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 deforestation from January 2008 through September 2012. Specifically, we track the proportion of newly cleared areas that are in new clusters, rather than on the periphery of existing clusters. We find that the moratorium reduced responsiveness of the creation of new clusters to agricultural prices. However, we also find that the overall rate of deforestation increased after controlling for agricultural prices, suggesting that developers merely shifted deforestation to the periphery of existing clusters.

Deforestation accounts for 12% 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 together accounted for 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 intent of the moratorium was to reduce overall deforestation, not just clearing activity in previously unexploited forest landscapes. The moratorium's scope, however, was limited to new concessions. 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. This land, which could be modeled with storage or option value models,

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may serve as an alternative to new clearing activity in order to smooth the supply of newly cleared land for agriculture. While these lands may not be directly impacted by the moratorium, we examine the indirect effect on forests within existing and irrefutable 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 on both types of land. The impact on the *overall* rate of clearing is therefore an empirical question.

Economic studies of the optimal development of resource pools have largely been limited to theoretical exercises. Objective data on resource extraction at a time scale commensurate with economic decision making have not been available. Recent developments in cloud computation and satellite imaging have allowed for a new class of data for empirical study. 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 severely 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. These data provide new information on the choice to intensify production in current resource pools or to open new pools for development. The ultimate objective of this study — which may not be fully addressed in this draft — is to provide empirical evidence toward or against standing theory on the pattern of resource extraction in the presence of large set-up costs and heterogeneous marginal costs..

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. In its place, bilateral agreements under the REDD framework have materialized, 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 to Indonesia, 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.

The conditions surrounding the moratorium are in constant flux. The map of affected areas is up for review every six months. These conditions create a climate of high risk to development of new clusters, whether or not they are in forest that is eligible for new concessions (secondary or degraded forests). The risk of re-zoning may be enough to deter new development. It is conceivable that initial clearing activity in new forests, even forests with legal concessions, may actually be *targeted* for re-zoning in the presence of rent-seeking, corrupt politicians.

There were three stages to the enactment of the moratorium. (1) Indonesia first 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 substantial 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 forestalling the release of Norway's pledged aid.

Data

The foundational data for this study is an original data set of deforestation for each 500-meter, forested 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 and time interval is assigned a normalized measure of forest clearing activity, based on daily images 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 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 up to 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 pixel count in Figure 1a. 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 distance 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)

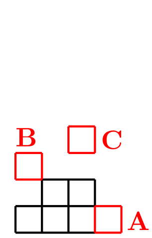
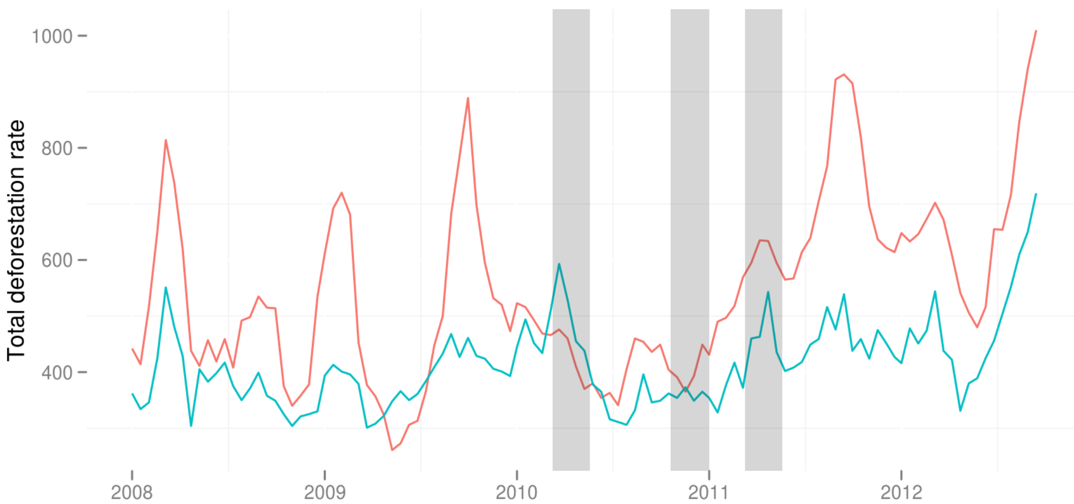


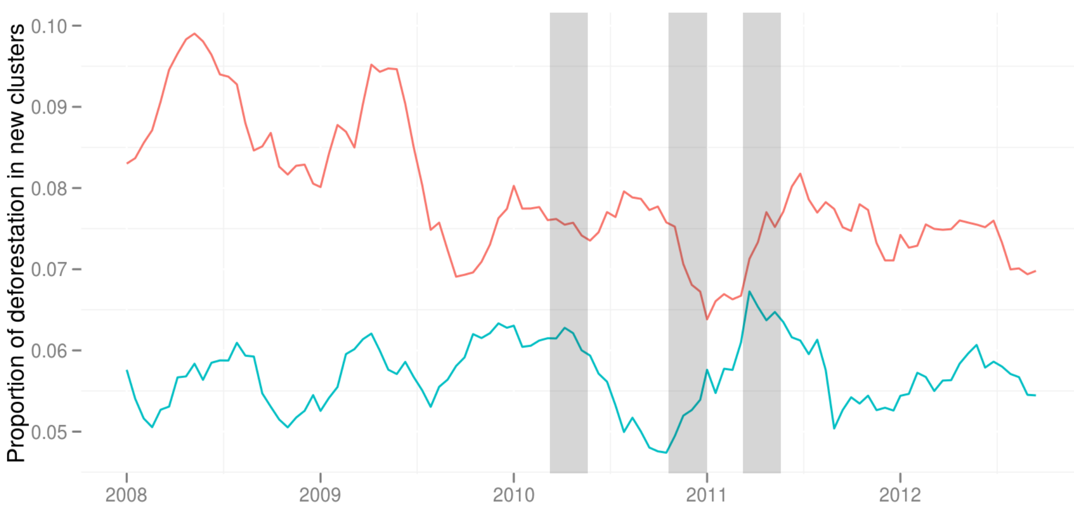
Figure 2: Illustration of clusters

[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.

data set, which provides a relatively coarse grid of precipitation measures (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.

The optimal development of deforestation clusters

Consider a two-factor production model with the two types of cleared land described in Section as two inputs to agricultural production. The static cost minimization problem is inadequate to model behavior of a profit maximizing firm, since deforestation is an investment that will pay out over time. Moreover,

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

there are two types of investment, distinct from the recurring costs after the land has been cleared: (1) the investment to begin a new cluster of deforestation, including the cost to build branching roads; and (2) the investment to clear each individual pixel, once the cluster has been started. Because the gains from "hiring" a new unit of capital are not instantaneous and the investment costs are borne over time, we adapt the two-factor production model to incorporate the dynamic optimization problem specified by Weitzman (1976, 1980). The purpose of generating the new machinery is to ensure that the stationary specification of the optimization is robust to its dynamic specification, albeit less detailed.

Framework

Following Weitzman's notation, define $G(\mathbf{K}, \mathbf{I})$ as the net current "take home" cash flow, where $\mathbf{K}$ is a vector of capital inputs and $\mathbf{I}$ is a vector of the associated fixed-cost investments. Dynamic optimization of $G(\cdot)$, or optimal control of $\mathbf{I}$, will define the time-path of capital development. This detailed information is incidental, however, for our relatively simple application to identify the impact of the moratorium on the aggregate rate of capital investment. For this application, Weitzman suggests an "old economist's trick" to collapse the dynamic problem to its stationary equivalent.

Consider, for example, the prototypical optimal control problem of the form:

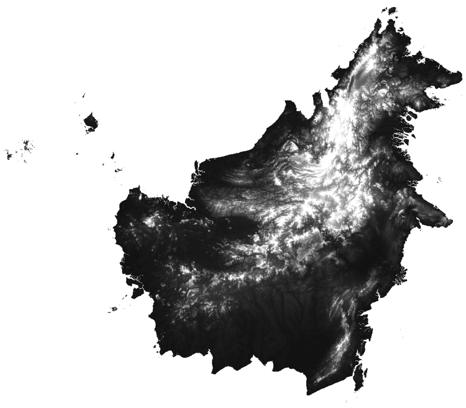
$$\max \int_0^\infty e^{-\rho t} G(\mathbf{K}_t, \mathbf{I}_t)\, dt$$

$$\begin{aligned} \text{subject to} \quad & \dot{\mathbf{K}}_t = \mathbf{I}_t \\ \text{and} \quad & \mathbf{K}_t \geq 0 \end{aligned}$$

where $\mathbf{K}_t$ is a vector of the cumulative stock for all capital inputs in time t and $\mathbf{I}_t$ is the level of investment for the corresponding capital inputs. The fundamental equation of capital theory sets the stationary rate of capital return *for each capital input* equal to the discount rate. The stationary rate of return, denoted $R(\hat{\mathbf{K}})$, is the relative value of capital when optimal investment is zero for all periods. The stationary solution will satisfy the system of equations:

$$R(\hat{\mathbf{K}}) = \frac{\partial G(\mathbf{K}, \mathbf{0})/\partial \mathbf{K}}{\partial G(\mathbf{K}, \mathbf{0})/\partial \mathbf{I}} = \rho \tag{1}$$

The firm will incur the immediate cost of capital only if the imputed net gain from capital exceeds the market rate for lending. The investment mix is subject to this external valve, such that the decision to invest



(a) Elevation

(b) Slope

(c) Accumulation

(d) Aspect

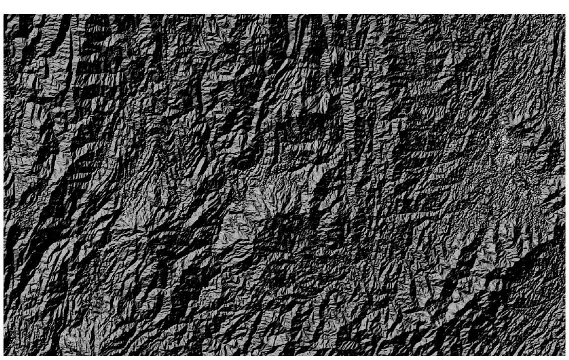
(e) Drop

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.

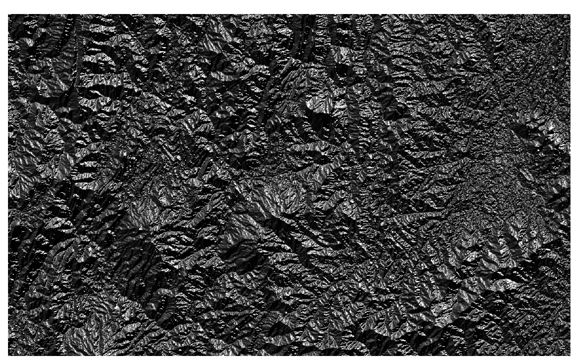
in any type of capital will be weighed against the going interest rate. Weitzman notes that while a firm may never actually achieve the stationary state, the investment decisions push the outcome in that direction.

Consider the standard two-factor production model, where k_1 is land on the periphery of existing cleared land and k_2 indicates land that would constitute a new cluster of cleared land. Further, let $\hat{k}_1$ and $\hat{k}_2$ be the stationary states associated with each capital input for agricultural production, noting that $\hat{k}_1$ and $\hat{k}_2$ are highly substitutable. Let $v(\hat{k}_1, \hat{k}_2)$ be a function that indicates the revenue product of the stationary capital levels, which is equivalent to the gross gain in the $G(\cdot)$ function. We are effectively extending Weitzman's framework by splitting the gain function in order to examine the dynamic substitution between capital inputs. Finally, let $\hat{v}(\cdot) = v(\cdot)/\rho$ indicate the present value of the revnue product. The purpose of setting up this machinery is to ensure that the stationary specification of the optimization problem is robust to its dynamic specification.

Figure (6) represents the tradeoff between stationary levels of inputs. The isoquant $\hat{v}(\hat{k}_1, \hat{k}_2) = \bar{v}$ represents the present value of a fixed level of revenue, which is the revenue side of the net gain function $G(\cdot)$. The optimized, stationary input mix is determined by the tangency of the present-value isocost line to the present-value isoquant curve. This is equivalent to where the ratio of the discounted marginal costs of the investments is equal to the marginal rate of technical substitution in present value terms. This allows for the two-tiered investment structure: an investment to open a new cluster and another investment for each pixel to expand



(a) Hillshade



(b) Flow direction

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

the cluster. The annuitized value of the initial, cluster-level investment can be rolled into the present value. The initial pixel of a cluster – the seed – serves as an indicator for the nascent cluster. This framework is consistent with the implicit cost framework built by Weitzman (1976). The optimality of the tangency can be seen by the following:

$$\frac{\partial G(\mathbf{K}, \mathbf{0})/\partial \mathbf{K}_1}{\partial G(\mathbf{K}, \mathbf{0})/\partial \mathbf{I}_1} = \rho = \frac{\partial G(\mathbf{K}, \mathbf{0})/\partial \mathbf{K}_2}{\partial G(\mathbf{K}, \mathbf{0})/\partial \mathbf{I}_2} \tag{2}$$

This implies, in turn, that the present value of the marginal rate of technical substution is equal to the relative expense of investment between the two land types.

$$\frac{\partial G(\mathbf{K}, \mathbf{0})/\partial \mathbf{K}_1}{\partial G(\mathbf{K}, \mathbf{0})/\partial \mathbf{K}_2} = \frac{\partial G(\mathbf{K}, \mathbf{0})/\partial \mathbf{I}_1}{\partial G(\mathbf{K}, \mathbf{0})/\partial \mathbf{I}_2} \tag{3}$$

What is the impact of a change in the relative investment cost? The original stationary input mix $(\hat{k}_1', \hat{k}_2')$ in Figure (6) reflects the original investment cost regime. The increase in the cost of investment to land type 2 will move the optimized miz along the curve to $(\hat{k}_1'', \hat{k}_2'')$, assuming a concave isoquant and high rate of substitution.

Note that the units of both $\hat{k}_1$ and $\hat{k}_2$ are land area, specifically pixels at 500-meter spatial resolution. The aggregate area in each time interval indicates the observed deforestation rate. A primary question of this paper is whether an increase in the the cost of an investment can *increase* the overall deforestation rate. Figure (6) indicates that, given the high substitution rate between land inputs, this behavior is theoretically possible, and in fact somewhat common. The isoquant reflects a scenario where $\hat{k}_2$ tends to be more productive than $\hat{k}_1$. This property is not hard to imagine. In fact, it is more likely than the alternative for many reasons. One reason, for example, is that the production of palm oil requires processing of the harvested kernels within 24 hours of picking. The proportion of spoiled product increases with the time between harvesting and processing. The processing facility is almost tautologically located closer to the early clearings than to the later clearings. The amount of product extracted for palm oil extracted from cleared land at the beginning of the cluster is greater. And the marginal product associated with the land will decline thereafter. The discounted value of the revenue product associated with a yet uncleared cluster will include the gains from the early pixels that are omitted from the forward gains of an existing cluster.[3]

It is also empirically true that land in new deforestation clusters tends to be at higher elevation and slope than land cleared on the periphery of existing clusters. Land with these characteristics is harder to prepare for agriculture; and the investment to employ this type of land is higher. Figure (**??**) shows the difference in elevation for Indonesian and Malaysian Borneo over time by clearing type. A difference in means test indicates that both the slope and elevation of land clearing is statistically different in Borneo. Taken together, these facts corroborate the higher investment costs indicated for $\hat{k}_2$ in Figure (**??**) as seen in the slopes.

Empirical rates of substitution

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

[3]The productivity could be modeled in the cost structure; but we separate the investment costs from the ongoing productivity. investment to get land to as productive as it will be. Once productive, the land will be more productive across pixels if it is near the processing plant.

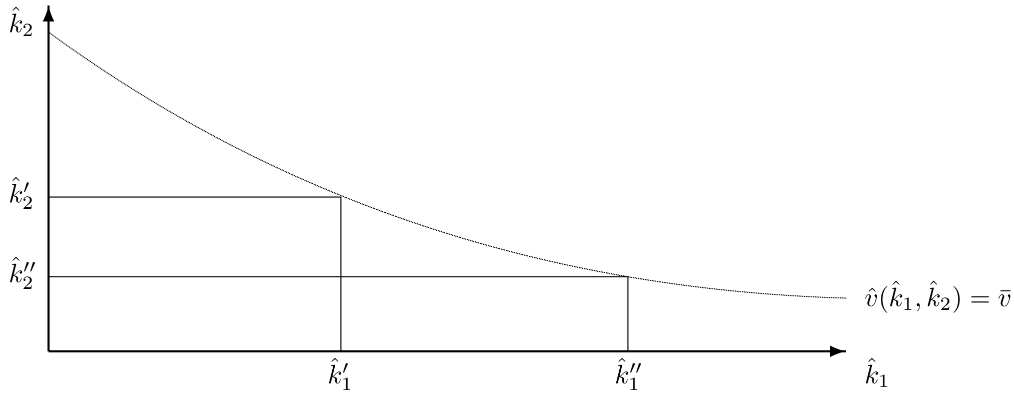
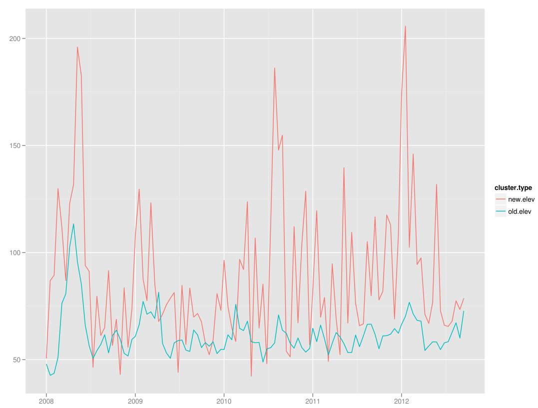
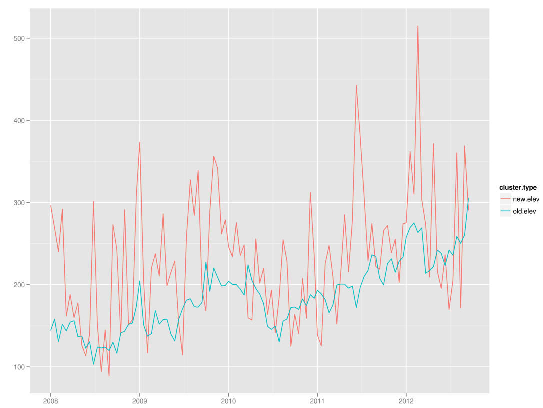


Figure 6: Illustration of an isoquant where the inputs exhibit a high degree of substitution in production and a low marginal rate of technical substitution.



(a) Elevation for Indonesian land clearing



(b) Elevation for Malaysian land clearing

Figure 7: Elevation of land clearing for different cluster types over time.

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 8. The land use change on both sides of the border is primarily driven by large-scale palm oil production. Likewise, the terrain is similar, even though Indonesian Borneo is roughly three times the size of Malaysian Borneo.[4] The difference in area between the treatment and control areas may introduce systematic and unobserved component in the residual variance, since developers in Indonesia Borneo may have more opportunity for exploration and cluster dispersion than their counterparts in Malaysian Borneo. This component, however, would only serve to increase the difference in dispersion between Indonesia and Malaysia during the treatment period. Our analysis in later sections will show that the moratorium dampened the difference in dispersion, such that the relative sizes of the treatment and control groups do not appreciably affect the found conclusions.

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, i.e., the treatment. We will allow this time period to vary to accommodate the three stages of the moratorium. Let C be the group indicator for Indonesia. The standard difference-in-differences model is given by

$$R_{it} = \gamma_0 + \gamma_1 M_t + \gamma_2 C_i + \tau(M_t \cdot C_i) + \beta \mathbf{x} + \epsilon_{it}, \tag{4}$$

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

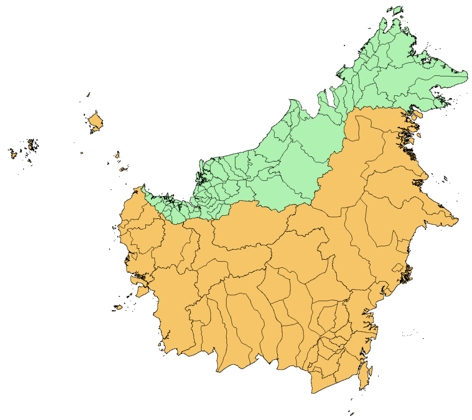


Figure 8: Sample area, Malaysia in green and Indonesia in orange. Borders indicate subprovinces.

where $\mathbf{x}$ is a vector of cofactors. The identifying assumption is that in the absence of the moratorium, the time trends in R_t between Indonesia and Malaysia would be 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 are the primary drivers of 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. In this initial study, the vector $\mathbf{x}$ includes the price of oil palm and the relative exchange rate of Indonesia's rupiah to Malaysia ringgit.

We employ a similar strategy to identify the impact of the moratorium on the spatial dispersion of deforestation. The reference model is almost identical to the model reported in Equation (4), except that the proportion of new deforestation in new clusters is the dependent variable:

$$P_{it} = \gamma_0 + \gamma_1 M_t + \gamma_2 C_i + \tau(M_t \cdot C_i) + \beta\mathbf{x} + \epsilon_{it} \tag{5}$$

Note that the average effect of the treatment for the treated is estimated by $\hat{\tau}$. Abadie (2005) considers the case when differences in observed characteristics create non-parallel outcome dynamics between treated and control groups. Abadie discusses the severe assumptions that underlie difference-in-differences estimation, especially with respect to lag structures of responses to exogenous shocks across the treated and controls. Take, for example, the current context, where a developers in the treated and control groups may have difference response times to either a sustained or short-term increase in palm oil price. Standard difference-in-differences will not yield a consistent estimate of the treatment effect. Abadie proposes a semi-parametric correction based on the observables in $\mathbf{x}$ to account for non-parallel effects in the outcome variable. Still, this correction is based on the trends of observable characteristics, whereas there may be dynamics that are dependent on the error structure. Any non-parallel shifting or stretching in the P_{it} time series of the treated and control groups will yield a mis-specified impact estimate of the treatment on the treated.

We propose an information theoretic approach to identification. Specifically, we attempt to uncover broad trends in the outcome variable by using common patterns in the residual variation. Through a non-parametric matching technique called dynamic time warping, we "snap" the treated series to comparable observations in the control series. This method is commonly used in time series classification and language detection, searching for discernible patterns in speech waveforms through idiosyncratic amplitudes and frequencies. A rigorous treatment of this method and its empirical properties is beyond the scope of this paper, but will be included as an appendix in subsequent versions of the paper. Instead, we present a very basic illustration of the outcome of the matching in Figure 9. A standard, uncorrected difference-in-differences estimator relies on a perfectly vertical comparison of observations. In other words, the dashed matching lines in Figure 9 would all be vertical, associating values within the same time period only. Time warping allows for flexible slopes, given constraints on the slope and distance of the matching lines. Figure 9 shows the result of the matching algorithm between the treatment and control P_{it} series. We can reconstruct the treated P_{it} series based on the matching lines toward a new series that is purged of non-constant lag structures in the error

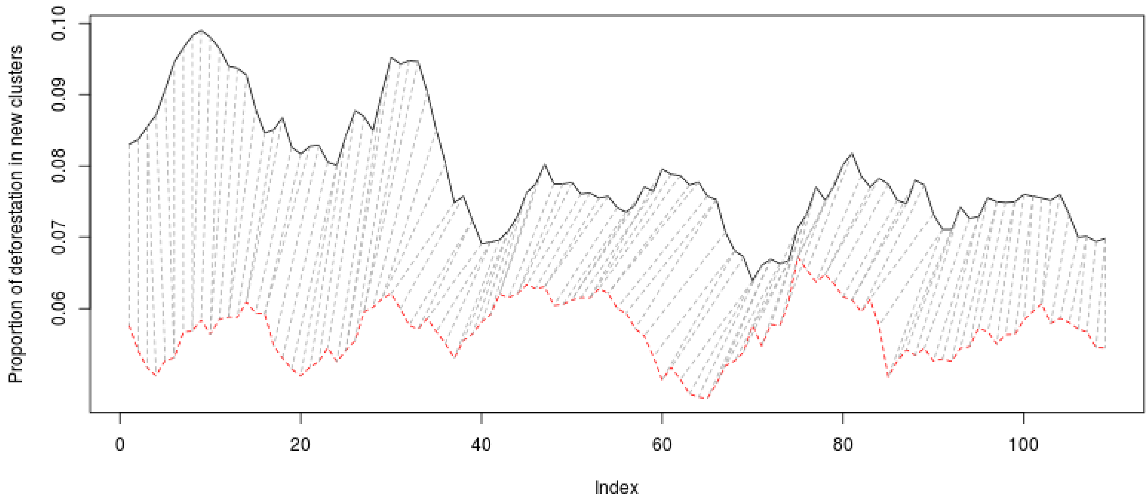


Figure 9: Dynamic time warping of the Indonesian (black, solid) series and the Malaysian (red, dashed) series. The gray matching lines match similar values across the two series, based on a set of matching penalties. The dates are replaced with index values.

term. This new series, the aligned series, may better characterize the comparable differences between the treatment and control groups that result from the treatment. The assumption, now, is that the unobserved micro-dynamics are *similar* across groups; but we don't need to assume that they are parallel or constant. This is a much looser and more tenable assumption.

Results

The results of the aggregate deforestation regression in Equation (4) are reported in Table 1. Column (1) defines the treatment period as occurring after the first stage of the moratorium, when it was first announced. This specification acknowledges that investment in new clusters is affected by expected returns. A credible announcement six months prior to enactment of a policy that could affect a long-term investment process could have just as much impact as the enforcement of the policy. Column (2) defines the treatment period as occurring after the second stage, and Column (3) after the final stage, when it was actually enacted. After May 20, 2011, no new concessions for clearing activity in primary forests should have been granted by local governments. There were some highly criticized exceptions; but the issuance of such concessions in the specified areas abruptly decreased.

The results in Table 1 suggest that the overall rate of deforestation *increased* as a result of the moratorium in Indonesia, after controlling for palm oil price. The price spiked when the moratorium was enacted and remained high throughout the treatment period, such that much of the variation in price is collinear with the treatment period indicator. Thus, given the multicollinearity, the price effect is not significant, but the parameters suggest that the effect of contemporaneous price is positive but with diminishing marginal effect. The somewhat surprising insignificance may also be the result of a lag structure that is not included in the regression.

The results of the proportion regression in Equation 5 are reported in Table 2. The results of the regression *after the Indonesia series was warped* are reported in Table 3. First note that the proportion of deforestation in new clusters is persistently higher in Indonesian Borneo than in Malaysian Borneo, revealed by the coefficient on `country`. This is surely derived from the relative sizes of the two countries in Borneo: the opportunity to create new clusters of deforestation is higher in Indonesian Borneo than in Malaysian Borneo because it is three times larger. The effect of the moratorium, however, was to reduce the responsiveness of P_{it} in Indonesia to economic indicators that generally drive dispersion of deforestation. Table 2 presents the results for the raw P_{it} with the columns specified as they were in Table 1. Given the high prices of oil palm, and the associated incentive to create new clusters of deforestation, the proportion in Indonesia *should have* hovered around 8.5%; but instead it has remained at around 7.5%, as if the price did not increase at all.

	(1)	(2)	(3)
(Intercept)	152.180	160.070	374.794***
	(140.814)	(120.799)	(125.366)
country	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)
price^2	−3.094	−4.320**	−0.130
	(1.984)	(1.729)	(1.771)
country: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 deforestation, R_{it}

	(1)	(2)	(3)
(Intercept)	3.702***	4.572***	4.147***
	(0.621)	(0.676)	(0.749)
country	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)
price^2	−2.092**	−1.281	−2.373**
	(0.875)	(0.968)	(1.058)
country: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 in new clusters, P_{it}

The results for the warped P_{it} series in Table 3 further support the conclusion that the moratorium reduced investment in new clusters of deforestation relative to the expansion of existing clusters, given the price of palm oil. The coefficient for the treatment effect, $\hat{\tau}$, is negative and highly significant. As in the previous tables, Columns (1), (2), and (3) define the treatment period based on the three different phases of the moratorium. The coefficient becomes less negative as the treatment period is shortened. One possible explanation is that, as time has progressed, the threat of enforcement of the moratorium has become less credible. The rate of violations reported in the Jakarta Post has certainly increased dramatically, with little official response.

The decreasing magnitude of the treatment in Columns (1), (2), and (3) of Table 3 could also be a statistical artifact. The time series plots in Figure 1b suggest that there may be multiple but discrete equilibria for investment patterns, based primarily on the return to investment in Indonesia. The difference between the Malaysian and Indonesian time series is first very large, and is commensurate the 2008 palm oil price spike and the subsequent rupiah devaluation. The difference does not respond to the 2010 price increase; but instead hovers at the lower equilibrium levels. In this context, extending the treatment period back to the first phase in May 2010 may falsely ascribe the persistent, lower equilibrium to the treatment. Columns (4), (5), and (6) add the relative exchange rate, the Indonesian rupiah over the Malaysian ringgit. The treatment effect does not change at all, but the price effect becomes more discernible as positive with diminishing marginal effect.

Policy implications

The primary objective of the 2011 moratorium was to reduce the overall rate of forest clearing activity in Indonesia. Our analysis of Borneo suggest that the moratorium may have had the opposite effect. Specifically,

	(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)
country	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)
$price^2$	−0.619	0.341	−1.020	−1.557	−1.933*	−2.633**
	(0.941)	(1.160)	(1.191)	(0.956)	(1.117)	(1.120)
country: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)
exchange 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

that the narrowly defined moratorium merely reduced the formation of new clusters of deforestation (conditional on high palm oil prices) but disproportionately increased deforestation around existing clusters. Land developers adjusted their development schedule in response to the moratorium; and in this readjustment, total deforestation increased, counter to the intentions of the moratorium. This study illustrates the need to consider broader definitions of additionality, permanence, and leakage when designing conservation policy.

The analysis also suggests that efforts to extend the two-year moratorium will be met with strong industry resistance, perhaps at an even greater intensity than was exhibited after the announcement of the original plan. Instead of pursuing new clusters of deforestation, developers may have used forest stock within existing concessions to smooth the supply of cleared land for agriculture. Extending the moratorium may actually disrupt the supply of cleared land, rather than forcing a short-term depletion of forested land. The fight over extending the moratorium has already begun; and we can expect that the agriculture sector will not accept further disruptions to development of primary forests. The Jakarta Post reported on December 7, 2012 that "Indonesia's Forestry Minister announced that he will recommend to the President that the moratorium be extended when it expires in May 2013. But in response, lawmakers in the House of Representatives threatened to freeze the budget for reforestation projects should Yudhoyono decide to extend the ban until the end of his term in 2014." Taken together, recent newspaper articles suggest that aggregate supply of cleared land was not significantly impacted by the moratorium, but merely reallocated through space and time. Extending the moratorium may actually have an appreciable effect on agriculture, as indicated by the increasing resistance to further conservation.

Reducing dispersion of deforestation may have secondary environmental benefits that run counter to the environmental degradation of aggregate clearing activity. Forest fragmentation threatens ecosystem resilience and biodiversity, and condensing deforestation may actually mitigate other unintended consequences of REDD programs that focus exclusively on aggregate forest clearing. Forest scientists assert that REDD may have "disastrous consequences for biodiversity" because of a singular focus on aggregate forest stocks, rather than the spatial distribution of clearing activity. At the very least, this fact supports the further study of the spatial distribution of deforestation, rather than a relatively narrow view of conservation.

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