.70	0.30	0.73	0.27
Number of large towns	49.65	0.81	58.64	40.63	58.49	40.82
Number of schools	35.79	0.63	42.38	29.19	44.10	27.50
Percentage of cleared area 1986	0.56	0.01	0.58	0.53	0.60	0.51
Number of observations	1877		940	937	939	938

(d) Dummy variable. [k]Areas around the parcel contemplate all the area within 10 km of the parcel. Splits of samples using the median.

3.3. Drivers of deforestation

In Table 2, we present the characteristics of the parcel that can drive deforestation decisions. We present statistics for the distances from the locations to ports, cities, towns, roads, schools, sawmills and cleared areas. We find these distances by calculating the magnitude of the shortest line between the parcel and any of these objects.

Parcels are classified in 12 ecological zones according to Holdridge Life Zone criteria (see Table 2). These zones reflect precipitation and temperature. Altitude, slope of the terrain and the direction that the slope faces (aspect) are also available. These variables characterize the ecological conditions of the parcel, which directly affect the productivity of the land and therefore the potential profits from clearing.

We also present statistics of the characteristics of the areas surrounding the parcels. We find the number of schools, large towns and sawmills within 10 km radius of each parcel. Additionally, we calculate the length of national and local roads, as well as the cleared land fraction within these areas. We use these characteristics to help control for local similarities in deforestation decisions that are not driven by spatial interactions.

4. Empirical strategy

The empirical identification of neighbors' interactions has been widely discussed in economics (e.g., Bayer and Timmins, 2003; Brock and Durlauf, 2001; Glaeser and Scheinkman, 2001; Irwin and Bockstael, 2002; Manski, 1993; Moffitt, 2001). Three issues make measuring neighbors' effects highly challenging: simultaneity; spatially correlated unobservable variables; and endogenous group formation.[7]

Following Moffitt, 2001, we explain our identification strategy with a simple model of two farmers, farmer i and neighbor n. The following equation reflects how parcel characteristics, x_i, n's probability of deforesting, p_n, and a random unobservable shock $_i$ affect farmer i' probability of deforesting, p_i,

$$p_i = \beta x_i + \rho p_n + \epsilon_i.$$

Similarly, we can express farmer n's probability of deforesting, p_n, as:

$$p_n = \beta x_n + \rho p_i + \epsilon_n.$$

There are two reasons why we cannot estimate directly ρ using ordinary least squares in the equations above. The first is simultaneity, i.e. that the probability that n deforests depends on the probability that i deforests and the probability that i deforests depends on the probability that n deforests. The second is that since i and n are located relatively close to each other, it is highly likely that the correlation

[7] Moffitt, 2001 groups the possible problems estimating social interactions in these three categories.

between ϵ_i and ϵ_n would be different than 0. This reflects two of the problems mentioned: spatially correlated unobservable variables and endogenous group formation. These issues imply that $cov(p_n, e_i)$ is different than 0.

We can, however, use a two-stage procedure with instrumental variables. We can rewrite the probability that n deforests in terms of all the exogenous variables as follows:

$$p_n = \pi_1 x_n + \pi_2 x_i + v_n.$$

In this first stage, using the equation above, we estimate the exogenous part of neighbors' deforestation decisions, $\hat{p}_n$, using the exogenous variables and the estimates of π_1 and π_2. We then can use $\hat{p}_n$ in the following equation

$$p_i = \beta x_i + \rho \hat{p}_n + {}_i,$$

and obtain the estimate of ρ.

We can obtain unbiased estimates as long as the following two conditions hold:

$$cov(p_n, x_n) \neq 0 \tag{1}$$

and

$$cov(e_i, x_n) = 0. \tag{2}$$

We can easily test if condition (1) holds in the first stage. We just need to test if π_1 is different than 0. This is shown below and preliminary evidence can be found in Table 2. We see there that the mean of neighborhood deforestation in the full sample is 12.57% but for observations with neighborhoods with high slopes neighborhood deforestation decreases to 7.82% and for observations with neighborhoods with low slopes neighborhood deforestation reaches 17.33%. Neighbors' slopes are definitely correlated with neighborhood deforestation.

Condition (2) is more difficult to prove. In fact, if there is only one instrument, condition (2) cannot be tested. However, if there are two instruments, one can assume that condition (2) holds for one of the instruments and test if it holds for the other.

As a second instrument, we use the characteristics of those neighbors of the individual i's neighbors' who are not also individual i's neighbors, x_{nn}. Again, $cov(p_i, x_{nn})$ should be different than 0. This is again supported by the evidence in Table 2. Neighborhood deforestation is significantly lower for those observations where neighbors' neighbors' have high slopes that for when neighbors' neighbors' have low slopes (7.69% versus 17.45%).

Condition (2) in this case can be rewritten as $cov(\epsilon_i, x_{nn})$ equal to 0. That can only be violated if there are unobservable drivers of deforestation that are correlated with slopes at more than 10 km away (neighbors' neighbors' characteristics), which seems highly unlikely. We test the validity of x_n and x_{nn} as instruments in the following section using the over-identification restriction test. The violation of this assumption seems even more unlikely, as we show below[8], when considering the number and the precision of the variables included as controls.

We also split the sample into observations with high and low neighbors' slopes and high and low neighbors' neighbors' slopes. We can then explore possible relationships between the instruments and observable characteristics of the parcel (see Table 2). Some observable characteristics do not seem to be highly correlated to the instruments (e.g. Distance to San José, Distance to the Atlantic Port Distance to Cleared Areas).

Other characteristics do seem to be highly correlated with the instruments (the differences in the samples are large), though their effects on deforestation are not always in the same direction. For instance, we would expect that as the length of national roads increases in the area around the parcel, deforestation will increase (as we found below). However, we find that places with high slopes (that would decrease deforestation) tend to have more national roads (that would increase deforestation) than places with lower slopes. Any unobservable variables that behaved similarly would bias the interaction coefficient downwards (against finding significance).

In Table 2, there are also other variables that are correlated with the instruments and with parcel's deforestation in such a way that would bias upwards our estimates. To reduce these sources of biases in either direction, we control for these characteristics with the information we have.

Finally, given that we are using x_n and x_{nn} for identification instead of p_n, correlation between ϵ_i and ϵ_n does not bias the estimates of ρ as long as condition (2) holds. However, if errors are spatially autocorrelated, the estimates in the second stage will be inefficient (Conley, 1999). In order to address this problem, we use spatially robust standard errors developed by Conley, 1999.

5. Results

To start, we present the first-stage results from two specifications. Specification 1 includes as the explanatory variables for individual deforestation all of the point's characteristics. Specification 2 includes those plus characteristics of surrounding areas (see Table 2 for a list of the variables in each group). Next we present the second-stage results from a linear form (2sls). As robustness tests, we include results from different neighborhood definitions, the inclusion of additional control variables, and the use of a non-linear second stage (2spls). These results are consistent with the presence of local interactions in deforestation decisions.

5.1. First stage

The first stage was estimated with a linear regression where the dependent variable was neighborhood deforestation and the independent variables were the instruments (neighbors' slopes and neighbors' neighbors' slopes), the surrounding areas' characteristics (in Specification 2) and the explanatory variables for individual deforestation decisions. These results are in Table 3.

We find that the effects of both neighbors' slopes and neighbors' neighbors' slopes on neighborhood deforestation are negative and significant. These are true in both specifications. The relationship between slopes and deforestation decisions is consistent with

Table 3
First stage dependent variable: Neighborhood deforestation linear models.

	Model 1	Model 2
Instruments		
Neighbors' slopes	−0.0069***	−0.0068***
Neighbors' neighbors' slopes	−0.0052***	−0.0062***
Surrounding areas' characteristics		
Length of national roads		0.0007***
Length of local roads		0.0002
Number of sawmills		−0.0002
Number of large towns		−0.0449***
Number of schools		0.0007
Cleared percentage		0.2525***
Cleared percentage squared		−0.1962***
Parcels' characteristics+	Included	Included
Parcels' biological zones+	Included	Included

Spatially corrected asymptotic standard errors to evaluate significance. *** indicates significance at 99% level. +Explanatory variables of 2nd stage included for efficiency.

[8] With the over-identification restriction tests with different controls.

previous findings in the literature. Thus the instruments are highly correlated with the endogenous independent variable (condition (1) holds).

As expected, the density of national roads has a positive and significant effect on deforestation. The presence of large towns, i.e. urban concentrations, actually decreases deforestation rates (as the deforestation frontier moves outward). We also find non-linear effects of the fraction of land already cleared within the 10 km radius in 1986 on neighborhood deforestation. In neighborhoods where the fraction of land cleared is small, deforestation increases as the fraction of cleared land increases (looking more like endogenous development). However, in neighborhoods where forest is scarce, deforestation decreases if forest scarcity (the fraction of cleared land) increases further.

5.2. Second stage: Linear estimates of interactions

Table 4 presents the estimates of the effects of neighborhood deforestation on individuals' decisions (ρ) using different strategies. Comparing OLS estimates (column 3) with 2SLS estimates (column 2), we find significant differences. This supports our a priori beliefs that it is very likely that neighborhood deforestation would be endogenous and thus also that using instrumental variables is necessary to get an unbiased estimate of such an interaction (see Hausman, 1978).

Table 4
Estimates of interactions (ρ) linear probability model dependent variable: Parcels' deforestation instruments: neighbors' slopes and neighboring neighbors' slopes.

Method	IV	IV	OLS
	(1)	(2)	
Neighborhood deforestation ($\hat{\rho}$)	0.73***	0.75***	0.88***
Parcel's characteristics			
Parcel's slope	−0.0039***	−0.0040***	−0.0033**
Distance to San José	0.0012*	0.0012*	0.0013**
Distance to Limnon	−0.0010**	−0.0009**	−0.0009**
Distance to caldera	−0.0011**	−0.0010**	−0.0011**
Distance to local roads	0.0024	0.0031	0.0032
Distance to national roads	−0.0026	−0.0002	−0.0008
Distance to sawmills	0.0003	0.0002	0.0004
Distance to schools	−0.0009	−0.0009	−0.0012
Proximity to cleared areas	−0.1264***	−0.1195***	−0.1144***
Distance to main towns	−0.0000	−0.0002	−0.0002
Parcel's biological zones			
Humid pre-montane	−0.0755**	−0.0653***	−0.0614*
Tropical humid	−0.0547*	−0.0435	−0.0443*
Very humid lower montane	0.0283	0.0269	0.0397
Tropical very humid	−0.0453	−0.0333	−0.0265
Tropical dry	−0.0707**	−0.0664**	0.0645
Pluvial pre-montane	0.0022	0.0037	0.0110
Pluvial lower montane	0.0167	0.0230	0.0319
Pluvial montane	0.1280	0.1384	0.1478
Surrounding areas' characteristics			
Length of national roads		0.0008*	0.0008*
Length of local roads		0.0001	0.0001
Number of sawmills		−0.0097	−0.0096
Number of main town		−0.0202	−0.0156
Number of schools		−0.0006	−0.0004
Percentage of cleared area		0.1521	0.1246
Percentage of cleared area^2		−0.1454**	−0.1195
Constant	0.3028***	0.2147***	0.1883***
Testing overidentifying restrictions			
P-value$^+$	0.79	0.96	

***, ** and * indicates significance at 99%, 95% and 90% level, respectively. Significance tests are based on spatially corrected standard errors.
$^+$ None of the H_0 are rejected. H_0: all IVs are uncorrelated with the error. All distances and lengths measured in kilometers.

We also see that controlling for the characteristics of surrounding areas does not significantly change the size or significance of the interaction parameter (column 1 versus column 2). The extra controls do make a difference in examining whether the independence of the instruments and the errors is a valid assumption. The tests of the over-identification restriction (bottom of the table) show that after controlling for neighboring areas characteristics, we are less likely to presume that one of the instruments is endogenous. Both tests, though, lead us to the conclusion that the instruments are not endogenous, i.e. that condition (2) for identification does hold.

Looking at the results for the parcel characteristics, as expected, access (e.g. distance to ports and distance to already cleared areas) affects the probability of deforestation. Some biological zones are also significant. Finally, the percentage of cleared area, as in the neighborhood regression, is an important determinant of deforestation.

5.3. Robustness tests and possible sources of bias

Table 5 presents robustness tests on the size of the neighborhood considered in our examination. Estimates for 8 km radius (Test 1) and 12 km radius (Test 2) are very similar to the results for the 10-km-radius neighborhood. As another robustness check (Test 3), we dropped neighbors close enough to the individual point in question that they might well be on the same farm (recalling that we do not have the farm boundaries). Results were also similar. When using these different neighborhood definitions, note that again we find no evidence that our instruments are endogenous (see over-identification restriction test at bottom of the table).

One might argue that highly sloped neighboring land directly affects productivity and, therefore, directly affects an individual's deforestation decision regardless of the neighbor's land choice. High slopes might generate shadow or water runoff, for instance. If so, then condition (2) (the exclusion restriction) would not hold. To address this possibility, in our Test 4 we include explicitly other variables that could control for such direct impacts, such as the amount of sun received by the parcel, the altitude and the direction in which the slope faces (an indicator of sun received). We again find that our estimates are positive and significant, that the coefficients do not

Table 5
Robustness tests linear probability model dependent variable: parcels' deforestation instruments: Neighbors' slopes and neighboring neighbors' slopes measures of interaction (ρ).

Model	Core	Test 1	Test 2	Test 3	Test 4	Test 5	Test 6
$\hat{\rho}$	0.75***	0.67***	0.71***	0.76***	0.77***	0.85***	0.82***
Spatially corrected s.e.	0.20	0.23	0.21	0.21	0.23	0.34	0.19
Controls:							
Parcel characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Surrounding areas characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Altitude, sun (hours) and aspect	No	No	No	No	Yes	No	No
Linear and square altitude, dis. to main towns and own slope	No	No	No	No	No	Yes	No
Instruments' specification$^+$	Linear	Linear	Linear	Linear	Linear	Linear	Non-linear
Neighborhood type:	10 km	8 km	12 km	10 km (c)	10 km	10 km	10 km
Testing overidentifying restrictions P-value^{++}	0.96	0.37	0.66	0.82	0.78	0.95	0.99

*** indicates significance at 99% level. $^+$ The non-linear specification includes quadratic and cubic forms of the instruments. $^{++}$ None of the H_0 are rejected. H_0: all IVs are uncorrelated with the error. (c) implies that observations that were too close were not considered neighbors and proximity was defined based on average farm size data.

Table 6
Reduced form effects of instruments ordinary least squares and propensity score matching dependent variable: Parcel deforestation decisions different control variables.

Observations	All	All	All	All
Instrument				
Neighbors' slopes	−0.0081***		−0.0074***	
Neighbors' neighbors' slopes		−0.0080***		−0.0071***
Controls:				
Parcel characteristics	Yes	Yes	Yes	Yes
Surrounding areas characteristics	Yes	Yes	Yes	Yes
Altitude, sun (hours) and aspect	No	No	Yes	Yes

*** indicates significance at 99% level, respectively.

change significantly and that the instrumental variables pass the tests of over-identification.

We test non-linear effects of instruments and controls. First, we test controlling for square terms of those variables that were highly correlated with the instruments: distance to main towns, parcels' own slope and altitude. We find that the effects are still positive and significant. Second, we use square and cubic terms of neighboring slopes and neighboring neighbors' slopes as instruments. The results are not significantly different to the core regression. Additionally, the set of instruments also passes the over-identification restriction.

Table 6 presents the reduced form effects of the instrument on the individual's deforestation decisions as a robustness test that simplifies the estimation process to a one regression. As expected, we find that the effects of neighbors' slopes and neighbors' neighbors' slopes on parcel's deforestation are negative and significant. As neighboring slopes increase, neighborhood deforestation decreases and, via the interaction on which we are focused, individual deforestation decreases. This holds for each instrument and when controlling for parcel's characteristics as well as the characteristics of areas surrounding the parcel. Even though neighbors' neighbors' slopes are at least 10 km away, effects are highly significant. With the results from over-identification tests, this supports that neighborhood deforestation affects individuals' deforestation decisions.

Yet, as mentioned in the introduction, there might be sources of bias in our estimates.[9] One example is measurement errors for some of our variables. For instance, if roads have lower quality in areas where neighboring slopes are steeper, deforestation might not take place not because neighbors are not deforesting but because access through these neighboring roads is difficult. In Costa Rica, we believe this is not the case. Most of the road investment takes place close to urban areas in the middle of the mountains and many roads in more remote mountain areas grant access to tourism and thus are well maintained.

Another example is farmers with different characteristics sorting themselves in ways correlated with slopes. For instance, wealthier people might live on flatter land and those with neighbors' with flatter land might be affected by neighbors' wealth and not their deforestation. Again, this is not necessarily the case in Costa Rica. Highly varied slope even in small areas forces wealthier and poorer neighborhoods to have steep and flat lands. Further, we control for neighborhood characteristics associated with neighborhood income.

Finally, sample bias might appear due to the sample we use being for those places without cloud cover. While we do not know a reason why interactions would not be present in rainy places, even if this were an issue still interactions are positive and significant in more than 88% of the country.

[9] We thank two anonymous referees for pointing some of these mechanisms out.

Table 7
Second stages interactions under different contexts dependent variable: Parcel deforestation decisions instruments: Neighbors' slopes and neighbors' neighbors' slopes neighborhood 10 km measures of interaction (ρ) controlling for parcel and surrounding areas characteristics.

	Close	Far
By distance to national parks		
Cutoff: 17 km.		
ρ	0.96**	0.53
Spatially corrected s.e.	(0.28)	(0.36)
Observations	1090	775
By distance to San José		
Cutoff: 97 km.		
ρ	0.83**	0.66
Spatially corrected s.e.	(0.21)	(0.60)
Observations	1020	845
By distance to main towns		
Cutoff: 1.8 km.		
ρ	0.93***	0.60
Spatially corrected s.e.	(0.25)	(0.38)
Observations	1112	753
By distance to roads^{+}		
Cutoff: 1.8 km.		
ρ	1.05***	−0.01
Spatially corrected s.e.	(0.22)	(0.37)
Observations	1177	688
Subset of neighbors	Lower altitude	Higher altitude
ρ	0.80**	0.59***
Spatially corrected s.e.	(0.38)	(0.20)
Observations	1270	1586

** and *** indicates significance at 95% and 99% level, respectively. $^{+}$ Distance to roads is the minimum distance to national and local roads.

5.4. Distinguishing mechanisms

As we discussed previously, these estimates are net effects that may well represent multiple mechanisms in which interactions between individual deforestation decisions take place. A positive interaction parameter suggests that strategic complementarities (positive interactions) are larger than strategic substitutability (negative interactions). Here, we try to identify contexts where the magnitude or even sign of the interaction parameter changes using subsamples. We split the sample three ways, using proximity to national parks, proximity to the Capital San José and proximity to roads. The results are shown in Table 7.

We find that interactions closer to the capital, main towns, and roads are larger. This might be due to a lower presence of strategic substitutability closer to cities and roads. Increased neighborhood production of agricultural goods is not likely to lower prices close to cities and roads as in more isolated markets.

We also find strong spatial reinforcement of deforestation or forest conservation decisions close to National Parks. Forest protection close to parks might bring more tourists that in turn promote more forest conservation. This strategic complementarity in deforestation decisions is not likely to occur further from parks.

Finally, we test if neighbors from higher altitudes have different or similar effects than neighbors from lower altitudes within the neighborhood (see Table 7). We find that the estimated interaction effects are positive and significant in both cases. The estimates are not statistically different and thus it is clear that our interaction estimates are not only the result of uphill neighbors' actions or uphill neighbors' land characteristics.

5.5. Non-linear probability models

We also use the probit two-stage estimation method (Maddala, 1983) specially constructed to deal with a system of two equations with a discrete dependent variable (individual's decision) and an

Table 8
Second stage non-linear models dependent variable: Parcel deforestation decisions instruments: Neighbors' slopes and neighbors' neighbors' slopes neighborhood 10 km measures of interaction (ρ) controlling for parcel and surrounding areas characteristics.

Strategy	Probit (1)	2SPLS (2)	2SPLS (3)
ρ	3.44***	3.01	3.11*
Spatially corrected s.e.	(0.70)	(2.20)	(1.76)
Instruments specification		Linear	Non-linear
Marginal effect+	0.44	0.42	0.35
Equilibria	Multiple	Unique	Unique
N	1843	1826	1826
Log likelihood	−547	−585	−583

* and *** indicates significance at 90% and 99% level, respectively.
+ The marginal effect is defined as, $\hat{\rho}\phi\left(\hat{\rho}p_n + \hat{\beta}\bar{x}\right)$ where ϕ is the probability distribution function of the normal and explanatory variables were evaluated at the mean (p_n and $\bar{x}$).

endogenous explanatory variable (neighbors' decisions) as in our case. Like in the linear case, we use the estimated reduced form coefficients, $\hat{\pi}_1$ and $\hat{\pi}_2$, and all the exogenous variables to predict neighborhood deforestation, $\hat{p}_n$. In the second stage, we substitute for neighborhood deforestation using its predicted values. We, then, estimate the interaction coefficient ρ, by standard likelihood methods.[10]

Table 8 presents the non-linear results. In the first column, the standard probit results show how significant the estimate of the interactions would appear if we had not addressed endogeneity. The second and third columns show estimates with of the interaction effect using different specifications of the instrumental variables. Both coefficients are positive and similar. The nonlinear specification is also significant. Only the linear specification and when using the spatially corrected standard errors is insignificant.

Positive coefficients raise the issue of multiple equilibria. Using the coefficients for each estimation in Table 8, we find the probabilities that a forest parcel in 1986 would be deforested by 1997 in equilibrium.[11] We find that if we do not address the problem of endogeneity, i.e. using the first-column coefficient, we would conclude that multiple equilibria exist. Estimating correctly, however, the interaction coefficient implies only one equilibrium.

There are two important implications of the correctly estimated interaction parameter. First, it makes the difference between believing in multiple equilibria (with implications for policies) and recognizing that there is only a single equilibrium. This is a significant gain. And second, positive interactions imply that the effects of changes in an individuals' incentives to deforest will expand over space. This too is relevant when thinking about the design of policy. The deforestation decision of one individual directly affected by a conservation or agricultural incentive that would reduce or increase deforestation will affect many neighboring decisions.

6. Conclusion

Finding appropriate policies that can balance environmental or development objectives is easier if we can understand the determinants of deforestation. We studied one of the key processes that determines the rate and the spatial pattern of tropical deforestation, the interdependency of individuals' deforestation decisions.

We used Two-Stage Least Squares and Probit Two-Stage Least Squares techniques to estimate neighbors' interactions in deforestation decisions, using neighbors' slopes and neighbors' neighbors' slopes as instruments. We found evidence that spatial interactions are positive and significant. This result is robust to a set of variations on the specification and to varying the size of neighborhoods.

Positive spatial interaction affects the quantity and expected spatial distribution of forest. Policies or other shocks that promote deforestation or forest conservation will spill over surrounding areas. This is important to consider when designing not only conservation policies but also agricultural development policies.

Further research might consider potential dynamics. For instance, individuals may well react to observed past neighbors' actions as in Bajari et al., 2004. While time dynamics with externalities in land use can be complex (see e.g. Turner, 2005), when the necessary data are available it may be worth extending the analyses above to consider dynamic spatial interactions in deforestation and forest conservation.

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[10] We follow the standard normalization assumption that the variance of the privately observed shocks, σ, is one as in Brock and Durlauf, 2001.
[11] The probabilities of deforestation in equilibrium can be computed by an iterative process. A vector of initial beliefs, $p^{(1)}$, generates a second set of beliefs, $p^{(2)}$ using, $p^{(2)}=\phi(\beta x_i+\rho p^{(1)})$, for each observation, where Φ represents the cumulative normal distribution function. The iterative process consists in computing ($p^{(1)}, p^{(2)}, \ldots, p^{(k)}$), until $p^{(k)}$ equals $p^{(k+1)}$. The set of probabilities of deforestation, $p^{(k)}$, is an equilibrium because it satisfies the set of simultaneous equation that determine each individuals' deforestation probability, which depends on others individuals' deforestation probabilities.

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