Cease and Disperse: An empirical study of targeted conservation and its impact on the optimal development of resource pools

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Abstract

This paper examines the impact of the 2011 Indonesian moratorium on the spatial distribution of deforestation. We take advantage of the national border that splits the island of Borneo into Malaysia and Indonesia, and examine the composition of incremental deforestation. Specifically, we track the proportion of newly cleared areas that are in new clusters, rather than on the periphery of existing clusters. We findn that the moratorium reduced responsiveness of the creation of new clusters to relevant agricultural prices. However, we also find that the overall rate of deforestation increased, even after controlling for agricultural prices, suggesting that developers merely shifted deforestation to the periphery of existing clusters.

Deforestation accounts for 10-15% of annual carbon emissions, as much as the combined emissions from the global transportation sector. Any viable effort to mitigate climate change must address deforestation, especially in Indonesia and Brazil which made up over 40% of global deforestation in 2011. The forest sector, however, is a non-trivial component of tropical economies. In Indonesia, it is estimated that 4% of annual GDP and 5% of national employment are associated with forest clearing activity. There exist incentives at every level to convert standing forest to financially productive land. As part of a grand Coasian bargain, Norway pledged US$1 billion in aid to Indonesia, conditional on a significant reduction of its deforestation rate. The Indonesian government immediately announced its intention to stop issuing new permits for the exploitation of primary forest. The two-year moratorium on new concessions was enacted in May 2011.

In this paper, we evaluate the impact of the moratorium on the spatial distribution of deforestation in Indonesia, using the island of Borneo as our sample area. The theoretical support for this study comes directly from Weitzman's (1975) model of the optimal development of resource pools. Weitzman describes the optimal extraction rule for multiple resource pools with arbitrary extraction costs. His model can be reformulated and extended to model a land developer's choice to expand existing clusters of deforestation or to begin a new cluster. Hartwick, *et al.* (1986) extend the general resource pool model to an exhaustible, non-reproducible resource with significant set-up costs to develop a new deposit. The authors show that there exist conditions that would destroy the incentive to develop new clusters, given the return on extraction. The conditions surrounding the moratorium are in constant flux, creating conditions of high risk to investment and lowering expected return. The map of affected areas is, in fact, up for review every six months. We would expect that the moratorium on new concessions would therefore reduce the expected return to the new clusters of deforestation. The land may or may not be eligible for development, even after exploration costs are incurred. It is conceivable that the land may actually be *targeted* for re-zoning in the

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presence of rent-seeking, corrupt politicians.

Previous theoretical studies indicate that the development of new clusters should be reduced with the enactment of the moratorium. The intent of the moratorium, however, was to reduce overall deforestation, not just that which occurs in new clusters. Meyfroidt *et al.* (2010) show that narrowly defined conservation efforts will displace deforestation to other, unprotected areas. Busch (2011) reports that a significant portion of forest in existing concessions remains untouched, even as new clusters are developed. The modeling of this storage behavior will not be addressed in this study; but it is clear that these forests are not directly impacted by the moratorium, which only restricts clearing activity in new concessions. The marginal rate of technical substitution between the two types of clearing activity toward a final agricultural product is dependent on the fixed and marginal costs of extraction. The impact on the *overall* rate of clearing is therefore an empirical question.

Empirical studies of deforestation, and the optimal development of resource pools in general, have been limited by available data. Satellite data provides a new opportunity for an overhead and objective assessment of forest conversion. Still, these data have not been previously accessible, given constraints on computational facilities to process the very large data sets. Chomitz and Nelson (2011) and Burgess *et al.* (2012) have utilized remotely sensed data to assess the impact of protected areas and political cycles on the conversion of forests. Even these studies, however, have been severly limited by the spatial and temporal resolution of the data on land use change. We are able to overcome these constraints with an original data set on tropical deforestation at 500-meter, 16-day resolution from satellite imagery.

The paper is organized as follows: (1) A description of the regulatory framework behind the Indonesian moratorium, (2) A brief description of the remotely sensed data on deforestation, (3) A presentation of the empirical strategy and (4) the results of the impact evaluation. Finally, we (5) suggest possible implications of the study, and its importance in broader conservation policy design.

Regulatory background

The United Nations has proposed an offset scheme to reduce tropical deforestation, under the REDD (Reducing Emissions from Deforestation and Degradation) framework. The initial intent was to "support countries' efforts to ... transform their forest sectors so as to contribute to human well-being and meet climate change mitigation and adaptation aspirations ... through performance-based payments." This (paraphrased) mission statement is exceedingly vague; and prospects for a comprehensive and global REDD program have begun to dwindle. Instead, bilateral agreements under the REDD framework have begun to materialize, most notably through Norway's pledge to support Indonesia's pledge to reduce carbon emissions by 26% between 2010 and 2020. With 80% of Indonesian carbon emissions emanating from land use change, Norway has promised US$1 billion in aid, contingent on verified emissions reductions from forest conversion. The first stage of the partnership has been the two-year suspension of new concessions for natural forest conversion. The total area affected by the moratorium amounts to 64 million hectares, roughly twice the size of Great Britain.

There were three stages to the enactment of the moratorium. (1) Indonesia signed a letter of intent with Norway on May 29, 2010, pledging to halt new land conversion concessions in primary forest. (2) The moratorium was supposed to take effect in January 2011, but after significant argument between the government, industry, and environmental groups, the moratorium was not actually implemented (3) until May 2011. Still, the extent of the moratorium is far from settled; and, in fact, every six months a *new* map of the affected forests is released. Uncertainty surrounding the parameters of the moratorium is non-trivial, and likely has implications for the development of forested land. Many reports have surfaced about illegal land clearing operations after May 2011 and associated bribes, potentially harming the release of Norway's promised funds.

Data

The foundational data for this paper report deforestation for each 500-meter pixel and each 16-day interval between January 1, 2008 and September 23, 2012 for Indonesian and Malaysian Borneo. The algorithm to identify deforestation from satellite imagery is described in a forthcoming paper by Hammer, *et al.* (2012). Each pixel-interval is assigned a normalized measure of forest clearing activity, based on the spectral signals from NASA's Moderate Resolution Image Spectrometer (MODIS) sensor on the Terra satellite. A pixel is flagged for clearing activity if the measure registers above 0.50. Only pixels that are in Borneo and were forested in January 2000 are considered in the analysis.[1] The deforestation data therefore constitute a panel with The deforestation data constitute a panel with $N = 2,384,095$ pixels and $T = 109$ time intervals, a total of about 260 million records. By September 23, 2012, there were $207,578$ pixels flagged with forest clearing activity in Borneo, indicating that approximately 8.71% of the study area has been subject to clearing activity since February 2000.[2] For reference, only 29% of forested area in Indonesia remained untouched by forest clearing activity in 2010 from baseline area estimates in 1900.

The overall rate of deforestation in Malaysian and Indonesian Borneo is presented in Figure 1a. The time series indicates the number of pixels detected in each 16-day interval. The shaded regions indicate the three stages of the moratorium, noting that there may be a two-month lag in the detection of clearing activity. Within each interval, the identified pixels are categorized into one of two groups: (1) pixels on the periphery of previously cleared clusters of deforestation, and (2) pixels that constitute a new, emerging cluster. Consider, for example, the illustration in Figure 2. The black, unlabeled pixels represent an existing cluster, while the red, labeled pixels indicate newly cleared areas. The red pixels would be counted toward the measure in Figure 1a for the current interval. The five newly identified pixels are grouped according to their distance to the nearest, existing cluster. The clustering rule that is used throughout this paper would classify pixels **A**, **B**, and **C** into Group 1, and pixels **D** and **E** into Group 2. The pixels are clustered using a hierarchical clustering algorithm, with Euclidean distance cutoffs to create discrete clusters. The predominant cutoff in this paper is roughly 1km between pixel centroids, or $2 \times (\textit{pixel dimension})$. The results in this paper are robust to other buffer lengths. And, in fact, there are interesting patterns in the data that can be uncovered by examining the slight differences in the results based on various buffer lengths. The proportion of clearing activity in new clusters for each interval is plotted in Figure 1b. Specifically, the proportion is $P_t = G_{2t}/(G_{1t} + G_{2t})$, where G_{kt} indicates the number of pixels in Group $k \in \{1, 2\}$ during time interval t.

Let $\mathbb{E}(\pi_{it})$ be the expected profit on the conversion of pixel i. The profit is a function of agricultural prices, risk of expropriation, and cost structure of the pixel, which is in turn dependent on the physical characteristics of the land. The response of P_t to changes in $\mathbb{E}(\pi_{it})$ will depend on the relative profit functions of pixels in Groups 1 and 2, and cannot be determined *a priori*. We therefore utilize data on (1) the price palm oil, the main agricultural product in Borneo, shown in Figure 3; (2) physical characteristics of the land, derived from the Shuttle Radar Topography Mission (SRTM), shown in Figure 4; and (3) rainfall from the NOAA Precipitation Reconstruction over Land (PREC/L) data set, which provides a relatively coarse grid of precipitation meatures (0.5 degree resolution) at monthly intervals. The data are processed and aligned at different resolutions, and snapped to the MODIS grid. The resampling procedures will be described in a follow-up paper; but have significant effects, given that some of the data sets are at much higher spatial resolution, as seen in the zoomed image in Figure 5.

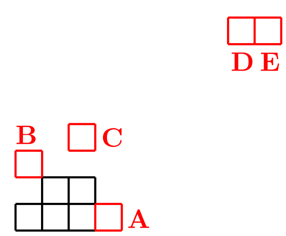
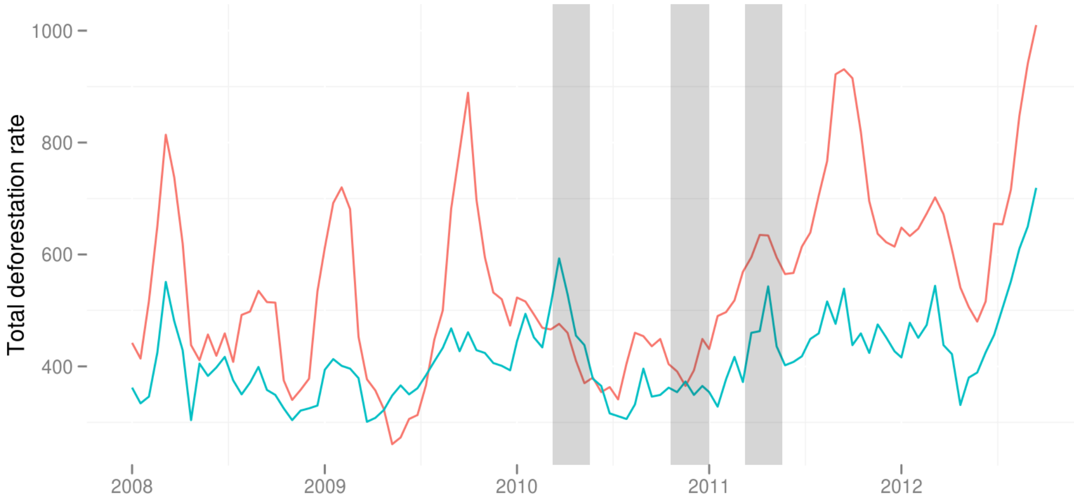


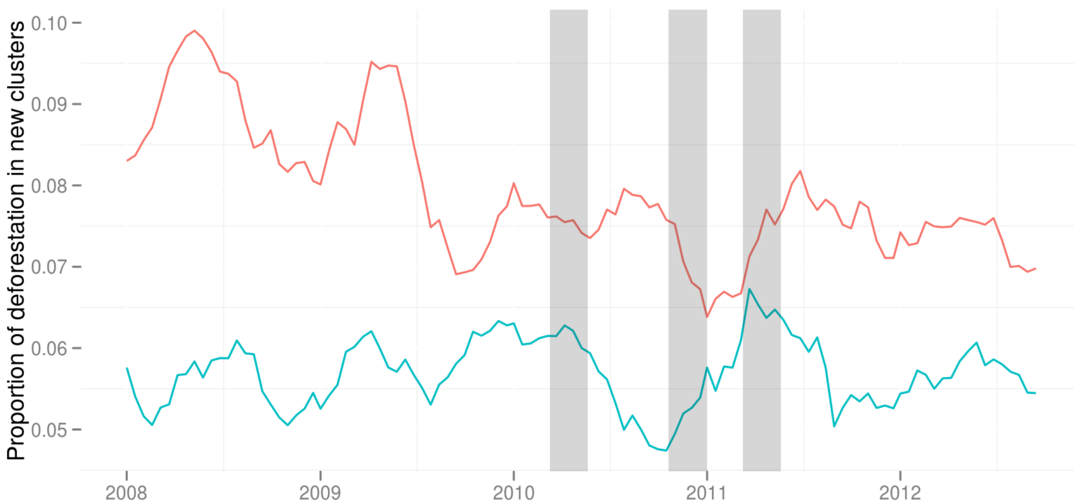
Figure 2: Illustration of clusters

[1] The definition of forest is based on the Vegetation Continuous Field (VCF) index from the MODIS sensor. The pixel is forested in 2000 if the VCF index is greater than 25. This standard also defines the study area for the Hansen *et al.* (2008) data set, which serves as the training data set in our algorithm. Additionally, Brunei is not included in the study, as the addition of another country only serves to complicate the analysis, and the small country only amounts to 1% of land area in Borneo.

[2] The precise interpretation of the deforestation identification measure can be found in Hammer *et al.* (2012). MODIS data are available from February 2000 onwards, but the incremental deforestation measure only begins in January 2008, to allow for training of the algorithm.



(a) Total number of alerts for each 16-day period.



(b) Two month moving average of proportion of new clearing activity that occurs in new clusters, rather than on the periphery of old clusters of deforestation.

Figure 1: Time series of overall deforestation and the spatial distribution of deforestation. Indonesia is in red and Malaysia is in blue. Shaded bars indicate the three stages of the moratorium.

Empirical strategy

Our goal is to identify the impact of the moratorium on the spatiotemporal patterns of deforestation in Indonesia. Specifically, we attempt to identify the impact on

1. The overall rate of deforestation R_t
2. The proportion P_t of deforestation that occurs in new clusters

We focus our attention on the island of Borneo, which is divided into Indonesia (73%) and Malaysia (26%) by the central Borneo highlands, seen in Figure 6. The land use change on both sides of the border is primarily driven by palm oil plantations. Likewise, the terrain is roughly similar, despite the fact that Indonesian

Figure 3: Palm oil price. Shaded regions indicate the three stages of the moratorium.

Borneo is roughly three times the size of Malaysian Borneo.[3] The difference in area between the treatment and control areas may introduce systematic error into the analysis, since developers in Indonesia Borneo may have more opportunity for exploration than their counterparts in Malaysian Borneo. We show later, however, that this would only serve to dampen the observed and significant results.

We utilize the basic difference-in-differences method to estimate the impact of the moratorium on overall deforestation. Let M be a binary variable that indicates the time interval of the moratorium. We will allow this time period to vary, given the three stages of the moratorium. Let C be the group indicator for Indonesia. The standard difference-in-differences model is given by

$$R_{it} = \gamma_0 + \gamma_1 M_t + \gamma_2 C_i + \tau(M_t \cdot C_i) + \beta \mathbf{x} + \epsilon_{it}, \tag{1}$$

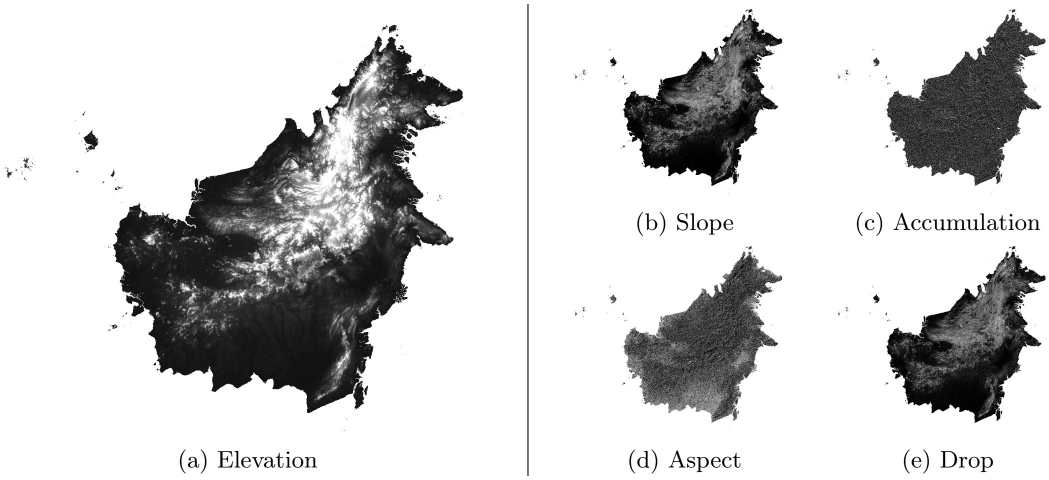
where $\mathbf{x}$ is a vector of cofactors. The identifying assumption is that in the absence of the moratorium, the relative time trends in R_t between Indonesia and Malaysia would be relatively stable after controlling for confounding variables. The crucial variables are the price of palm oil and the relative value of the Indonesian and Malaysian currency, which will drive the difference between deforestation rates in the two countries. The price peaked at the same time that the moratorium was enacted, as shown in Figure 1a; and controlling for price and the relative value of currency

Results

The results of the regression described in Equation (1) are reported in Table 1. Model 1 defines the treatment period as occuring after the first stage of the moratorium, when it was first announced. Model 2 defines the treatment period to be when it was supposed to be enacted; and Model 3 when it was actually enacted.It is clear that after controlling for palm oil prices, the treatment effect is both positive and significant. The moratorium actually increased the difference between the Indonesian and Malaysian deforestation rates, over what would have been determined by price alone. Moreover, the results in Table 1 indicate that price has a positive but diminishing effect on the rate of deforestation in Borneo.

The opportunity to create new clusters of deforestation, then, is higher in Indonesia than in Malaysia, and is reflected by the higher P_t in Indonesia in Figure 1b. If anything, however, this would only serve to increase the upper bound for P_t and support the following findings.

[3]This fact will be shown in forthcoming versions of this paper by rigorously comparing the raster images in Figure 4



(a) Elevation

(b) Slope

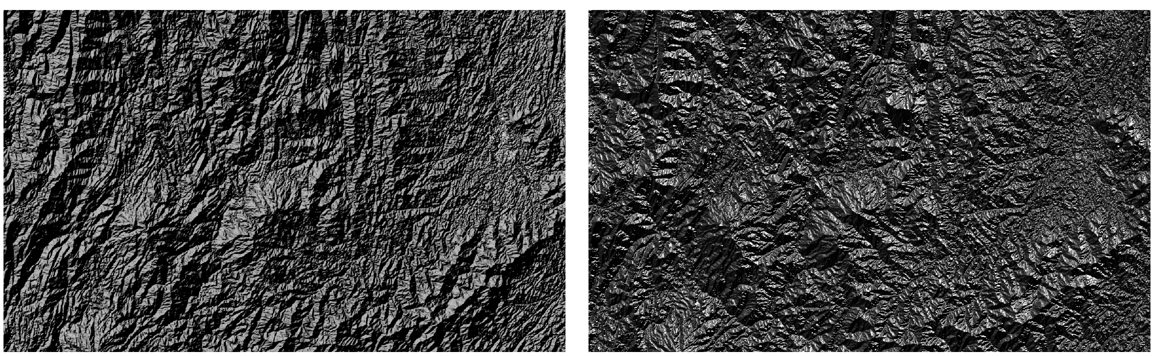
(c) Accumulation

(d) Aspect

(e) Drop

Figure 4: Map of the digital elevation model (left) with derived data sets (right) indicating slope, water accumulation, direction of slope (aspect), and the steepest drop at 90m resolution.

Policy implications



(a) Hillshade

(b) Flow direction

Figure 5: Detailed images of two derived data sets for the same area.

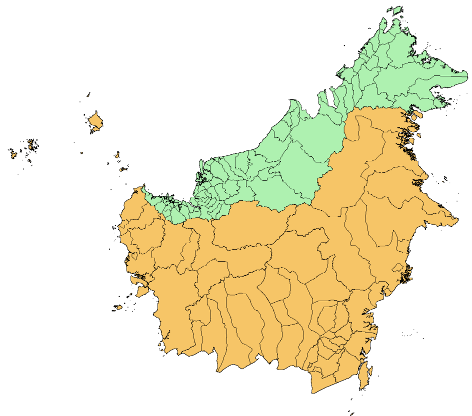


Figure 6: Sample area, Malaysia in green and Indonesia in orange. Borders indicate subprovinces.

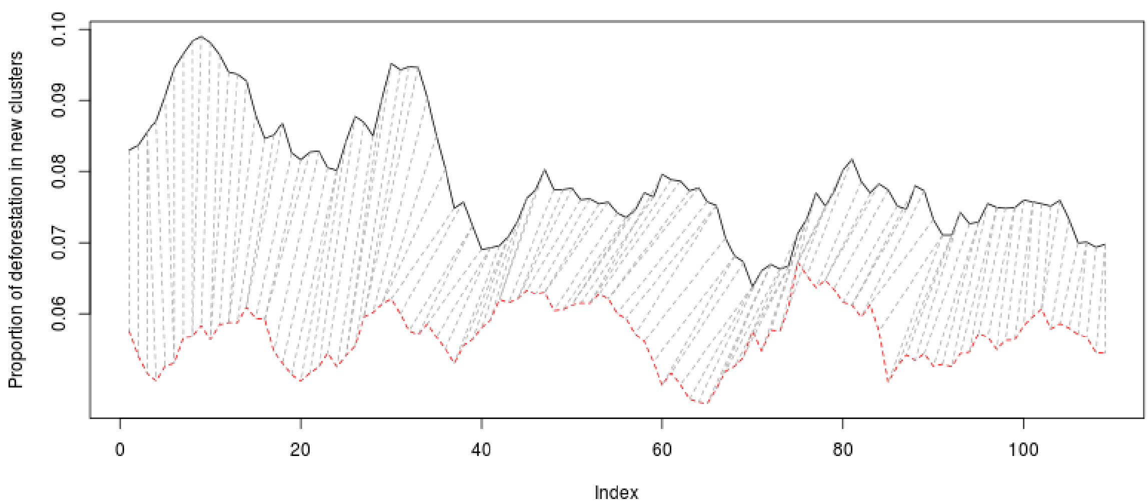


Figure 7

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	(1)	(2)	(3)
(Intercept)	152.180	160.070	374.794^{***}
	(140.814)	(120.799)	(125.366)
cntry	98.200^{***}	89.029^{***}	94.321^{***}
	(22.961)	(17.884)	(16.786)
post	16.257	90.026^{***}	75.732^{***}
	(26.324)	(23.489)	(23.495)
price	57.582^{*}	65.233^{**}	3.290
	(34.131)	(29.389)	(30.508)
I(price^2)	-3.094	-4.320^{**}	-0.130
	(1.984)	(1.729)	(1.771)
cntry:post	65.430^{**}	113.321^{***}	127.615^{***}
	(32.621)	(29.523)	(31.476)
R^2	0.290	0.460	0.462
Adj. R^2	0.274	0.447	0.449
Num. obs.	218	218	218

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 1: Total rate of deforestation.

	(1)	(2)	(3)
(Intercept)	3.702^{***}	4.572^{***}	4.147^{***}
	(0.621)	(0.676)	(0.749)
cntry	2.631^{***}	2.564^{***}	2.367^{***}
	(0.101)	(0.100)	(0.100)
post	-0.372^{***}	0.050	-0.084
	(0.116)	(0.131)	(0.140)
price	4.407^{***}	2.437	3.981^{**}
	(1.506)	(1.645)	(1.823)
I(price^2)	-2.092^{**}	-1.281	-2.373^{**}
	(0.875)	(0.968)	(1.058)
cntry:post	-0.842^{***}	-0.954^{***}	-0.537^{***}
	(0.144)	(0.165)	(0.188)
R^2	0.834	0.796	0.769
Adj. R^2	0.830	0.791	0.763
Num. obs.	218	218	218

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 2: Proportion of deforestation in new clusters

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	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	4.269^{***}	5.516^{***}	4.791^{***}	5.202^{***}	6.947^{***}	6.430^{***}
	(0.668)	(0.810)	(0.843)	(0.704)	(0.773)	(0.813)
cntry	2.619^{***}	2.404^{***}	2.311^{***}	2.619^{***}	2.404^{***}	2.311^{***}
	(0.109)	(0.120)	(0.113)	(0.106)	(0.110)	(0.103)
post	-0.502^{***}	-0.003	-0.109	-0.299^{**}	0.257^{*}	0.073
	(0.125)	(0.158)	(0.158)	(0.135)	(0.150)	(0.147)
price	2.470	-0.117	2.002	4.939^{***}	5.693^{***}	6.828^{***}
	(1.620)	(1.972)	(2.052)	(1.729)	(2.010)	(2.023)
I(price^2)	-0.619	0.341	-1.020	-1.557	-1.933^{*}	-2.633^{**}
	(0.941)	(1.160)	(1.191)	(0.956)	(1.117)	(1.120)
cntry:post	-1.036^{***}	-0.813^{***}	-0.722^{***}	-1.036^{***}	-0.813^{***}	-0.722^{***}
	(0.155)	(0.198)	(0.212)	(0.151)	(0.181)	(0.194)
exch.rate				-0.739^{***}	-1.448^{***}	-1.399^{***}
				(0.211)	(0.222)	(0.217)
R^2	0.808	0.708	0.708	0.819	0.757	0.756
Adj. R^2	0.804	0.701	0.701	0.814	0.750	0.749
Num. obs.	218	218	218	218	218	218

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 3: Warped proportion of deforestation in new clusters

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