District Subdivision and the Location of Smallholder Forest Conversion in Sumatra

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Abstract

A unique GIS data set from Indonesia that distinguishes smallholder and plantation operations is used to test the impact of district subdivision, which enhances local control of natural-resource revenues, on the location of smallholder forest conversion. Nonparametric analyses find that in subdivided districts, smallholders convert forests on steeper land that is further from the nearest road and deeper into the forest. Smallholders are also less responsive to forest protection in subdivided districts. District subdivision imposes a welfare loss of $1,734 to $5,256 per hectare (in 2010 USD) from the increased carbon emissions associated with smallholder conversion deeper in the forest. *JEL*: C14, Q15

Key Words: Decentralization, Forest conversion, Nonparametrics

1 Introduction

Tropical forests are particular natural resources with several related ecosystem services that have become an international concern due to the emission of greenhouse gases stemming from conversion of these forests to production systems. Reducing greenhouse gas emissions from tropical forest conversion is viewed as a critical component of plans to mitigate the effects of anthropogenic climate change, as forest clearing accounts for an estimated 12-15% of global greenhouse gas emissions (van der Werf et al., 2009). Efficient management of these resources includes the location of forest conservation and conversion, due to landscape heterogeneity.

The management of tropical forests in Indonesia is of global concern as this nation is in the top three in terms of extant stands of tropical forest and has forests that are home to countless endemic species. Rapid conversion to production systems has made Indonesia the top-ranked nation for deforestation (Margono et al., 2014), and consequently among the highest green-house gas emitters.

A key change in Indonesia with implications for forest conversion was the decentralization that occurred in the wake of Suharto's resignation of the presidency in 1998 due to the Asian financial crisis of 1997. To keep the nation intact, the post-Suharto regime decentralized the management of natural resources in Indonesia. As a result, district agencies were responsible for managing the resources in their territories and were more responsible for revenue generation than under the centralized power structure of Suharto's regime.

Given the financial pressures associated with the depreciation of the rupiah following the Asian financial crisis and claims of inequitable distribution of royalties from Jakarta, resource-rich regions were vocal in their demand for more of the revenue raised from natural resources (forests, gas, oil) to stay under local control (Hofman and Kaiser, 2004). Following Suharto's resignation in 1998, laws were enacted to transition control of these resources to the district agencies (Potter and Badcock, 2001), and as a result many districts subdivided, ostensibly to secure as much control of their resources as possible (Burgess et al., 2012). Analysis of the determinants of district subdivision found that large, ethnically-clustered districts with high staffing levels and substantial natural resource stocks were more likely to rezone between 1998 and 2000 (Fitrani et al., 2005).

Previous research has considered the impact of this wave of district subdivision in Indonesia on aggregate deforestation. Regardless of the mechanism studied, this work has shown that subdivision leads to more forest conversion and plantation activity. Burgess et al. (2012) finds that the increased number of political jurisdictions increased deforestation due to logging and reduced timber prices across Indonesia, which is consistent with districts engaged in Cournot competition as firms choose where to log. Suwarno et al. (2015) uses surveys of government officials and stakeholders to evaluate forest governance quality. The authors find that deforestation has increased in Central Kalimantan as a result of district subdivision, because the quality of forest governance declined with district subdivision.

In this paper, we explore the impact of district subdivision in the wake of Suharto's resignation on the location of smallholder forest conversion in Sumatra. Previous studies have shown that while decentralization of natural resource management can offer empowerment and democratization of local communities as well as poverty reduction through more equitable access to resources, decentralization can in fact lead to further marginalization of poor and disadvantaged groups, with resource control accruing to the most powerful stakeholders (e.g., Berkes, 2010; Colfer and Capistrano, 2002; Larson and Soto, 2008; Ribot et al., 2006). In Indonesia, district agencies grant concessions to plantation operators that convey secure property rights to the plantations and collect royalties from plantation operations. Smallholder production systems are not taxed and are not formally recognized by these agencies, meaning that smallholder tenure is insecure in the presence of plantations. The increased level of plantation activity in subdivided districts is expected to impact smallholder forest conversion given previous research documenting tensions between these two forces of forest conversion (see e.g., Afrizal, 2007; Casson, 2000; Colchester et al., 2006; McCarthy, 2004; Potter, 1999; Suyanto, 2007; Suyanto et al., 2004).

Using a unique GIS dataset of 2008 land use and land cover that distinguishes between smallholder and plantation production at a fine spatial scale, we explore the proximate determinants of smallholder forest conversion in subdivided and non-subdivided districts between 2000 and 2008. We estimate these determinants on a randomly-drawn set of pixels as well as on a set of pixels that lie within five kilometers of a district with the other subdivision status to ensure that the observed differences in the likelihood of smallholder conversion are due to district subdivision.

Our analysis shows that the proximate causes of smallholder conversion vary across districts with different subdivision status. Specifically, we find that smallholders in non-subdivided districts have a revealed preference for low-slope parcels that are near the edge of the forest and close to the nearest road. In subdivided districts, the location of smallholder production is not affected by slope or distance to the nearest road, and there is only a small reduction in conversion probability associated with increasing distance from the forest edge. These results suggest that the location of smallholder forest conversion, and therefore its private returns and external costs, is affected by district subdivision. We find that district subdivision leads to additional costs to society, stemming from increased CO_2 emissions due to the location of smallholder conversion further into the forest in subdivided districts, of $1,734 to $5,256 per hectare.

Our findings suggest that policy action to encourage efficient forest management in Sumatra must address both the location and amount of forest conversion. Doing so requires a comprehensive approach that acknowledges both smallholders and plantations as forces of forest conversion, unlike the 2011 trial moratorium on plantation concessions in extant forests in Sumatra. We show that district subdivision, with a focus on generation of natural-resource royalties, leads to increased external costs of smallholder forest conversion, indicating that decentralization may have increased the challenges to effective forest management in Indonesia.

2 Study Area Background

President Suharto's New Order regime, which was in power from 1966-1998, was strong and highly-centralized. Under this system, royalties generated from the management of natural resources (e.g., agricultural plantations, petroleum extraction, and timber harvest) were sent to the seat of the federal government in Jakarta for redistribution to local government agencies. The centralized distribution of locally-generated tax revenues was not popular among officials from particularly resource-rich regions of the nation who felt that the access to these resources had too frequently been granted to private-sector corporations with ties to decision-makers in Jakarta (Potter and Badcock, 2001).[1]

Suharto was forced to resign his Presidency due to fallout from the 1997 financial crisis in Asia, which sent the rupiah into a major depreciation that lasted through 1998. During this time, there were calls by resource-rich provinces for independence, and Indonesia underwent an extensive, and immediate, wave of decentralization under the new regime to appease calls for more regional autonomy, while maintaining the extent of the nation (Potter and Badcock, 2001).

Several pieces of legislation facilitated the transfer of authority to provincial and district governments, allowing resource-rich regions to retain a greater share of the revenues generated within their jurisdictions (Potter and Badcock, 2001). Law 22 on Regional Governance and Law 25 on Fiscal Balancing were issued in May of 1999 and together provided a foundation for the decentralization of administrative and regulatory authority primarily to the district level. Law 22 defined the sectors that would move to district control from federal management, including agriculture, forests and fisheries, mining, environment, and land use. Law 25 simultaneously established that more income from natural-resource sales would be directed to districts and established that the districts would be expected to take more active roles in seeking their own sources of revenue. Together, these laws aimed to increase the generation of district royalties through increased natural-resource use, including increased issuance of concessions to plantation operators.

In the wake of the national legislation supporting local oversight of natural resources, many districts chose to subdivide following the end of Suharto's reign. By altering district borders, officials in district agencies would give themselves greater control over the natural resources found within their districts. Between 1998 and 2008, the total number of districts in Indonesia increased from 292 to 483, as local governments attempted to exert maximum control over the natural resource royalties originating in their district (Burgess et al., 2012).

The Provinces of Riau, Jambi, and West Sumatra on the island of Sumatra have experienced a significant amount of forest conversion since the mid-1990s, chiefly as a result of the rising price of palm oil that has made oil palm plantations quite profitable in the region (figure 1). These provinces cover an area of approximately 17 million hectares. From 1990 to 2008, 7 million hectares of forest, or 58% of the total forested area in 1990, in these provinces was converted to production systems (figure 2). The two broad categories of production systems responsible for forest conversion within these three provinces of Sumatra are industrial plantation systems and smallholder operations. While plantations are responsible for the majority of forest conversion in this area, smallholder production has been responsible for approximately 30% of forest conversion since 1990.

Tensions exist between these two drivers of forest conversion because smallholders only have informal rights to forested parcels on the landscape. Smallholder production systems are frequently interrupted by corporations developing plantations that have been granted forest concessions by government agencies (Suyanto et al., 2004). Government agencies have incentives to provide plantation concessions, as revenues from these systems generate royalties that are used to support government activities, whereas smallholders are typically not taxed (Potter and Badcock, 2001).

Concessions are granted to corporations without acknowledgement of the informal cultivation rights that have been used to allocate areas for harvest within rural communities. This can result in two outcomes: incorporation of the communal producers into the corporate production system, or the forced, uncompensated relocation of smallholder production to lands not covered by the corporate lease rights.[2] Given that these agreements are perceived to be unfair, local smallholders rarely participate in these arrangements and most plantations, including those in the nucleus system, rely on labor imported from other islands (e.g., Java) (McCarthy, 2007).

Wages offered to local smallholders in exchange for plantation labor are typically viewed as unjust by smallholders and promised payments are occasionally not delivered, while land-grabbing by plantations is not an infrequent occurrence (Afrizal, 2007; Colchester et al., 2006). Suyanto (2007) provides examples of smallholder production being cleared by plantations through the use of fire, even when the land was not included in the formal concession to the plantation operator. Disputes between smallholders and plantations in the nuclear estate scheme often culminate in violence (Casson, 2000).

The next section presents a model of smallholder forest conversion, in which the location of smallholder conversion is affected by district subdivision. The model predictions will be tested using data on the location of smallholder forest conversion in Sumatra.

3 Model of smallholder location choice

Assume that there is a single production system and that smallholders attempt to maximize the expected returns to production by choosing a location in the forest at which to establish cultivation systems.[3] The choice of conversion location is reduced to a one-dimensional problem to clearly motivate the empirical analysis, which considers a vector of parcel characteristics related to forest conversion. Let d measure the distance from the forest edge at which conversion occurs. The net returns to production conditional on maintaining control of the production system, $\pi(d)$, are given by

$$\pi(d) = P \times Y(d) - C(d)$$

where P represents the market price for the good produced, $Y(d)$ represents the yield of the product, and $C(d)$ represents the cost of conversion and production, which is expected to increase at an increasing rate with distance from the forest edge ($C'(d)$, $C''(d) \geq 0$, $C'(0) = 0$).[4]

Plantation activity is expected to be higher in subdivided districts than in non-subdivided districts. This assumption follows from the findings that deforestation increased following district subdivision in previous studies (e.g., Burgess et al., 2012; Suwarno et al., 2015).

Let S represent a district's subdivision status, with $S = 1$ indicating a district that has been subdivided, and $S = 0$ indicating a district that has not. Let $L(d, S)$ represent the probability that a forest patch is converted by a plantation. Assume that the probability of plantation interruption is decreasing in distance from the forest edge for the same reason that smallholder production costs increase with distance from the forest edge. Further, assume that $L(0, S = 1) > L(0, S = 0)$ and that $L'(d, 0) \leq L'(d, 1) \leq 0 \; \forall \; d$, meaning that subdivision increases plantation activity at all distances from the forest edge. Such an outcome might describe a situation in which subdivided districts attract plantations in the hopes of generating royalties from concessions and competition drives plantations further into the forest in these districts.

To incorporate the probability of a smallholder losing control of the land to a plantation, consider the following progression of events. At the start of the period, the smallholder makes a choice about the distance from the forest edge at which to convert the forest to production. Before the end of the period, smallholder production is either interrupted by plantation activity or allowed to continue. At the end of the period, the smallholder receives the returns from production if her operation is not interrupted by plantations. If smallholder production is interrupted by plantation operations, then the smallholder receives compensation, if any, from the plantation manager at the end of the period. Then, the smallholder's problem is given by

$$\max_{d}(1 - L(d, S))\pi(d) + L(d, S)W(d) \tag{1}$$

where $W(d)$ represents the compensation that the smallholder receives from the plantation operator for taking her land, which again decreases with increasing forest-edge distance (i.e., $W'(d) < 0$, $W''(d) > 0$).

Recall that $L(0, S = 1) > L(0, S = 0)$ by assumption. Given this, it follows that

$$(1 - L(0, 0))\pi(0) + L(0, 0)W(0) > (1 - L(0, 1))\pi(0) + L(0, 1)W(0)$$

meaning that the expected value of smallholder conversion at the forest edge in non-subdivided districts is greater than that in subdivided districts. This result generates an empirically-testable prediction related to the probability of smallholder conversion at the forest edge:

> Prediction 1: The probability of smallholder conversion at the forest edge will be greater in non-subdivided districts than in subdivided districts

The optimal location of smallholder forest conversion, d^*, satisfies

$$(1 - L(d^*, S))\pi'(d^*) = L'(d^*, S)[\pi(d^*) - W(d^*)] - L(d^*, S)W'(d^*) \qquad (2)$$

The LHS of equation 2 represents the change in the expected net returns of smallholder production if she is able to maintain control of her production system with increasing forest-edge distance, $\pi'(d^*)$, which is the marginal cost of moving production further into the forest. The RHS of equation 2 represents the change in the expected net returns of smallholder production conditional on losing control of the land to the plantation operator, which is the marginal benefit of moving production deeper into the forest. Then, the optimal distance into the forest at which the smallholder should locate conversion satisfies:

$$\pi'(d^*) = \frac{L'(d^*, S)[\pi(d^*) - W(d^*)] - L(d^*, S)W'(d^*)}{(1 - L(d^*, S))} \qquad (3)$$

Comparative statics can be used to relate the optimal location of forest conversion in subdivided and non-subdivided districts. Note that $\frac{\partial \pi'(d^*)}{\partial L(d^*,S)} = \frac{-W'(d^*)}{(1-L((d^*,S))^2} \geq 0$. Also note that $\frac{\partial \pi'(d^*)}{\partial L'(d^*,S)} = \frac{\pi(d^*)-W(d^*)}{1-L(d^*,S)} \geq 0$. This term is strictly positive with insecure smallholder tenure (meaning that $\pi(d) > W(d)$).

Given these results, it is left to compare $L(d^*, 0)$ and $L(d^*, 1)$. Because $L(0, 0) < L(0, 1)$ and $L'(d, 0) \leq L'(d, 1) \; \forall \; d$, the above comparative statics indicate that $d_1^* > d_0^*$, where d_0^* and d_1^* are the optimal locations of conversion in non-subdivided and subdivided districts, respectively. This result leads to the following prediction:

> Prediction 2: At some positive distance into the forest, the probability of smallholder conversion in subdivided districts will be greater than that in non-subdivided districts.

The above results suggest how district subdivision can have efficiency effects regarding the location of smallholder conversion. In an effort to escape plantation taking, smallholders may convert forest that is undesirable to plantations, lowering the returns to smallholder production. The model presents this issue in the context of edge distance, though its predictions can easily be extended to other parcel characteristics (e.g., distance to the nearest road, slope, etc.). Of additional concern from a welfare perspective is that the external costs of forest conversion, including edge effects that impact endemic species and the loss of ecosystem-service production, which are not captured in the smallholder's problem, increase with conversion of more remote forest patches. In our welfare analysis, we will focus on the edge effect regarding carbon storage and sequestration, which was recently shown to be more significant and persistent than previously thought (Chaplin-Kramer et al., 2015b).

Based on existing results from the literature, this model assumes that district subdivision increases plantation activity due to an underlying need to generate revenues from the management of local natural resources. Therefore, district subdivision is predicted to affect the location of smallholder conversion, which may lead to welfare losses due to the increased external costs of forest conversion away from the forest edge. The predicted effects will be tested using detailed land-use and land cover data from central Sumatra.

4 Data

This analysis explores how district subdivision affects whether or not forested land is converted to smallholder production systems, given the presence of plantation operations on the landscape. Satellite data provides the best opportunity to account for both legal and illegal forest conversion, which is necessary to obtain accurate estimates of conversion rates and the determinants of conversion (Burgess et al., 2012).

4.1 Data sets

The key data for this analysis are maps of land-use and land cover (LULC) from 2000 and 2008. The 2000 LULC map is based on Landsat imagery and identifies pixels as either forest or non-forest. The map of LULC in 2008 is derived from manual classification of Landsat and IRS-P6 imagery with validation through ground checks (Setiabudi, 2008). The 2008 LULC map was commissioned by World Wildlife Fund Indonesia and has been used in recent policy and research efforts related to the Sumatran Tiger (e.g., Bhagabati et al., 2012, 2014). The combination of high-resolution satellite imagery and ground-truthing allows for detailed LULC classification in the 2008 map that includes identification of both smallholder and plantation operations.

The dependent variables in our analyses measure whether or not a pixel converts from forest to smallholder production between 2000 and 2008. The binary indicator variable takes on a value of 1 if the pixel is engaged in any of the following smallholder production systems in 2008: smallholder oil palm, smallholder rubber, or mixed agriculture. As mentioned above, the nucleus estate system of oil palm production essentially involves smallholders working as sharecroppers on land controlled by oil palm plantation operators (referred to as plasma production).

The presence of plasma smallholder operation could complicate our exploration of the effects of district subdivision on smallholder production if it were mistakenly included with other smallholder oil palm operations. Fortunately, the data includes a separate category, smallholder oil palm plantation, that describes the plasma system. The main results of our binary analysis (smallholder or not) exclude this category of production from our classification of smallholder systems. We include this production as a separate category in our multivariate analysis, meaning that there are four categories of smallholder production (smallholder oil palm, smallholder rubber, mixed agriculture, and plasma oil palm).

In addition to LULC information, several different biophysical and infrastructural data layers were combined to generate pixel characteristics that would be expected to determine the probability of a pixel being converted from forest to intensive management. These data layers were combined for use in earlier analyses (Bhagabati et al., 2012, 2014) and the details of their development are provided in Bhagabati et al. (2014). A 90 meter digital elevation model (DEM) from HydroSHEDS (http://www.hydrosheds.org/) was resampled using bilinear interpolation to generate a DEM at 30 meter resolution. This data layer was used to estimate elevation and slope information for each of the pixels from the 2008 land-cover map. Annual average precipitation information is provided by WorldClim (http://www.worldclim.org) at a resolution of approximately 1 km. Information on soil depth comes from the FAO GeoNetwork spatial data portal for most of the study area.[5] In areas with peat soils, the information on soil depth comes from Wetlands International (Wayhunto and Subagjo, 2003). Finally, separate layers of built infrastructure were used to identify the distance between the forested pixels of interest and the roads, settlements, and towns that impact the forest conversion decision.

The 2008 LULC map encompasses six watersheds in Central Sumatra, covering portions of Jambi, Riau, and West Sumatra Provinces. The map has a spatial resolution of 30 meter by 30 meter pixels, derived from the underlying Landsat imagery. The advantage of this high resolution is that it mitigates some of the measurement error associated with coarser-scale satellite data, such as MODIS, which has a resolution of 250 meters by 250 meters. The disadvantage of Landsat imagery is that these satellites do not revisit the same area with great frequency (there are one to two weeks between visits to the same area, as opposed to one to two days for MODIS). In humid, tropical regions, like Indonesia, much of the landscape is obfuscated by cloud cover year-round. Given the relatively long revisit time of Landsat, it is likely that Landsat-derived images will include significant cloud-covered extents in this region. As a result, landscape-level analysis of conversion may not accurately reflect true conversion rates, and such large-scale calculations may be biased if natural forests are more likely to be covered by clouds than managed production systems (Burgess et al., 2012).

4.2 Data selection

The unit of observation in the following econometric analyses is a 30-meter by 30-meter pixel. This unit was chosen because it matches the spatial resolution of the 2008 LULC map. However, the forest conversion decisions made on the Sumatran landscape by smallholders and plantation managers take place at different spatial scales. Smallholders may convert between one and 20 hectares of forest at a time. The difference between the resolution of the LULC map and the scale of forest-conversion requires that steps be taken to ensure the independence of the outcome variable across pixels in the following parametric and nonparametric analyses. The data selection process as well as the choice of regression models were undertaken in pursuit of this goal.

Figure 3 illustrates the locations of a set of 13,025 pixels randomly-drawn from the set of pixels that were forested in 2000. Of the full set of pixels, 9,767 pixels lie within districts that were subdivided, while the remaining 3,258 pixels lie in districts whose borders were unchanged. Table 1 presents summary statistics of the physiogeographic characteristics of the 13,025 randomly-drawn pixels that were forested in 2000.

The location of smallholder operations seems to vary based on district subdivision, with conversion of pixels further into the forest and further from the nearest settlement in subdivided districts. However, it also appears that smallholder production occurs on lower-elevation and lower-sloped pixels in subdivided districts. In general, the subdivided districts seem to have more favorable pixel characteristics (e.g., elevation, slope, nearest road and town distances) than the non-subdivided districts. This outcome makes it less likely that we would observe smallholders in more remote locations in these districts simply due to increased competition with plantations, allaying endogeneity concerns. Still, with multiple proximate determinants of smallholder conversion, we are unable to identify the mechanism driving the location of smallholder conversion through a comparison of means. To explore the causal relationship between pixel characteristics, district subdivision, and smallholder conversion, we turn to the econometric analysis.

5 Econometric methods

Chomitz and Gray (1996) provide the econometric template for most ensuing studies of land-cover change in the tropics (e.g., Kerr et al., 2000; Nelson and Hellerstein, 1997; Pfaff, 1999; Vance and Geoghegan, 2002). Our exploration of district subdivision and the location of smallholder production is guided by this existing work and also employs nonparametric estimation techniques, which allow for unrestricted interaction between explanatory variables and considers flexible functional forms. We use the nonparametric techniques to explore the reliability of commonly-applied parametric models, including the spatial autoregressive linear probability model, in the context of forest conversion.

5.1 Parametric approach

Assume that the land rent on parcel j engaged in production system k, R^*_{jk}, is defined as the difference between the value of outputs and inputs, Q_{jk}, and Y_{jk}, at their respective location-specific prices, P_{jk} and C_{jk}:

$$R^*_{jk} = P_{jk}Q_{jk} - C_{jk}Y_{jk} \tag{4}$$

Spatially-disaggregated price and yield data, namely P, C, and Q, are not available for every parcel j on the landscape. Assume that prices vary spatially as a function of a vector of parcel-specific variables, Z_{jk}, related to the distance to markets, including distance to the nearest road or town. Further assume that parcel characteristics will impact the yield of production on parcel j, so let M_{jk} represent a vector of productivity shifters allowing for spatial heterogeneity in production, as it might be expected for crop yields to vary across the landscape based on parcel elevation and slope. To explore the impact of district subdivision, include a district-level indicator of subdivision, S_j. We include district indicator variables to absorb the group-level shocks induced by the inclusion of a variable measured at the district level and return η_{jk} to homoskedastic, idiosyncratic error terms. We add province indicator variables to control for district- and province-level characteristics that have been explored as determinants of subdivision and deforestation in previous studies, including, notably, corruption (Burgess et al., 2012; Suwarno et al., 2015). Standard errors are clustered at a level of two-kilometer by two-kilometer cells to acknowledge the difference in scale between pixels and smallholder conversion decisions.[6] Then, the rent on parcel j engaged in smallholder production system k, R^*_{jk}, becomes:

$$R^*_{jk} = f(Z_{jk}, M_{jk}, S_j, D_j, P_j) + \eta_{jk} \tag{5}$$

where D_j is a vector of district indicator variables and P_j is a vector of province indicator variables.

We can allow the determinants of smallholder forest conversion to be entirely different across subdivided and non-subdivided districts, an approach motivated by the predictions from the theoretical model regarding different locations of smallholder conversion across district types, by splitting the sample of forested parcels into those located in subdivided districts and those located in non-subdivided districts. This approach leads to:

$$R^*_{jk} = S_j(f(Z_{jk}, M_{jk}, D_j, P_j)) + (1 - S_j)(g(Z_{jk}, M_{jk}, D_j, P_j)) + \omega_{jk} \tag{6}$$

where S_j is an indicator function taking on a value of one if parcel j lies in a district that was subdivided following Suharto's resignation and is zero otherwise. The choice of production system is described using a logit or multinomial logit model, in which the observed outcome, smallholder conversion (R_{jk}), takes on values based on the latent variable's magnitude relative to a threshold value (McFadden, 1973)

To account for the difference between the scale of observation and the scale of forest conversion by both plantations and smallholders, we estimate a spatial autoregressive linear probability model, in which the W matrix is row-normalized and based on k nearest neighbors between pixels, occurs through two-stage least squares, with WX as the instrument for WR^* (Drukker et al., 2013; Kelejian and Prucha, 1998, 1999).

5.2 Nonparametric approach

To ensure that the results are not driven purely by parametric assumptions, a nonparametric approach to estimating the probability of smallholder and plantation forest conversion is also employed. The steps in the nonparametric analysis mirror those of the parametric approach; the advantage of the nonparametric approach is that it is robust to mis-specification in the functional form and in the distribution of the unobservables. To describe the nonparametric methodology, start with equation 6:

$$R^*_{jk} = S_j(f(Z_{jk}, M_{jk}, D_j, P_j)) + (1 - S_j)(g(Z_{jk}, M_{jk}, D_j, P_j)) + \omega_{jk}$$

In the nonparametric approach, $f(Z_{jk}, M_{jk}, D_j, P_j)$ and $g(Z_{jk}, M_{jk}, D_j, P_j)$ are allowed to be completely unknown. The nonparametric approach further makes no assumptions regarding the joint distribution of the unobservables $\psi(\omega_0, \omega_1, ...\omega_K)$.

The goal of this analysis is to estimate the probability of smallholder conversion, R, which is based on the latent returns to production, R^*, across different sets of pixels. The specific unknown probability of interest is:

$$P(R_j = k | Z_j, M_j, D_j, P_j) = \phi(Z_j, M_j, D_j, P_j) = \phi(k, x)\,, \qquad k = 0, 1, ..., K \tag{7}$$

where $\phi(k,x)$ is some unknown function. A feasible estimator for equation 7 can be obtained using the generalized product kernel function of Racine et al. (2004):

$$\hat{\phi}(k,x) = \frac{\sum_{j=1}^{n} K_{\gamma_1}(R_j,k)K_{\gamma_2}(X_j,x)}{\sum_{j=1}^{n} K_{\gamma_2}(X_j,x)} \tag{8}$$

where $K_{\gamma_2}(X_j,x)$ has the following representation:

$$K_{\gamma_2}(X,x) = W_h(X_j^c,x^c)L(X_j^d,x^d,\lambda) \tag{9}$$

$$W_h(X_j^c,x^c) = \prod_{p}^{r_1} \frac{1}{h_p} w\Big(\frac{X_j^c - x_p^c}{h_p}\Big) \tag{10}$$

$$L(X_j^d,x^d,\lambda) = \prod_{p}^{r_2} \lambda_p^{I(x_p^d \neq X_j^d)}(1-\lambda_p)^{1-I(x_p^d \neq X_j^d)} \tag{11}$$

where X^c are continuous variables such as elevation or precipitation while X^d are discrete variables such as the Jambi or Riau province indicator variables. The dimensions of X^c and X^d are r_1 and r_2 respectively. γ_1 and $\gamma_2 = [h_p, \lambda_p]$ are the bandwidth parameters for the R and X variables. The kernel function for the discrete dependent variable has the following representation:

$$K_{\gamma_1}(R,k) = \gamma_1^{I(k \neq R_j)}(1-\gamma_1)^{1-I(k \neq R_j)} \tag{12}$$

The analysis is designed to detect differences in the preferred location for smallholder production as a result of a district's subdivision status. To do so, the probability of smallholder conversion, $\hat{\phi}$, is estimated separately for pixels located in subdivided and non-subdivided districts. To limit the possibility that differences in average marginal effects are due to evaluation of these densities at different values of the explanatory variables (due to different ranges of values for the explanatory variables in each of the district types, as suggested by table 3), the separately-estimated functions $\hat{\phi}$ are evaluated at all of the $13,025$ points to determine the average marginal effect of changes in each explanatory variable.

As shown in figure 3, the districts that were subdivided following the end of Suharto's regime are relatively concentrated spatially. To ensure the robustness of our results, we consider the full sample and then conduct the same analysis using only parcels that lie within five kilometers of a district with a different subdivision status. In addition to this simple analysis, we also employ more formal approaches to addressing concerns regarding the endogeneity of the subdivision indicator used in the analysis.[7]

Taking the approach related to group unconfoundedness found in Rosenbaum (1987), we assess whether our subdivision indicator satisfies the unconfoundedness (exogeneity) assumption required for the reliable interpretation of our results. Recall that S_j is an indicator function equal to one if a district was subdivided and zero otherwise. For unconfoundedness to hold, we require that $S_j \perp\!\!\!\perp R(0), R(1)|X$. To apply the group unconfoundedness approach to our problem, consider taking two subgroups of observations in the *non-subdivided* districts we denote by $G = c_1, c_2$. By comparing the response variable across these two subgroups, we can assess whether one of the groups is comparable to the *subdivided* districts. As described in Imbens and Rubin (2015), we can formally test this by estimating the following difference:

$$H_0 : \tau = E\big[E(R|G = c_1, X) - E(R|G = c_2, X)\big] = 0 \tag{13}$$

Rosenbaum (1984) proves that a failure to reject H_0 is equivalent to a failure to reject the equality of the distributions of unobservables across each group under consideration. A failure to reject H_0 provides evidence in favor of unconfoundedness, thus supporting the validity of our results.

5.3 Specification Testing

To investigate whether mis-specification is present within the parametric models described in Section 5.1, the Fan et al. (2006) nonparametric bootstrap test of conditional distributions is employed for each of the parametric models estimated.[8] This test looks for evidence that the true conditional distribution is different from that implied by an arbitrary parametric specification. The null hypothesis in Fan et al. (2006) is that the true population distribution is equal to some parametric conditional distribution given by $\phi(R = k|X = x, \beta)$. Formally:

$$H_0 : Pr[\phi(R = k|X = x) = \phi(R = k|X = x, \beta)] = 1 \text{ for some } \beta \in \Omega \tag{14}$$

For a logit model, $\phi(R = k|X = x, \beta) = R\Lambda(\beta x)+(1-R)(1-\Lambda(\beta x))$ where Λ is the standard logistic distribution function. Rejection of the null hypothesis suggests mis-specification in the parametric model, which casts doubt on the reliability of the parametric results, due to either an incorrect distributional assumption on the unobservables or function specification.

6 Results

Results of the specification testing of the functional-form assumptions made by the logit, multinomial logit, and spatial autoregressive linear probability models of forest conversion are presented first. The results of the nonparametric analysis testing the predictions about smallholder conversion in the subdivided and non-subdivided districts follows.

6.1 Specification testing

Table 2 presents the results of the specification test depicted in equation 14 above. The results show that the functional form and error distribution assumptions of each of the proposed parametric models are rejected via the nonparametric bootstrap test of conditional distributions based on subdivided ($N = 9,192$) and non-subdivided ($N = 3,258$) subsamples.

This result implies that the coefficient estimates and resulting marginal effects provided by each of these parametric models are inconsistent.[9]

There are numerous explanations for the rejection of the proposed models. The logit model might be rejected because it aggregates production systems and fails to acknowledge spatial autocorrelation. The multinomial logit model might be rejected for its assumption of the independence of irrelevant alternatives and the omission of spatial autocorrelation. The spatial autoregressive linear probability model may be rejected due to a functional form mis-specification or a mis-specified weight matrix. Any of these models might be rejected based on their assumed distribution of the error terms. Given the myriad sources of mis-specification associated with each of these models, the specification test proposed by Fan et al. (2006) is only able to reject the assumptions of the model, not provide insight into the particular assumption that fails to hold. Due to the rejection of each of the proposed parametric specifications of smallholder conversion, the paper will proceed with a focus on the results of the nonparametric approach.

6.2 Smallholder conversion

Table 3 presents the results of the determinants of smallholder forest conversion for the binary analysis. Specifically, the table presents the average marginal effects for the explanatory variables displayed in the table. These results show that the probability of smallholder conversion decreases with increasing slope, distance from the forest edge, and distance from the nearest road for pixels located in non-subdivided districts. Additionally, pixels in these districts are less likely to be converted to smallholder production if they are located in protected areas.[10] Notably, elevation has no impact on the probability of smallholder conversion for the pixels in these districts, which is a different result from that in the subdivided districts, where the probability of smallholder conversion decreases with increasing elevation. The difference between the marginal effect of each of these variables across subdivided and non-subdivided districts is statistically significant, except for distance from the nearest road. These results suggest that smallholder conversion in subdivided districts occurs in locations that would not be favored in non-subdivided districts.

To gauge the magnitude of the impact of district subdivision on smallholder forest conversion probability, table 4 reports the change in conversion probability for a one standard deviation change in the explanatory variables relative to a standard deviation change in the dependent variable. With respect to a one standard deviation change in forest edge distance, road distance, and protected area, the impact in non-subdivided districts is 5.68, 4.82, and 17.14 times larger than the impact in subdivided districts. Table 5 reports the impacts with respect to the unconditional mean of conversion in subdivided and non-subdivided districts. A one standard deviation change in forest edge distance, road distance, and protected area in the non-subdivided districts leads to a 74%, 48%, and a 16% increase in conversion probability over the unconditional probability of conversion. This suggests that moderate changes in forest edge distance, road distance, and a change in protection status have very substantial economic impacts when compared to the unconditional probability of conversion.

To pinpoint the source of the average marginal effects and to directly address predictions 1 and 2 from the model of smallholder conversion, figures 4-7 show the point-wise conversion probabilities and the point-wise derivatives for forest edge and road distance for the binary analysis. The probability of conversion is highest at the forest edge in both the subdivided and non-subdivided districts, with the conversion probability greater in the non-subdivided districts than in the subdivided districts over the first one kilometer into the forest (figure 4). This result is consistent with prediction 1, and it supports the idea that the increased plantation activity in subdivided districts drives smallholders further into the forest than they would choose to be with less plantation threat. Regarding the prediction that the probability of smallholder conversion in the forest interior would be greater in subdivided districts than non-subdivided districts, we see that the point estimate of conversion probability is in fact greater in subdivided districts from 1.5 to 5 kilometers into the forest, though the difference is not statistically significant.

The largest marginal effect for the non-subdivided districts occurs at 1.25 kilometers from the forest edge, reducing the conversion probability by about 4%, which is twice the average marginal effect (figure 5). The marginal effect is roughly constant for the subdivided districts. The marginal effects in the non-subdivided districts are significantly less than those in the subdivided districts between 0.5 and 1.75 kilometers into the forest, which is additional support for prediction 2.

The probability of smallholder conversion is greater at the road's edge in non-subdivided districts than in subdivided districts, which is consistent with prediction 1, when applied to road distance. While the gap in estimated conversion probability narrows substantially between 2 and 5 kilometers from the nearest road, it is never greater in the subdivided districts, which does not support prediction 2 in this context (figure 6). Figure 7 shows the point-wise marginal effects for the subdivided and non-subdivided districts as distance from the nearest road varies. The marginal effect for the subdivided districts is effectively zero at most distances, except for the 2.5-3.25 kilometer range, where the marginal effect is positive. The existence of positive marginal effects over a range of distances from the nearest road in subdivided districts is some support for prediction 2 in this context. For the non-subdivided districts, the marginal effect is negative and statistically different from zero over the first three kilometers from the nearest road.

Given the spatial concentration of subdivided districts in the study area, we would like to ensure that the results can be attributed to district subdivision. While the inclusion of district indicator variables in the models ensures that unobserved district characteristics (e.g., corruption) are not responsible for the observed results, it is possible that an omitted variable that might determine smallholder conversion decisions (e.g., local climatic conditions) could be driving the results. To explore the robustness of our results, we conduct the same analysis whose results are displayed in table 3 on a subset of pixels that lie within 5 kilometers of the border of a district whose subdivision status is different from that of the district in which the pixel is located. The results described above are robust across this subset of pixels, confirming our confidence that the change in smallholder conversion-location preferences is due district rezoning.[11]

To explore the exogeneity of subdivision status, we report the results for the group unconfoundedness test in table 8. Recall that a failure to reject the null is evidence in favor of the exogeneity of the subdivision status. To form valid subsets for which to test unconfoundedness, we consider groupings based on the distance of a non-subdivided pixel from a subdivided district border starting at 1km and ending at 20km. It is clear from the results that we *fail to reject* the null in 18 of the 20 groupings considered. In fact, in the 2 cases for which the null is rejected, the upper bound in the 95% confidence interval contains a near zero number. The results suggest that group unconfoundedness, and therefore exogeneity, is likely to hold in the analysis.

To explore the possibility that the binary results might be dampened by aggregating different smallholder production systems, we also utilize a multinomial analysis. These results are depicted in table 6.[12] The average marginal effects depicted in this table again indicate that smallholder conversion occurs in different locations based on district subdivision status, with the differences suggesting that smallholder conversion in subdivided districts occurs at locations that would not be preferred in subdivided districts. This result is consistent with the predictions of the model of smallholder forest conversion, in which subdivision is associated with increased plantation activity that threatens smallholder systems, forcing them into locations that would be undesirable when facing lower levels of plantation threat. For oil palm production, the probability of conversion decreases with increasing elevation and forest edge distance and is significantly lower in protected areas in non-subdivided districts; these effects are significantly dampened in subdivided districts, with the magnitude of the average marginal effect for these variables decreasing by roughly 85, 17, and 17 times, respectively in the subdivided districts.

Figure 8 illustrates how the probability of conversion to smallholder oil palm production varies at different distances from the forest edge across the subdivided and non-subdivided districts. These results show that smallholder oil palm production pushes into the forest interior from the forest edge in subdivided districts in contrast to outcomes in non-subdivided districts, where the forest edge is the preferred location for oil palm production. The results in this figure offer support for both predictions from the theoretical model, in which subdivision is associated with increased plantation activity that threatens smallholder systems. The increased probability of smallholder oil palm conversion in the forest interior in subdivided districts relative to non-subdivided districts emphasizes that the results in tables 3 and 6 are not merely due to the fact that there is less smallholder forest conversion overall in subdivided districts.

The results for plasma oil palm systems also seem to support the idea that smallholder location choice is affected by district subdivision. Recall that in this partnership, smallholders effectively act as sharecroppers on land controlled by plantation operators. As a result, we might expect that the determinants of plasma oil palm systems would not vary between subdivided and non-subdivided districts and that these systems would locate in areas with different characteristics than independent smallholder oil palm production. The results seem to support these expectations. First, there are only two statistically significant differences in the average marginal effects across our explanatory variables (precipitation and distance from the nearest town) for this production system, and one of these differences is of marginal significance (town distance). Neither of the significant differences are for variables that had differential impact on the probability of independent smallholder oil palm production across district subdivision status. Furthermore, the difference in average marginal effect between subdivided and non-subdivided districts, across all variables with statistically significant differences, with the exception of precipitation and protected area, is of a different sign for independent smallholder oil palm production relative to plasma systems.

The results for mixed-agriculture smallholder systems again offer some support for the displacing effect of district subdivision on smallholder forest conversion in Sumatra. Specifically, these systems are 7.26 times more responsive to forest edge distance in non-subdivided districts than in subdivided districts, meaning that these systems might be expected to be located further from the forest edge in subdivided districts, which is consistent with the predictions from the theoretical model. Furthermore, there is no significant decrease in the likelihood of forest conversion to smallholder mixed-agriculture production on pixels located within protected areas in subdivided districts, while the deterrence is significant at the 5% level in non-subdivided districts. There is less evidence provided by the results for smallholder rubber production. One explanation for the lack of differences in conversion location for rubber production is that these trees grow in the wild and adult trees might be tapped where they grow naturally, avoiding the need to wait for seedlings to mature.

7 Welfare Impacts of the Location of Smallholder Forest Conversion

The concern about conversion of less-desirable forests in subdivided districts is that these areas may not have been converted in non-subdivided districts. Given the vast amount of endemic biodiversity contained in the forests of Sumatra and the suite of ecosystem services provided by those same forests that generate tangible benefits both globally (e.g., carbon sequestration and storage) and locally (e.g., avoided sedimentation, storm-peak reduction), it seems clear that the external costs of forest conversion vary spatially and that these costs will increase as conversion occurs in more remote locations.

The private and social benefits and costs of forest conversion vary spatially, making the location of conversion a key determinant of the welfare effects of such action.[13] The literature demonstrating the negative impacts of edge effects on biodiversity and forest health is quite robust (see e.g., Broadbent et al., 2008; Gascon et al., 2000; Laurance et al., 2001). By increasing the extent of forest that is abutted by non-forest land covers, edge effects due to remote forest conversion can generate adverse ecological outcomes, including increased susceptibility to fires (Cochrane and Laurance, 2002); reduced species richness (Benitez-Malvido and Martinez-Ramos, 2003); changes in micro-climates that can impact agricultural productivity (Williams-Linera et al., 1998); and increased CO_2 emissions due to increased mortality among large trees (Laurance et al., 2000). Recent work has highlighted that the carbon stored in forest biomass increases substantially with increasing distance from the forest edge, meaning that forest conversion to agricultural production in the interior of the forest can significantly increase CO_2 emissions (Chaplin-Kramer et al., 2015a,b). These ecological changes negatively affect social welfare through reductions in the value of ecosystem services provided by the extant forest as well as potential losses of biodiversity.

Our welfare analysis of the impact of district subdivision on the location of smallholder production in Sumatra will focus only on the additional social cost of carbon emissions due to the location of smallholder forest conversion in response to a district's subdivision status.[14] These welfare losses are admittedly a lower-bound on the actual external costs of changes in the location of smallholder conversion due to district subdivision, as they do not include values of other lost ecosystem services and negative impacts on biodiversity associated with smallholder conversion in the forest interior. Still, the magnitude of this single effect illustrates the potential welfare gains available from improved forest management in Sumatra.

The goal of the welfare analysis is to identify the social cost of the excess carbon emitted due to district subdivision, which drives smallholders further into the forest, where there is more forest carbon. We use a weighted average of the parameter estimates based on data from lowland Sumatran forests in Chaplin-Kramer et al. (2015b) to derive the following equation linking carbon storage with forest edge distance: $C = 289.5 - 168.4e^{-0.73d}$, where d measures the pixel's distance from the forest edge and C is the metric tons of Carbon stored per hectare. Using the smallholder model from the subdivided districts, conversion probabilities are computed from the characteristics of the pixels located in the non-subdivided districts. Each pixel is classified as predicted to convert to smallholder production if $P(R = 1|X_i) > 0.1913$, where 0.1913 is the threshold conversion probability value that balances the specificity and sensitivity of the nonparametric model. Figure 9 plots the predictive capacity for the nonparametric model for smallholder production in a subdivided district; with the threshold of 0.1913, the model accurately predicts 98% of both positive and negative outcomes. Then, the average distance from the forest edge within a subdivided district is calculated for each of the 399 samples. The sample of average forest edge distances under the conditions in the non-subdivided districts is developed by bootstrapping the average distance of the 175 points that converted to smallholder production between 2000 and 2008.

Having generated these samples, we next calculate the biomass associated with the forest located at each distance from the forest edge in both the subdivided and non-subdivided samples, using the equation from Chaplin-Kramer et al. (2015b) for lowland forests in Sumatra. We determine the additional forest carbon lost due to district subdivision by bootstrapping 1000 samples of the difference in forest carbon stored in forest pixels converted to smallholder production with and without subdivision. This process generates a mean difference in carbon storage of 44.14 metric tons per hectare, meaning that, due to their location further into the forest, pixels converted in subdivided districts have on average 44.14 additional metric tons of carbon per hectare. The bootstrapped 95% confidence interval of this difference is 40.03 to 45.23 metric tons of carbon per hectare.

The welfare impact of this excess carbon lost due to district subdivision can be estimated by converting the additional metric tons of carbon associated with smallholder forest conversion further into the forest in subdivided districts to metric tons of CO_2 and multiplying this amount by the social cost of carbon (SCC). The SCC is intended to represent the monetized damages due to an incremental increase in carbon emissions, including (though not limited to) changes in agricultural productivity, human health, property damages due to increased flood risk, and the value of ecosystem services (Greenstone et al., 2011).[15] We use three estimates of the SCC that account for a range of emissions scenarios and discount rates in the year 2010: \$21.4 (average emissions, 3% discount rate), \$35.1 (average emissions, 2% discount rate), \$64.9 (95th %ile emissions, 3% discount rate) (Interagency Working Group on Social Cost of Carbon, 2010).

Given these amounts, the average per-hectare cost of the altered location of smallholder conversion following district subdivision due to additional carbon emissions ranges from \$1,734 to \$5,256, with an average of \$2,843.[16] For some perspective, average per capita consumption in this part of Sumatra (the West Sumatra Province) was \$881 (in 2010 dollars) according to the Indonesian Family Life Survey conducted by RAND in 2007. That the average increased per-hectare external cost of smallholder forest conversion is 3.23 times greater than average per capita consumption in the region emphasizes the inefficiency due to changes in location of smallholder conversion and also suggests that policy interventions could alleviate this source of welfare loss.

8 Conclusion

We take advantage of a uniquely detailed GIS dataset to explore how district subdivision in Indonesia impacts the location choice and associated external costs of smallholder forest conversion. Our analysis shows that smallholders convert different forest locations within districts that have been subdivided relative to those that have not; this finding holds when the models are estimated on the full set of randomly-drawn pixels that were forested in 2000 as well as a subset of pixels that lay within five kilometers of the nearest district with a different subdivision status. Specifically, smallholders are located on more marginal lands (steeply-sloped, further from the forest edge and nearest road) within subdivided districts, supporting predictions from a simple model of smallholder conversion. Our analysis also shows that the likelihood of conversion to smallholder mixed agriculture or oil palm systems increases for forested pixels within protected areas within subdivided districts, *ceteris paribus*. This response leads to a welfare loss as the private returns to conversion are lower in these areas and the external costs, as measured only by excess CO_2 emissions, are greater, with per hectare external costs that are several times greater than the per capita consumption levels in the region.

The results allow for some commentary on the impact of decentralization on welfare outcomes. While a strain of the theoretical literature shows that local authorities may be better suited to improve local welfare through provision of public goods than a central government (e.g., Besley and Coate, 2003), there is theoretical justification for both improved and worsened natural resource management due to decentralization, stemming from either a race to the top among jurisdictions in competition for constituents who might vote with their feet (see e.g., Oates and Schwab, 1996; Tiebout, 1956) or a race to the bottom among jurisdictions aiming to appease firms that are sensitive to the costs of compliance with environmental and social regulations (see e.g., Andersson, 2003; Gibson and Lehoucq, 2003; Musgrave, 1997). As emphasized by Ostrom (1990), institutional context is a key determinant of decentralization outcomes, making it difficult to come up with consensus support for either of the above theorized outcomes. McCarthy (2004) finds that in Kalimantan, with uncertainty about property-rights security and governance responsibilities, decentralization led to a race to exploit forest resources.

Our analysis suggests that the focus on increasing local government control of natural-resource extraction royalties may offset some of the benefits of these increased royalties by failing to protect the livelihoods of smallholders. These results are consistent with those presented in Suwarno et al. (2015). Increased attention to the plight and behavior of smallholders might be achieved with more formalized smallholder tenure, which would make smallholders another royalty source for district agencies. More secure smallholder property rights could alleviate some of the displacement predicted by the above model and demonstrated in our empirical analysis. Additionally, the results of our welfare analysis suggest meaningful carbon benefits associated with prevention of smallholder forest conversion deeper into the forest. Carbon offset payments for reducing emissions from deforestation and degradation (REDD+) might achieve greater emission reductions by acknowledging smallholders as agents of forest conversion and including this stakeholder group more directly in the forest-management process. In examining the formation of comanagement agreements between resource users and the state, in which the state achieves lower management costs by allowing increased resource use, Engel et al. (2013) suggests that the inclusion of carbon rights in forest comanagement agreements would further motivate communities to increase forest carbon stocks. In short, our findings suggest that further inclusion of smallholder behavior in natural resource management decisions might improve outcomes under decentralization.

Although we are able to identify differences in smallholder behavior across districts based on subdivision status, the mechanism behind this result can not be determined in our analysis. The two most likely pathways are that subdivided districts are characterized by more plantation activity, leaving smallholders with less desirable land, or that smallholders locate their operations on marginal lands in areas with high threat of plantation operations due to insecure smallholder tenure. The first alternative would be predicted via a von Thunen or Alonso bid-rent model in a landscape with a functioning market for land. The latter alternative seems more relevant for outcomes in Indonesia, where smallholder land tenure is insecure. This explanation is also supported by the existing literature.

In the mid 1980s, the predominant driver of forest conversion in the tropics shifted from smallholder farmers to well-capitalized farmers, loggers, and ranchers whose products are shipped to consumers around the world (Rudel et al., 2009). As these two different forces come to occupy the same landscapes, it is not uncommon for conflicts to arise between them. In a meta-analysis of studies on deforestation, Rudel et al. (2009) finds that insecure tenure was significantly more likely to be a main cause of deforestation in Southeast Asia in the 1990s then it was during the 1980s; over this time period, plantation agriculture became a more likely determinant of deforestation, while small farmers became less likely to be a key source of deforestation. A study from Sumatra reports that increased plantation presence, and an associated increase in the transmigrant population, in the mid 1980s to the early 1990s led to increased encroachment on primary forests by smallholders in the area (Angelsen, 1995). The smallholders were forced to cede the land that had been under their use, as their community-recognized land rights were not recognized by government-supported logging, transmigration, or plantation projects (Dove, 1987). In a meta-analysis of the proximate and underlying causes of deforestation in the tropics, Geist and Lambin (2001) notes that two-thirds of the examples of poverty-driven deforestation are associated with the underlying cause of property rights arrangements, related to issues such as insecure ownership, quasi open access, and low empowerment of local user groups.

While there has not been much focus on the location of forest conversion, theory predicts that poorly-defined property rights will increase deforestation of a given forest parcel through an increased discount rate (Mendelsohn, 1994) and promote activities with low-capital intensity (Deacon, 1994). Empirical analyses support these predictions (e.g., Araujo et al., 2009; Otsuki et al., 2002).[17] In agricultural systems, lack of well-defined access has been shown to reduce investment and yield (Banerjee et al., 2002; Hornbeck, 2010). Our results, and the context of the region in which they were obtained, suggest that insecure tenure may also affect the location of forest conversion, which has implications for the private and social net benefits of such action. Future work that identifies the impact of insecure smallholder tenure on the location of forest conversion in the tropics would be a meaningful contribution to the literature and of great use to policy makers in tropical nations.

The conditions that exist in forested regions of tropical nations often prevent optimal management of this important source of local and global social benefits, stemming from their production of valuable ecosystem services. Our research effort sheds light on how the presence of heterogeneous drivers of forest conversion leads to particular inefficiencies in the management of these valuable global resources through inefficient spatial distribution of conversion in areas with more localized resource control. Additional research into how governments in these regions might best allocate their limited resources to monitoring and enforcement, development of missing institutions, and anti-corruption measures is necessary to ensure that these areas are as well equipped as possible to mitigate and adapt to anthropogenic climate change.

References

Afrizal. The nagari community, business and the state. *Forest Peoples Programme and Perkumpulan SawitWatch*, 2007.

K. Andersson. What motivates municipal governments? uncovering the institutional incentives for municipal governance of forest resources in bolivia. *Journal of Environmental Development*, 12(1):5–27, 2003.

A. Angelsen. Shifting cultivation and "deforestation": A study from indonesia. *World Development*, 23(10):1713–1729, 1995.

C. Araujo, C.A. Bonjean, J-L. Combes, P.C. Motel, and E.J. Reis. Property rights and deforestation in the brazilian amazon. *Ecological Economics*, 68(8-9):2461–2468, 2009.

A.V. Banerjee, P.J. Gertler, and M. Ghatak. Empowerment and efficiency: Tenancy reform in west bengal. *Journal of Political Economy*, 110:239–280, 2002.

J. Benitez-Malvido and M. Martinez-Ramos. Impact of forest fragmentation on understory plant species richness in amazonia. *Conservation Biology*, 17:389–400, 2003.

F. Berkes. Devolution of environment and resource governance: Trends and future. *Environmental Conservation*, 37(4):489–500, 2010.

Timothy Besley and Stephen Coate. Centralized versus decentralized provision of local public goods: a political economy approach. *Journal of Public Economics*, 87:2611–2637, 2003.

N.K. Bhagabati, T. Barano, M.N. Conte, D. Ennaanay, O. Hadian, E. McKenzie, N. Olwero, A. Rosenthal, M. Suparmoko, A. Shapiro, H. Tallis, and S. Wolny. A green vision for sumatra: Using ecosystem services information to make recommendations for sustainable land use planning at the province and district level. *World Wildlife Fund and the Natural Capital Project*, 2012.

N.K. Bhagabati, T. Ricketts, T.B.S. Sulistyawan, M.N. Conte, D. Ennaanay, O. Hadian, E. McKenzie, N. Olwero, A. Rosenthal, H. Tallis, and S. Wolny. Ecosystem services reinforce sumatran tiger conservation in land use plans. *Biological Conservation*, 169: 147–156, 2014.

E.N. Broadbent, G.P. Asner, M. Keller, D.E. Knapp, P.J.C. Oliveira, and J.N. Silva. Forest fragmentation and edge effects from deforestation and selective logging in the brazilian amazon. *Biological Conservation*, 141:1745–1757, 2008.

R. Burgess, M. Hansen, B.A. Olken, P. Potapov, and S. Sieber. The political economy of deforestation in the tropics. *Quarterly Journal of Economics*, 127(4):1707–1754, 2012.

A. Casson. *The hesitant boom: Indonesia's oil palm subsector in an era of economic crisis and political change.* CIFOR, Bogor, Indonesia, 2000.

R. Chaplin-Kramer, I. Ramler, R. Sharp, N.M. Haddad, J.S. Gerber, P.C. West, L. Mandle, P. Engstrom, A. Baccini, S. Sim, C. Mueller, and H. King. Degradation in carbon stocks near tropical forest edges. *Nature Communications*, 6:1–6, 2015a.

R. Chaplin-Kramer, R. Sharp, L. Mandle, S. Sim, J. Johnson, I. Butnar, L. Mila i Canals, B.A. Eichelberger, I. Ramler, C. Mueller, N. McLachlan, A. Yousefi, H. King, and P.M. Kareiva. Spatial patterns of agricultural expansion determine impacts on biodiversity and carbon storage. *Proceedings of the National Academy of Sciences of the United States of America*, 112(24):7402–7407, 2015b.

K.M. Chomitz and D.M. Gray. Roads, land, markets, and deforestation: A spatial model of land use in belize. *World Bank Economic Review*, 10:487–512, 1996.

M.A. Cochrane and W.F. Laurance. Synergistic interaction between habitat fragmentation and fire in evergreen tropical forests. *Journal of Tropical Ecology*, 18:311–325, 2002.

M. Colchester, N. Jiwan, Andiko, M. Sirait, A.Y. Firdaus, A. Surambo, and H. Pane. *Promised Land: Palm Oil and Land Acquisition in Indonesia: Implications for Local Communities and Indigenous Peoples.* Forest Peoples Programme, Perkumpulan Sawit Watch, HuMA, and the World Agroforestry Centre., 2006.

C.J.P. Colfer and D. Capistrano. *The Politics of Decentralisation. Forest, People and Power.* Earthscan, London, United Kingdom, 2002.

M.N. Conte. Valuing ecosystem services. In S. Levin, editor, *Encyclopedia of Biodiversity.* Princeton University Press, 2013.

Mark Coppejans and Holger Sieg. Kernel estimation of average derivatives and differences. *Journal of Business & Economic Statistics*, 23(2):211–225, April 2005.

M.H. Costa and J.A. Foley. Combined effects of deforestation and double atmospheric co2 concentrations on the climate of amazonia. *Journal of Climate*, 13:18–34, 2000.

M.H. Costa, A. Botta, and J.A. Cardille. Effects of large-scale changes in land cover on the discharge of the tocantins river, amazonia. *Journal of Hydrology*, 283:206–217, 2003.

R.T. Deacon. Deforestation and the rule of law in a cross-section of countries. *Land Economics*, 70(4):414–430, 1994.

K. Deininger and B. Minten. Determinants of deforestation and the economics of protection: An application to mexico. *American Journal of Agricultural Economics*, 84(4):943–960, 2002.

I. Douglas. The impact of land-use changes, especially logging, shifting cultivation, mining and urbanization on sediment yields in humid southeast asia: A review with special reference to borneo. In D.E. Walling and B.W. Webb, editors, *Erosion and Sediment Yield:*

Global and Regional Perspectives. International Association of Hydrological Sciences Publication, 1996.

M.R. Dove. The perception of peasant land rights in indonesian development: Causes and implications. In J.B. Raintree, editor, *Land, Trees and Tenure*. International Centre for Research on Agroforestry and Land Tenure Center, Nairobi and Madison, WI, 1987.

D.M. Drukker, H. Peng, I.R. Prucha, and R. Raciborski. On two-step estimation of a spatial autoregressive model with autoregressive disturbances and endogenous regressors. *Econometric Reviews*, 32:686–733, 2013.

S. Engel, C. Palmer, and A. Pfaff. On the endogeneity of resource comanagement: Theory and evidence from indonesia. *Land Economics*, 89(2):308–329, 2013.

Yanqin Fan, Qi Li, and Insik Min. A nonparametric bootstrap test of conditional distributions. *Econometric Theory*, 22(4):587–613, Aug. 2006.

P.J. Ferraro, M.M. Hanauer, and K.R.E. Sims. Conditions associated with protected area success in conservation and poverty reduction. *Proceedings of the National Acadamy of Sciences*, 108(34):13913–13918, 2011.

R. Fisman. Estimating the value of political connections. *The American economic review*, 91(4):1095–1102, 2001.

F. Fitrani, B. Hofman, and K. Kaiser. Unity in diversity? the creation of new local governments in a decentralising indonesia. *Bulletin of Indonesian Economic Studies*, 41(1): 57–79, 2005.

C. Gascon, B.G. Williamson, and G.A.B. da Fonseca. Receding forest edges and vanishing reserves. *Science*, 288:1356–1358, 2000.

H.J. Geist and E.F. Lambin. What drives tropical deforestation? a meta-analysis of proximate and underlying causes of deforestation based on subnational case study evidence. Technical report, LUCC International Project Office, LUCC Report Series no. 4, Louvain-la-Neuve (Belgium), 2001.

C. Gibson and F. Lehoucq. The local politics of decentralized environmental policy. *The Journal of Environment and Development*, 12(1):29–49, 2003.

M. Greenstone, E. Kopits, and M. Wolverton. Estimating the social cost of carbon for use in u.s. federal rulemakings: A summary and interpretation. MIT Department of Economics Working Paper No. 11-04, 2011.

Peter Hall. On kullback-leibler loss and density estimation. *The Annals of Statistics*, 15(4): 1491–1519, 1987a.

Peter Hall. On the use of compactly supported density estimates in problems of discrimination. *Journal of Multivariate Analysis*, 23:131–158, 1987b.

Peter Hall, Jeffrey S. Racine, and Qi Li. Cross-validation and the estimation of conditional probability densities. *Journal of the American Statistical Association*, 99(468):1015–1026, 2004.

W. Härdle and T. Stoker. Investigating smooth multiple regression by the method of average derivatives. *Journal of the American Statistical Association*, 84(408):986–995, December 1989.

Tristen Hayfield and Jeffrey Racine. Nonparametric econometrics: The np package. *Journal of Statistical Software*, 27(i05), 2008.

B. Hofman and K. Kaiser. The making of the big bang and its aftermath: A political economy perspective. In J. Alm, M.V. Jorge, and S.M. Indrawati, editors, *Reforming Intergovernmental Fiscal Relations and the Rebuilding of Indonesia*. Edward Elgar, Cheltenham, U.K., 2004.

R. Hornbeck. Barbed wire: Property rights and agricultural development. *Quarterly Journal of Economics*, 125(2):767–810, 2010.

Guido Imbens and Donald Rubin. *Causal Inference for Statistics and Biomedical Sciences: An Introduction.* Cambridge University Press, New York, NY, 2015.

G.W. Imbens and J.W. Wooldridge. Recent developments in the econometrics of program evaluation. *Journal of Economic Literature*, 47(1):5–86, 2009.

Interagency Working Group on Social Cost of Carbon. Technical support document: Social cost of carbon for regulatory impact analysis under executive order 12866., 2010.

P.K. Kareiva, H. Tallis, G. Daily, T. Ricketts, and S. Polasky, editors. *Natural Capital: Theory and Practice of Mapping Ecosystem Services.* Oxford University Press, 2011.

H.H. Kelejian and I.R. Prucha. A generalized spatial two-stage least squares procedure for estimating a spatial autoregressive model with autoregressive disturbances. *Journal of Real Estate Finance and Economics*, 17:99–121, 1998.

H.H. Kelejian and I.R. Prucha. A generalized moments estimator for the autoregressive parameter in a spatial model. *International Economic Review*, 40:509–533, 1999.

S. Kerr, A.S. Pfaff, A. Sanchez, and M. Boscolo. *What role for tropical forests in climate change mitigation? The Case of Costa Rica.* Harvard University Press., Cambridge, MA, 2000.

A.M. Larson and F. Soto. Decentralisation of natural resource governance regimes. *Annual Review of Environment and Resources*, 33:213–239, 2008.

W.F. Laurance, P. Delamonica, S.G. Laurance, H.L. Vaconcelos, and T.E. Lovejoy. Rainforest fragmentation kills big trees. *Nature*, 404, 2000.

W.F. Laurance, T.E. Lovejoy, H.L. Vaconcelos, E.M. Bruna, R.K. Didham, P.C. Stouffer, C. Gascon, R.O. Bierregaard, S.G. Laurance, and E. Sampaio. Ecosystem decay of amazonian forest fragments: a 22-year investigation. *Conservation Biology*, 16(3):605–618, 2001.

P. Levang. *Ayo ke tanah sabrang: transmigrisi di Indonesia.* Kepstakaan Populer Gramedia., Jakarta, 2003.

P.D. Little and M. Watts. *Living under contract: contract farming and agrarian transformation in Sub-Saharan Africa.* University of Wisconsin Press., Madison, WI, 1994.

B.A. Margono, P.V. Potapov, S. Turubanova, F. Stolle, and M.C. Hansen. Primary forest cover loss in indonesia over 2000-2012. *Nature Climate Change*, 4:730–735, 2014.

J.F. McCarthy. Changing to gray: Decentralization and eht emergence of volatile socio-legal configurations in central kalimantan, indonesia. *World Development*, 32(7):1199–1223, 2004.

J.F. McCarthy. Shifting resource entitlements and governance reform during the agrarion transition in sumatra, indonesia. *Journal of Legal Pluralism*, 55:65–122, 2007.

J.F. McCarthy and R.A. Cramb. Policy narratives, landholder engagement, and oil palm expansion on the malaysian and indonesian frontiers. *The Geographic Journal*, 175(2): 112–123, 2009.

D. McFadden. Conditional logit analysis of qualitative choice behavior. In P. Zarembka, editor, *Frontiers in Econometrics.* Academic Press, New York, 1973.

R. Mendelsohn. Property rights and deforestation. *Oxford Economic Papers, New series*, 46:750–756, 1994.

R. Musgrave. Devolution, grants, and fiscal competition. *Journal of Economic Perspectives*, 11(4):65–72, 1997.

G.C. Nelson and D. Hellerstein. Do roads cause deforestation? using satellite images in econometric analysis of land use. *American Journal of Agricultural Economics*, 79(80-88): 277–282, 1997.

W.E. Oates and R. Schwab. The theory of regulatory federalism: The case of environmental management. In W.E. Oates, editor, *The economics of environmental regulation.* Edward Elgar, Cheltenham, UK, 1996.

E. Ostrom. *Governing the commons: The evolution of institutions for collective action.* Cambridge University Press., New York, 1990.

T. Otsuki, I. Hardie, and E.J. Reis. The implication of property rights for joint agriculture timber productivity in the brazilian amazon. *Environment and Development Economics*, 7(2):299–324, 2002.

A.S.F. Pfaff. What drives deforestation in the brazilian amazon? evidence from satellite and socioeconomic data. *Journal of Environmental Economics and Management*, 37(1):26–43, 1999.

S.L. Pimm and P. Raven. Biodiversity: Extinction by numbers. *Nature*, 403:843–845, 2000.

R.S. Pindyck. Climate change policy: What do the models tell us? *Journal of Economic Literature*, 51(3):860–872, 2013.

L. Potter. Tree planting in indonesia: trends, impacts, and directions. *CIFOR Ocassional Paper*, 1999.

Lesley Potter and Simon Badcock. *The Effects of Indonesia's Decentralisation on Forests and Estate Crops in Riau Province: Case Studies of the Original Districts of Kampar and Indragiri Hulu*. CIFOR, Bogor, Indonesia, 2001.

Jeffrey S. Racine, Qi Li, and Xi Zhu. Kernel estimation of multivariate conditional distributions. *Annals of Economics and Finance*, 5:211–235, 2004.

J.C. Ribot, A. Agrawal, and A.M. Larson. Recentralising while decentralising: How national governments re-appropriate forest resources. *World Development*, 34:1864–1886, 2006.

Paul Rosenbaum. From association to causation in observational studies: The role of tests of strongly ignorable treatment assignment. *Journal of the American Statistical Association*, 79(385):41–48, 1984.

Paul Rosenbaum. The role of second control group in an observational study. *Statistical Science*, 2(3):211–225, 1987.

P.R. Rosenbaum and D.B. Rubin. Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *The American Statistician*, 39 (1):33–38, 1985.

D.B. Rubin. Using propensity scores to help design observational studies: application to the tobacco litigation. *Health Services and Outcomes Research Methodology*, 2(3):169–188, 2001.

T.K. Rudel, R. Defries, G.P. Asner, and W.F. Laurance. Changing drivers of deforestation and new opportunities for conservation. *Conservation Biology*, 23(6):1396–1405, 2009.

B. Setiabudi. *Analysis of 1990-1995-2000-2005-2007 Land use dynamics in Riau province and its surrounding areas, Sumatra, Indonesia.* WWF Indonesia, 2008.

Philip Shaw, Marina-Selini Katsaiti, and Brandon Pecoraro. On the determinants of educational corruption: the case of ukraine. *Contemporary Economic Policy*, 33(4):698–715, October 2015.

E.A. Stuart. Matching methods for causal inference: A review and a look forward. *Statistical science: a review journal of the Institute of Mathematical Statistics*, 25(1):1–21, 2010.

A. Suwarno, L. Hein, and E. Sumarga. Governance, decentralisation and deforestation: The case of central kalimantan province, indonesia. *Quarterly Journal of International Agriculture*, 54(1):77–100, 2015.

S. Suyanto. Underlying cause of fire: Different form of land tenure conflicts in sumatra. *Mitigation and Adaptation Strategies for Global Change*, 12:67–74, 2007.

S. Suyanto, G. Applegate, R.P. Permana, N. Khususiyah, and I. Kurniawan. The role of fire in changing land use and livelihoods in riau-sumatra. *Ecology and Society*, 9(1):15, 2004.

C. Tiebout. A pure theory of local expenditures. *Journal of Political Economy*, 64:416–424, 1956.

G.R. van der Werf, D.C. Morton, R.S. DeFries, J.G.J Olivier, P.S. Kasibhatla, R.B. Jackson, G.J. Collatz, and J.T. Randerson. Co2 emissions from forest loss. *Nature Geoscience*, 2: 737–738, 2009.

C. Vance and J. Geoghegan. Temporal and spatial modeling of tropical deforestation: A survival analysis linking satellite and household survey data. *Agricultural Economics*, 27: 317–332, 2002.

R.S. Wayhunto and H. Subagjo. Maps of area of peatland distribution and carbon content in sumatera, 1990-2002. pages Wetlands International–Indonesia Programme and Wildlife Habitat Canada (WHC), Bogor, Indonesia., 2003.

G. Williams-Linera, V. Dominguez-Gastelu, and M.E. Garcia-Zurita. Microenvironment and floristics of dfferent edges in a fragmented tropical rainforest. *Conservation Biology*, 12: 1091–1102, 1998.

Table 1: Characteristics of Randomly-Selected Pixels

	2008 Plantations		2008 Smallholders		All Other Pixels	
	Non-subdivided	Subdivided	Non-subdivided	Subdivided	Non-subdivided	Subdivided
Elevation (10s m)	12.75	7.71***	11.69	8.28***	13.69	7.20***
	(0.52)	(0.29)	(0.78)	(0.54)	(0.20)	(0.12)
Slope (percent)	4.07	2.74*	4.11	2.18***	5.56	2.31***
	(0.24)	(0.13)	(0.36)	(0.25)	(0.09)	(0.05)
Soil Depth (mm)	3416.60	3189.44	1386.67	1361.36	2046.70	3131.91***
	(105.98)	(59.62)	(159.52)	(110.61)	(40.43)	(24.06)
Precipitation (m)	2449.55	2453.84	2621.18	2631.74	2500.55	2433.19***
	(7.16)	(4.03)	(10.52)	(7.30)	(2.68)	(1.59)
Forest Edge Distance (km)	0.77	2.23***	0.27	0.40***	0.99	1.33***
	(0.09)	(0.05)	(0.14)	(0.10)	(0.04)	(0.02)
Road Distance (km)	7.52	5.68***	2.75	2.69	5.44	4.35***
	(0.23)	(0.13)	(0.78)	(0.25)	(0.09)	(0.05)
Settlement Distance (km)	19.60	19.07	14.28	16.41**	16.39	16.92**
	(0.46)	(0.26)	(0.70)	(0.49)	(0.15)	(0.11)
Town Distance (km)	56.27	57.32***	77.19	79.98**	71.88	56.20***
	(1.64)	(0.92)	(2.47)	(1.71)	(0.63)	(0.37)
Protected Area	0.06	0.23***	0.09	0.09	0.11	0.18***
	(0.02)	(0.01)	(0.03)	(0.02)	(0.01)	(0.00)
Observations	400	1,264	175	364	2,683	7,564

Notes: Mean values for the various pixel characteristics are reported. The standard deviation for each variable is reported in parentheses. One, two, and three stars indicate 10 percent, 5 percent, and 1 percent significance levels, respectively.

Table 2: P-values under different null models:

P-values under H_0:	
H_0: Logistic Model	
Subdivided	Non-subdivided
0	0
H_0: Multinomial Logistic Model	
Subdivided	Non-subdivided
0	0
H_0: SAR LPM	
Subdivided	Non-subdivided
.005	.0075

Notes: P-values under $H_0 : Pr[\phi(R = k|X = x) = \phi(R = k|X = x, \beta)] = 1$ for some $\beta \in \Omega$.

Table 3: Nonparametric Results for Determinants of Smallholder Forest Conversion

Independent Variable	$\hat{\theta}_{\mathbf{SD}}$	$\hat{\theta}_{\mathbf{NSD}}$	$\hat{\theta}_{\mathbf{SD}} - \hat{\theta}_{\mathbf{NSD}}$
Elevation (10s m)	-.00037***	0	-.00037***
	(.000081)	(0)	(.000081)
Slope	0	-.00017**	.00017**
	(0)	(.000059)	(.000059)
Square-root Soil Depth	0	-.00000024***	.00000024***
	(0)	(.000000073)	(.000000073)
Precipitation	.000047**	.00026***	-.00021***
	(.000026)	(.000055)	(.000059)
Forest Edge Distance	-.0037***	-.021***	.017***
	(.0011)	(.0045)	(.0046)
Road Distance	-.0011	-.0053***	.0042
	(.0015)	(.0018)	(.0023)
Settlement Distance	.00027	-.0018	.0021
	(.00035)	(.0016)	(.0016)
Town Distance	.00055	.00013	.00042
	(.00073)	(.00032)	(.0008)
Protected Area	-.0014***	-.024***	.022***
	(.00035)	(.0068)	(.0069)
Province Indicators	Yes	Yes	Yes
District Indicators	Yes	Yes	Yes
Observations	9,192	3,258	

Notes: The binary dependent variable takes on a value of 1 if the pixel is converted from forest to smallholder production (mixed agriculture, palm oil, rubber, with plasma oil palm production excluded) between 2000 and 2008. The unit of observation is a 30-meter by 30-meter pixel. Average marginal effects, based on evaluations of each $\hat{\phi}$ function on all $13,025$ pixels, reported. 2 km clustered, bootstrapped standard errors are reported in parentheses. The difference column reports $\hat{\theta}_{SD} - \hat{\theta}_{NSD}$ with the bootstrapped standard errors in parentheses. One, two, and three stars indicate 10 percent, 5 percent, and 1 percent significance levels, respectively.

Table 4: Impact of a one standard deviation change in a X variable on conversion probability relative to σ_y and its relative impact.

Variable	**Impact Subdivided**	**Impact Non-subdivided**	**Relative Impact**
Forest Edge Distance (km)	0.0149***	0.085***	5.68***
Road Distance (km)	0.0114	0.055***	4.82
Protected Area	0.0011***	0.019***	17.14***

Notes: The impact is defined as $I_i = \left|\frac{\sigma_x \hat{\theta}_i}{\sigma_y}\right|$ for $i = SD, NSD$ with the relative impact given by $RI = \frac{I_{NSD}}{I_{SD}}$.

Table 5: Impact of a one standard deviation change in a X variable on conversion probability relative to unconditional conversion probability (μ_y) and its relative impact.

Variable	**Impact Subdivided**	**Impact Non-subdivided**	**Relative Impact**
Forest Edge Distance (km)	0.176***	0.736***	4.19***
Road Distance (km)	0.134	0.477***	3.55
Protected Area	0.013***	0.164***	12.64***

Notes: The impact is defined as $I_i = \left|\frac{\sigma_x \hat{\theta}_i}{\mu_y}\right|$ for $i = SD, NSD$ with the relative impact given by $RI = \frac{I_{NSD}}{I_{SD}}$.

Table 6: Nonparametric Multivariate Results for Determinants of Smallholder Forest Conversion

	$\hat{\theta}_{\mathbf{SD}}$				$\hat{\theta}_{\mathbf{NSD}}$				$\hat{\theta}_{\mathbf{SD}} - \hat{\theta}_{\mathbf{NSD}}$			
Independent Variable	Mixed	Oil	Rubber	Plasma	Mixed	Oil	Rubber	Plasma	Mixed	Oil	Rubber	Plasma
Elevation (10s m)	.00002	-.000013	-.00013***	-.0000082	.00088***	-.0011***	.000079	.00015	-.00086***	.001***	-.00021	-.00016
	(.000028)	(.000012)	(.000029)	(.000015)	(.00028)	(.00025)	(.00012)	(.00011)	(.00028)	(.00025)	(.00012)	(.00011)
Slope	-.000045**	-.000025*	-.000072*	.00003	0	0	0	0	-.000045**	-.000025*	-.000072*	.00003
	(.000018)	(.000014)	(.000029)	(.000021)	(0)	(0)	(0)	(0)	(.000018)	(.000014)	(.000029)	(.000021)
Square-root Soil Depth	-.000000043**	.00000006	-.000000088**	.000000021**	-.00000018*	-.00000014	-.00000011	.00000005	.00000014	.0000002	.000000021	-.000000028
	(.000000022)	(.000000023)	(.000000032)	(.000000023)	(.000000091)	(.00000019)	(.000000074)	(.000000094)	(.000000092)	(.00000019)	(.000000081)	(.000000099)
Precipitation	-.000023	.000026*	.000036**	.000022**	0	0	0	0	-.000023	.000026*	.000036**	.000022**
	(.000022)	(.000019)	(.000021)	(.000015)	(0)	(0)	(0)	(0)	(.000022)	(.000019)	(.000021)	(.000015)
Forest Edge Distance	-.00062***	-.00053**	-.0021***	-.00023	-.0045***	-.0089***	-.0011	-.00014	.0039***	.0084***	-.0011	-.000083
	(.00024)	(.00034)	(.00083)	(.00042)	(.0012)	(.0018)	(.0012)	(.0013)	(0.0013)	(.0019)	(.0015)	(.0014)
Road Distance	.000024	.00094	-.0021*	-.00023	-.00028	-.00058	-.0013***	.00076**	.0003	.0015	-.00076	-.00098
	(.00062)	(.00067)	(.0012)	(.00043)	(.00062)	(.00048)	(0.0005)	(.00035)	(.00085)	(.00086)	(.0013)	(.00058)
Settlement Distance	-.000049	.00011	-.000018	.00015	-.00018	.00064	.002**	.00028	.00013	-.00053	-.0021**	-.00014
	(.00017)	(.00017)	(.00026)	(.00011)	(.00056)	(.00099)	(.00075)	(.0004)	(.00059)	(.001)	(.00079)	(.00042)
Town Distance	.00017	-.00043	.00038	-.00023	.00033	.0014	-.00017	-.0015***	-.00016	-.0018	.00055	.0013*
	(.00027)	(.00044)	(.00058)	(.00032)	(.00068)	(.00084)	(.00043)	(.00056)	(.00074)	(.00094)	(.00071)	(.00063)
Protected Area	.00012	-.00063***	-.00032*	.00009	-.0012**	-.011*	.0034	-.00021***	.0013**	.011*	-.0037	.0003
	(.00011)	(0.00021731)	(.00016)	(.000087)	(.00048)	(.0053)	(.0049)	(.00039)	(.00049)	(.0053)	(0.0049)	(.00039)
Province Indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,192	9,192	9,192	9,192	3,258	3,258	3,258	3258				

Notes: The dependent variable takes on a value of 1 if the pixel is converted from forest to mixed agriculture, 2 if the pixel is converted from forest to palm oil, 3 if the pixel is converted from forest to rubber, and 4 if the pixel is converted from forest to plasma oil palm between 2000 and 2008. The unit of observation is a 30-meter by 30-meter pixel. Average marginal effects, based on evaluations of each $\hat{\phi}$ function on all $13,025$ pixels, reported. 2 km clustered, bootstrapped standard errors are reported in parentheses. The difference columns report $\hat{\theta}_{SD} - \hat{\theta}_{NSD}$ with the bootstrapped standard errors in parentheses. One, two, and three stars indicate 10 percent, 5 percent, and 1 percent significance levels, respectively.

9 Appendix

9.1 Nonparametric methods

This section provides additional detail about the nonparametric approach employed in our empirical analysis. The most important consideration when estimating a nonparametric model is the choice of bandwidth parameters γ_1 and γ_2. The likelihood cross-validation method is used to calculate the bandwidths. This approach minimizes the following expression:

$$L = -\sum_{j=1}^{n} ln\hat{\phi}_{-j}(R_j|X_j) \tag{15}$$

where $\hat{\phi}_{-j}$ is the leave-one-out estimator of the conditional density. As noted by Hall (1987a) and Hall (1987b), using likelihood cross-validation can produce bandwidths that oversmooth the data in the presence of fat-tailed distributions. This outcome could potentially lead to inconsistent estimates for $\phi(k, x)$.[18] An alternative to likelihood cross-validation is least squares cross-validation, which is shown to asymptotically smooth out irrelevant regressors in Hall et al. (2004). We are modeling conditional probability functions, which have a bounded range, ruling out fat-tails, so we employ likelihood cross-validation.

Racine et al. (2004) shows that the estimator presented in equation 8 performs very well in Monte Carlo simulations under a variety of data-generating processes, including a probit and multinomial probit specification. The authors also show that their estimator dominates misspecified parametric estimators and only exhibits a slight loss of efficiency when compared to correctly specified parametric models. Shaw et al. (2015) shows that the nonparametric estimator is also robust to endogeneity generated under a standard bivariate or simultaneous probit population model. Given the similarity between probit and logit models, we expect similarly strong performance from this estimator when applied to logit models as well.

Although the nonparametric estimation of the conditional density is informative, we are more interested in presenting the average derivatives for the continuous variables and the average differences for the discrete variables. If X_1^c is the continuous variable of interest, then the population average derivative can be expressed as:

$$\theta = E\Big[\frac{\partial P(R_j = k|X_1^c, X_2^c, ..., X_{r_1}^c, X^d)}{\partial X_1^c}\Big] = \int_{X_1 \in S_1^c}\int_{X_2 \in S_2^c} \cdots \int_{X_{r_1} \in S_{r_1}^c} \sum_{X^d \in S_{r_2}^d} \frac{\partial \phi(X_1^c, X_2^c, ..., X_{r_1}^c, X^d)}{\partial X_1^c} \times f(X_1^c, X_2^c, ..., X_{r_1}^c, X^d) dX_1 dX_2 \ldots dX_{r_1} \tag{16}$$

where $f(X_1^c, X_2^c, ..., X_{r_1}^c, X^d)$ is the joint density function for all of the continuous variables X^c and the discrete variables X^d with X_1^c being the variable of interest. The main focus on estimating the average derivative and the average difference is due to the fact that these estimators are easy to compare to existing parametric estimates and they have a much faster rate of convergence as compared to pointwise nonparametric estimates. Härdle and Stoker (1989) and Coppejans and Sieg (2005) show that common average derivative and difference estimators exhibit root-N convergence even when the pointwise derivatives converge at a much slower rate.

To estimate θ, the conditional probability is first estimated and then a central-difference formula is employed for continuous variables. The estimator can be expressed as follows:

$$\hat{\theta} = \frac{1}{n}\sum_{j=1}^{n}\Big[\frac{\hat{\phi}(k|X_{j1}^{c}+\tau, X_{j2}^{c}, ..., X_{jr_1}^{c}, X_{j}^{d}) - \hat{\phi}(k|X_{j1}^{c}-\tau, X_{j2}^{c}, ..., X_{jr_1}^{c}, X_{j}^{d})}{2\tau}\Big] \tag{17}$$

where τ is the chosen approximation error.[19] For discrete variables, the average difference estimator can be constructed as follows:

$$\hat{\theta} = \frac{1}{n}\sum_{j=1}^{n}\Big[\hat{\phi}(k|X_{j1}^{c}, X_{j2}^{c}, ..., X_{jr_1}^{c}, X^{d}=c_1) - \hat{\phi}(k|X_{j1}^{c}, X_{j2}^{c}, ..., X_{jr_1}^{c}, X^{d}=c_2)\Big] \tag{18}$$

where c_1 and c_2 are discrete values of interest. If X_d is a zero-one variable then we might have $c_1 = 0$ and $c_2 = 1$.

9.2 Robustness Checks

Table 7: Nonparametric Results for Determinants of Smallholder Forest Conversion Within 5 km of Border

Independent Variable	$\hat{\theta}_{\mathbf{SD}}$	$\hat{\theta}_{\mathbf{NSD}}$	$\hat{\theta}_{\mathbf{SD}} - \hat{\theta}_{\mathbf{NSD}}$
Elevation (10s m)	-.000091	-.0063***	.0062***
	(.00029)	(.0024)	(.0024)
Slope	-.0005	.00015	-.00064*
	(.00036)	(.00015)	(.00039)
Square-root Soil Depth	0	0	0
	(0)	(0)	(0)
Precipitation	0	-.000075	.000075
	(0)	(.00012)	(.00012)
Forest Edge Distance	0	-.007*	.007*
	(0)	(.0036)	(.0036)
Road Distance	.0018	-.0029***	.0047**
	(.0017)	(.00069)	(.0019)
Settlement Distance	-.0053*	-.0014**	-.0039
	(.0029)	(.00067)	(.003)
Town Distance	.002**	-.0002**	.0022**
	(.0014)	(.0001)	(.0014)
Protected Area	0	-.051***	.051***
	(0)	(.0087)	(.0087)
Province Indicators	Yes	Yes	Yes
District Indicators	No	No	No
Observations	847	594	

Notes: The binary dependent variable takes on a value of 1 if the pixel is converted from forest to smallholder production (mixed agriculture, palm oil, rubber, with plasma oil palm production excluded) between 2000 and 2008. The unit of observation is a 30-meter by 30-meter pixel. Average marginal effects, based on evaluations of each $\hat{\phi}$ function on all $13,025$ pixels, reported. 1 km clustered, bootstrapped standard errors are reported in parentheses. The difference column reports $\hat{\theta}_{SD} - \hat{\theta}_{NSD}$ with the bootstrapped standard errors in parentheses. One, two, and three stars indicate 10 percent, 5 percent, and 1 percent significance levels, respectively.

Table 8: Test Results for Group Unconfoundedness by km Grouping

km	$\hat{\tau}$	km	$\hat{\tau}$
1	0.0096	11	-0.032
	[-0.061, 0.045]		[-0.051, -0.00078]
2	-0.0078	12	-0.015
	[-0.027, 0.028]		[-0.036, 0.013]
3	0.0038	13	-0.021
	[-0.022, 0.028]		[-0.042, 0.0083]
4	0.0019	14	-0.02
	[-0.021, 0.031]		[-0.044, 0.0071]
5	-0.036	15	-0.018
	[-0.099, 0.02]		[-0.037, 0.009]
6	-0.031	16	-0.025
	[-0.091, 0.013]		[-0.045, 0.0014]
7	-0.037	17	-0.025
	[-0.097, 0.0052]		[-0.044, 0.0012]
8	-0.029	18	-0.017
	[-0.05, -0.00003]		[-0.052, 0.0068]
9	-0.027	19	-0.03
	[-0.042, 0.0044]		[-0.065, 0.0027]
10	-0.022	20	-0.031
	[-0.045, 0.0068]		[-0.065, 0.0019]

Notes: The binary dependent variable takes on a value of 1 if the pixel is converted from forest to smallholder production (mixed agriculture, palm oil, rubber, with plasma oil palm production excluded) between 2000 and 2008. The unit of observation is a 30-meter by 30-meter pixel. The observed difference between each group is reported as $\hat{\tau}$ along with the 95% confidence interval in brackets below the observed difference.

Table 9: Normalized Differences

	Full Sample			Within 5 km of Border		
	Subdivided	Non-Subdivided	Normalized Difference	Subdivided	Non-Subdivided	Normalized Difference
Elevation	8.47	13.47	0.284	14.09	17.23	0.166
	(9.64)	(14.73)		(12.50)	(14.31)	
Slope	2.70	5.31	0.334	4.25	6.66	0.271
	(4.21)	(6.58)		(5.18)	(7.27)	
Soil Depth	2924.94	2174.42	-0.254	2464.04	2010.31	-0.155
	(2297.23)	(1862.10)		(2200.73)	(1923.94)	
Precipitation	2459.22	2500.62	0.191	2487.03	2484.97	-0.009
	(154.55)	(151.79)		(173.58)	(151.91)	
Forest Edge Distance (Km)	1.43	0.92	-0.211	1.29	1.04	-0.128
	(2.03)	(1.25)		(1.54)	(1.18)	
Road Distance (Km)	4.49	5.55	0.147	4.88	5.02	0.02
	(4.37)	(5.78)		(4.56)	(4.98)	
Town Distance (Km)	58.71	70.24	0.210	16.69	15.71	-0.081
	(26.92)	(47.70)		(8.75)	(8.39)	
Settlement Distance (Km)	17.46	16.66	-0.062	55.19	53.35	-0.044
	(9.53)	(8.77)		(33.20)	(25.62)	
Protected Area	0.172	0.103	-0.141	0.28	0.23	-0.077
	(0.31)	(0.38)		(0.45)	(0.42)	

9.3 Parametric results

Table 10: Logit Results for Determinants of Smallholder Forest Conversion

Independent Variable	$\hat{\theta}_{\mathbf{SD}}$	$\hat{\theta}_{\mathbf{NSD}}$	$\hat{\theta}_{\mathbf{SD}} - \hat{\theta}_{\mathbf{NSD}}$
Elevation (10s m)	-.0033***	-.0011***	-.0023**
	(.001)	(.0004)	(.001)
Slope	-.0021	-.0023***	.00021
	(.0014)	(.00093)	(.0016)
Square-root Soil Depth	-.000018***	-.0000048	-.000013*
	(.0000047)	(.0000053)	(.0000072)
Precipitation	.00022***	.000041***	.00018**
	(.000043)	(.00001)	(.000044)
Forest Edge Distance	-.046***	-.044***	-.0019
	(.0072)	(.011)	(.013)
Road Distance	.0022	-.0023**	.0046**
	(.0016)	(.0014)	(.0022)
Settlement Distance	.00071	-.00039	.0011
	(.0005)	(.00065)	(.00082)
Town Distance	.00033*	-.00027*	.00059**
	(.00019)	(.00015)	(.00024)
Protected Area	-.042***	-.0042	-.038***
	(.0057)	(.012)	(.014)
Province Indicators	Yes	Yes	Yes
District Indicators	Yes	Yes	Yes
Observations	9,192	3,258	

Notes: The binary dependent variable takes on a value of 1 if the pixel is converted from forest to smallholder production (mixed agriculture, palm oil, rubber, with plasma oil palm production excluded) between 2000 and 2008. The unit of observation is a 30-meter by 30-meter pixel. Average marginal effects, based on evaluations of each $\hat{\phi}$ function on all $13,025$ pixels, reported. 2 km clustered, bootstrapped standard errors are reported in parentheses. The difference column reports $\hat{\theta}_{SD} - \hat{\theta}_{NSD}$ with the bootstrapped standard errors in parentheses. One, two, and three stars indicate 10 percent, 5 percent, and 1 percent significance levels, respectively.

Table 11: Multinomial Logit Results for Determinants of Smallholder Forest Conversion

	$\hat{\theta}_{\mathbf{SD}}$				$\hat{\theta}_{\mathbf{NSD}}$				$\hat{\theta}_{\mathbf{SD}} - \hat{\theta}_{\mathbf{NSD}}$			
Independent Variable	Mixed	Oil	Rubber	Plasma	Mixed	Oil	Rubber	Plasma	Mixed	Oil	Rubber	Plasma
Elevation (10s m)	-.000083	-.0028***	-.00031	-.00034	-.001***	-.0011***	.00002	.000059	.00091**	-.0016*	-.00033	-.0004
	(.00026)	(.00091)	(.00045)	(.00032)	(.00033)	(.00061)	(.000075)	(.00022)	(.00042)	(.0011)	(.00045)	(.00037)
Slope	-.00054	-.0011	-.0011	.00037	-.0000052	-.0022**	-.00038***	-.00024	-.00054	.0011	-.00074	.00061
	(.00037)	(.0011)	(.00085)	(.00042)	(.0007)	(.0013)	(.0002)	(.00043)	(.00078)	(.0018)	(.00086)	(.00063)
Square-root Soil Depth	-.0000035***	-.0000039	-.000006**	.0000019	-.0000042*	.0000026	-.0000052*	-.00000032	.00000072	-.0000064	-.00000079	.0000022
	(.000001)	(.0000049)	(.0000034)	(.0000015)	(.0000042)	(.0000041)	(.0000032)	(.0000011)	(.0000044)	(.0000064)	(.0000047)	(.0000019)
Precipitation	-.000014	.00029***	.000048*	.000098***	.000011*	.000011**	.0000041*	-.000012***	-.000025*	.00028***	.000042	.00011***
	(.00001)	(.000042)	(.00003)	(.000023)	(.000007)	(.0000084)	(.0000024)	(.0000057)	(.000013)	(.000044)	(.00003)	(.000024)
Forest Edge Distance	-.0072***	-.0084***	-.03***	-.0049**	-.016***	-.025**	-.005***	-.0097***	.0082	.017**	-.025***	.0048
	(.003)	(.0033)	(.0073)	(.0025)	(.0082)	(.028)	(.0025)	(.0076)	(.0087)	(.028)	(.0079)	(.008)
Road Distance	-.00067*	.00083	.0017	.0006	-.0027***	-.00094	.000047	-.0015***	.0021	.0017	.0016	.0021**
	(.00038)	(.0011)	(.0014)	(.00052)	(.0024)	(.0026)	(.00034)	(.00082)	(.0024)	(.0028)	(.0014)	(.00099)
Settlement Distance	-.00028***	.0014***	-.00055	-.00089***	-.0013***	.00077	-.000057	.000048	.00099**	.00066	-.00049	-.00094***
	(.00013)	(.00036)	(.00041)	(.00032)	(.0005)	(.0009)	(.00017)	(.00029)	(.00052)	(.00097)	(.00044)	(.00044)
Town Distance	.000085*	-.00035**	.00034***	-.00025***	.00013	-.00024	.000018	-.000072	-.000041	-.00011	.00032***	-.00018
	(.000061)	(.00014)	(.00012)	(.000082)	(.000098)	(.00013)	(.000042)	(.000069)	(.00012)	(.00019)	(.00013)	(.00011)
Protected Area	.003	-.027***	-.017***	.0053	.00012	-.0075	.0011	-.0058***	.0029	-.019**	-.018***	.011**
	(.0049)	(.0042)	(.0038)	(.0073)	(.015)	(.055)	(.0035)	(.0023)	(.015)	(.055)	(.0052)	(.0076)
Province Indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,192	9,192	9,192	9,192	3,258	3,258	3,258	3,258				

Notes: The dependent variable takes on a value of 1 if the pixel is converted from forest to mixed agriculture, 2 if the pixel is converted from forest to palm oil, 3 if the pixel is converted from forest to rubber, and 4 if the pixel is converted from forest to plasma oil palm between 2000 and 2008. The unit of observation is a 30-meter by 30-meter pixel. Average marginal effects, based on evaluations of each $\hat{\phi}$ function on all 13,025 pixels, reported. 2 km clustered, bootstrapped standard errors are reported in parentheses. The difference columns report $\hat{\theta}_{SD} - \hat{\theta}_{NSD}$ with the bootstrapped standard errors in parentheses. One, two, and three stars indicate 10 percent, 5 percent, and 1 percent significance levels, respectively.

Table 12: SAR LPM ($k = 2$) Results for Determinants of Smallholder Forest Conversion

Independent Variable	$\hat{\theta}_{\mathbf{SD}}$	$\hat{\theta}_{\mathbf{NSD}}$	$\hat{\theta}_{\mathbf{SD}} - \hat{\theta}_{\mathbf{NSD}}$
Elevation (10s m)	-.0018***	-.0018***	.000042
	(.00063)	(.00052)	(.00082)
Slope	-.00048	-.0035***	.003**
	(.00077)	(.00089)	(.0012)
Square-root Soil Depth	-.0000033***	-.0000006	-.0000027
	(.0000011)	(.0000029)	(.0000031)
Precipitation	.00017***	.00017***	.0000057
	(.000047)	(.000051)	(.000069)
Forest Edge Distance	-.0053***	-.0075**	.0022
	(.0016)	(.0033)	(.0037)
Road Distance	.0019***	.00014	.0017
	(.0007)	(.00091)	(.0012)
Settlement Distance	.00019	-.00056	.00074
	(.00026)	(.00051)	(.00057)
Town Distance	-.00019**	-.00027	(.000076)
	(.00009)	(.00017)	(.00019)
Protected Area	-.037***	.025*	-.062
	(.01)	(.014)	(.017)
$\hat{\rho}$	0.052	.32**	-0.26
	(.23)	(.13)	(.26)
Province Indicators	Yes	Yes	Yes
District Indicators	Yes	Yes	Yes
Observations	9,192	3,258	

Notes: The binary dependent variable takes on a value of 1 if the pixel is converted from forest to smallholder production (mixed agriculture, palm oil, rubber, with plasma oil palm production excluded) between 2000 and 2008. The unit of observation is a 30-meter by 30-meter pixel. The reported coefficients are based on evaluations of each $\hat{\phi}$ function on all $13,025$ pixels. Asymptotic standard errors are reported in parentheses. The difference column reports $\hat{\theta}_{SD} - \hat{\theta}_{NSD}$ with the bootstrapped standard errors in parentheses. One, two, and three stars indicate 10 percent, 5 percent, and 1 percent significance levels, respectively.

9.4 Bandwidth selection

Table 13: Optimal bandwidths for binary and multinomial nonparametric models.

	Binary		Multinomial	
Variable	**Subdivided**	**Non-subdivided**	**Subdivided**	**Non-subdivided**
Conversion	0.003417204	0.006317783	0.004966546	0.00861
Elevation (10s m)	5.88E+00	25020140	8.437085	4.409206
Slope (percent)	1.49E+07	11.62745	7.197138	5320717
Square-root Soil Depth (mm)	5186197231	4610.643	4482.164	2547.73
Precipitation (km)	27.18313	29.88205	21.99456	111721695
Forest Edge Distance (km)	0.5643313	0.3404008	0.6046659	0.4188318
Road Distance (km)	0.5918519	0.9241033	0.6263591	1.532027
Settlement Distance (km)	2.161359	0.8394453	1.957415	1.075925
Town Distance (km)	0.9639768	5.252566	0.8906773	1.064054

Notes: The bandwidths are chosen for the binary nonparametric model excluding plasma production and the multinomial nonparametric model including plasma production. Bandwidths for the other models under consideration are available upon request.

Notes

[1]Fisman (2001) uses an event-study approach to explore the value of political connections to Indonesian firms from 1995-1997, finding that political connections may be responsible for a large-percentage of a well-connected firm's value.

[2]Oil palm plantations developed a particular means of incorporating smallholders into plantation production systems through the nuclear estate scheme (McCarthy and Cramb, 2009), which follows a protocol supported by the World Bank and other sources of capital (Little and Watts, 1994). Under this arrangement, plantations gain access to land that was under the *de facto* control of local landholders and allow these individuals to manage small areas of oil palm that had been planted by the plantation manager with an understanding that the smallholders would sell their output solely to their affiliated plantation (referred to as plasma operations) (Levang, 2003). These arrangements subject smallholders to monopsony conditions and the plantations tend to operate with limited transparency, leading to smaller than expected payments and a lack of clarity about when, if ever, the land would be returned to smallholder control (McCarthy, 2007; Potter, 1999).

[3]The choice of forest conversion is a dynamic problem; however, we can explore the issue in a static context by making an assumption about the decision rule used to determine the timing of forest conversion. If we assume that the deforestation choice (i.e., whether or not to deforest a patch at time t conditional on the plot being forested at this point) can be reduced to comparing the benefits from having the plot remain in forest relative to those of deforestation in time $t+1$, then the conversion choice can be studied as a static problem.

[4]There is no evidence to motivate a specific relationship between yield and forest-edge distance. We proceed by assuming that the relationship between profit and forest-edge distance is driven by the relationship between cost and distance from the forest edge (namely, $\pi'(d) \leq 0$).

[5]This data is available for download from (http://www.fao.org/geonetwork/srv/en/main.home)

[6]These cells include $4,444$ 30-meter by 30-meter pixels and cover an area of 400 hectares, which is 20 times larger than the maximum smallholder production system of 20 hectares.

[7]Estimating the impact of district subdivision may be complicated by the possibility that forests in these districts have characteristics that make conversion undesirable. Table 9 in the appendix displays the normalized differences, the difference in means between subdivided and non-subdivided districts divided by the square root of the sum of the variances across both district types (Rosenbaum and Rubin, 1985; Stuart, 2010), of our observable characteristics, showing that they are quite similar in both the full sample and the sample of pixels within five kilometers of a district with the other subdivision status (Imbens and Wooldridge, 2009; Rubin, 2001).

[8]All code was written in Matlab and is available upon request. We would also direct the reader to the NP package in R as described in Hayfield and Racine (2008).

[9]The results of each of the inconsistent parametric models are presented in tables 10-12 in the appendix.

[10]The possibility that protected areas serve as a refuge from plantations when facing a high threat of plantation conversion could explain the heterogeneous effectiveness of protected areas in addressing issues of conservation and poverty that have been reported in the literature (e.g., Ferraro et al. (2011)).

[11]These results are depicted in table 7 in the appendix.

[12]Table 13 presents the optimal bandwidth for the various explanatory variables in the binary and multinomial analyses.

[13]There is a substantial amount of carbon stored in the above- and below-ground biomass of tropical forests that is released as CO_2 when forests are burned prior to agricultural production. Furthermore, some tropical forests are located on peat soil, which releases methane into the atmosphere when these areas are drained and burned prior to production. In addition to the global damages associated with the release of these gases, the inefficient conversion of tropical forests may lead to costs that are borne by the local populations through reduced provision of valuable ecosystem services. Several of the ecosystem services provided by tropical forests are lost with forest conversion, leading to reduced water quality (Douglas, 1996), increased and more damaging flooding events (Costa et al., 2003), changes in local climate regimes that might affect crop yield (Costa and Foley, 2000), as well as the reduction in habitat for endemic animal and plant species (Pimm and Raven, 2000).

[14]While the valuation of ecosystem services is theoretically straightforward, there are a number of practical challenges that make the implementation of these techniques difficult (Conte, 2013). Furthermore, mapping the provision of ecosystem services is a challenging, and data-intense task, even when efforts are made to describe the biophysical processes in accessible ways (Kareiva et al., 2011).

[15]Pindyck (2013) details the numerous challenges associated with accurate estimation of the SCC.

[16]These values are calculated using the average additional metric tons of carbon per hectare ($44.14), converting it to dry biomass (multiplying by 0.5), then converting it to metric tons of CO_2 (multiplying by 3.67) and finally multiplying it by the three different estimates of the SCC.

[17]Deininger and Minten (2002) finds no impact of property rights after controlling for biophysical factors.

[18]Given that our nonparametric estimates substantially outperform all of the alternative parametric models under consideration, loss of consistency is not a valid concern in our case, which differs meaningfully from the conditions explored in Hall (1987a) and Hall (1987b). See figures 9-11 for a graphical representation of relative performance.

[19]It is well known that truncation error for the central-difference approximation is $O(\tau^2)$. τ is chosen to be 1×10^{-12} which is smaller than the relative error due to rounding in floating point arithmetic.