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 bisects the island of Borneo into Malaysia and Indonesia and examine the distribution of deforestation from January 2008 through September 2012. We examine the proportion of deforestation on the periphery of existing, cleared areas versus deforestation that constitutes a new cluster of cleared land. We find that the moratorium reduced the dispersion of deforestation, but increased the overall rate of deforestation. This behavior can be easily explained with basic principles in producer theory, which has not been a focus of the international dialogue on conservation policy.

Deforestation accounts for 12% of annual carbon emissions, nearly as much as the global transportation sector. Any viable effort to mitigate climate change must address deforestation. This is a difficult proposition, however, since most deforestation occurs in tropical countries, which rely heavily on cleared land as an input for agriculture. Indonesia, for example, is responsible for roughly 20% of annual deforestation, worldwide [FAO]; but the agricultural sector, broadly defined, contributed almost 10% to gross domestic product in 2007. The rural economy relies heavily on products derived from cleared land, and there exist incentives at every level to convert standing forest to fiscally productive land. As part of a grand Coasian bargain, Norway has 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.

This paper evaluates the effectiveness of the moratorium in Indonesia. Midway through the initiative, the impact of the conservation policy is highly contested. The Indonesia goverment claims a resounding success, with the Minister of Forestry announcing that "the moratorium ... has proven to effectively reduce forest destruction" and that the forest clearing rate has declined by at least one-third since the moratorium was instituted. On the other hand, various environmental groups insist that the moratorium has had no effect on aggregate clearing activity; and Greenpeace claims that deforestation has actually increased since the moratorium. Greenpeace contends that illegal clearing activity and poorly defined moratorium maps are at the root of the increased clearing rate. The Jakarta Globe reported in May 2012 that over 10% of existing forests in Kalimantan, Indonesia were cleared in the previous year. Satellite imagery supports the claim of accelerating deforestation in Indonesia, despite the moratorium. This paper tests the hypothesis that the deforestation rate in Indonesia increased *because* of the moratorium.

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An outright ban on a specific type of clearing is a blunt policy instrument with almost certain impacts beyond the directly sanctioned forests. International conservation groups have focused on a particular type of geographic "leakage" to identify the true additionality of the policy, seeking to answer the question of whether forests were actualy conserved or clearing activity was merely pushed to a different country or province. This type of behavior is consistent with basic trade or production theory. There has been a surprising lack of attention paid to leakage across different clusters within the country, potentially because of a lack of detailed data. Leakage is merely substitution across geographic boundaries, or even through time. The focus of this paper is to examine the substition across different types of clearing activity on the aggregate level of forest conversion, based on the net revenue structure of the cleared land.

We use an original data set derived from satellite imagery to identify deforestation at 500-meter resolution with 16-day updates. These data, along with recent advances in parallel processing, allow for an unprecedented empirical study of the spatial development of deforestation clusters. The theoretical support for this paper is derived from the foundational work by Weitzman (1976, 1980, 2003) on the optimal development of resource pools. Each collection of contiguous pixels that are suitable for agriculture can be modeled as separate resource pools. The land owner has the choice to intensify development on the periphery of existing cluster or to expand the number of clusters in yet untouched forest landscape. The structure of costs and returns of *peripheral deforestation* is very different from that of *remote deforestation*. Deforestation in each time period can therefore be partitioned into peripheral and remote deforestation, based on its location relative to existing clusters of cleared pixels. The distinction is substantive due to the different net benefit schedules.

We apply Weitzman's optimal control framework to basic producer theory, noting that cleared land is a capital input of production for agriculture. The two types of clearing activity – peripheral and remote – are differentiated inputs in production. Nascent clusters, identified by remote clearing, tend to be associated with a higher marginal product in our sample area. The up-front cost of establishing a new cluster, however, is non-trivial as new, high-volume roads have to be built through intact forest landscapes. We focus our attention on the island of Borneo, which is bisected into Malaysia and Indonesia. Only the Indonesian side, the Kalimantan province, was directly affected by the moratorium. Our identifying assumption is that the spatial pattern and rate of deforestation on the Malaysian side, the Sarawak province, was unaffected by the policy. We argue for the validitiy of this assumption in the following sections.

Our primary finding is that the moratorium shifted input use away from remote clusters and toward peripheral clearing activity, with an overall increase in the rate of forest clearing activity in Indonesia. A simple difference-in-differences approach is applied to compare the spatial development of deforestation in Malaysia and Indonesia. The results are robust up to a wide array of variations on the parameters of the study. The results suggest that developers more than offset the reduction in remote clearing with peripheral clearing activity. Moreover, the results warn against narrowly defined conservation policy. Very basic principles in producer theory and optimal control can explain this type of behavior, which was not even considered in the initial design of the moratorium. As with many poorly defined policies, the moratorium treated developers as inanimate objects rather than maximizing agents, yielding an unintended but avoidable outcome.

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 launched a global framework in 2008 to reduce tropical deforestation, called the REDD (Reducing Emissions from Deforestation and Degradation) initiative. The initial intent of REDD 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." The stated objective of the REDD initiative is exceedingly vague, and the shortcomings of REDD have become clear, partly stemming from the fact that the scope and objective of the program is so poorly defined. The prospect for a comprehensive and global REDD program has diminished significantly since its launch. 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 was 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 for development of remote clusters, whether or not they are in natrual forests that are eligible for new concessions. 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. A series of news reports on corruption and bribery surrounding the moratorium gives credence to this assertion. Given the uncertainty of the spatial and temporal extent of the moratorium, the effect has been to increase the relative, expected cost of developing outside of existing concessions. Further research into whether the moratorium could be modeled as a fixed, two-year period can be done; but it smore likely that, since the parameters are so blurry, we would expect developers to behave as if the cost of investment increased in these areas.

There were three stages 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. Many reports have surfaced about illegal land clearing operations after May 2011 and associated bribes, potentially forestalling the release of Norway's pledged aid. There have been few, if any, reports of existing concessions being revoked. The ultimate effect of the moratorium, then, has been an increase in uncertainty surrounding remote and yet unlicensed clusters of forest with the potential to be converted to agricultural land. The value assessments of land within existing concessions, however, remains fairly stable. The amount of land within existing concessions is non-trivial. As of 2011, only 30% of land within the existing concessions had been cleared in Indonesia, leaving a significant land area that could be cleared, even if no new concessions were granted.

The optimal development of deforestation clusters

Weitzman (1976) presents the basic form for the optimal extraction of a depletable resource from an array or resource pools under general cost conditions. His solution reveals that the sequencing of extraction, and thereby the intensity of extraction over a fixed time period, are highly dependent on the dynamic cost structure, rather than just the instantaneous costs of extraction. Many extensions have been published since, both generalizing his result and offering very specific applications. The extraction decisions are based on the evolution of the cost structure of extraction. These studies, however, have been overwhelmingly theory based papers, since detailed information on individual pools have not been available. We offer an empirical application of this optimal control framework, with the added generalization that the extracted resource is an input in the production of an agricultural product.

Framework

Following Weitzman's (2003) notation, define $G(\mathbf{K}, \mathbf{I})$ as the net current "take home" cash flow of agriculture, 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 determine the time-path of capital development. The detailed path of development is incidental, however, in determining the aggregate effect of a change in the investment vector. For this type of application, Weitzman suggests an "old economist's trick" to collapse the dynamic problem to its stationary equivalent. Consider the prototypical optimal control problem of the form, with ρ indicating the competitive interest rate:

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

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

where $\mathbf{K}_t$ indicates the cumulative stock of capital inputs in time t and $\mathbf{I}_t$ is the instantaneous investment in 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 $R(\mathbf{K})$, is the annuitized value of capital, evaluated at $\mathbf{K}$. The stationary solution is the optimal level of capital, when investment is zero for all time. The stationary solution will satisfy the following 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 competitive interest rate. The investment mix is subject to this external valve, such that the decision to invest 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. A valid question, however, is why the steady state in this scenario is where there is zero investment, unlike many resource extraction problems. The answer is two-fold. First, land is used as an input to production in a competitive market. Land will only be hired up to the point where the marginal cost is equal to the marginal revenue product. Within a small country, the price of the input does not evolve to reflect growing scarcity, as in many exhaustible resource problems. Second, we assume that, with proper management (e.g., crop rotation), there is no long-term depreciation of the land input in the production of crops. The stationary solution closely mirrors the static approach often found in location models, which may also be suitable to explain the spatial patterns of deforestation. It is a worthwhile exercise, however, to frame this empirical study within the vast, literature in resource development, which is often framed as a dynamic programming problem.

Now, consider the standard two-factor production model, where k_1 is land on the periphery of existing clusters of deforestation and k_2 is land in remote forests that, if cleared, would constitute a new cluster of deforestation. Let $\hat{k}_1$ and $\hat{k}_2$ be the stationary states associated with each capital input, noting that $\hat{k}_1$ and $\hat{k}_2$ are highly substitutable in agricultural production. Finally, let $v(\cdot)$ be the gross revenue function and $\hat{v}(\cdot) = v(\cdot)/\rho$ be the present value of gross revenue, half of Weitzman's net gain function. It follows that $\hat{v}(\hat{k}_1, \hat{k}_2)$ is the present value of the stationary levels of capital inputs to agricultural production.

Figure (1) 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 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:

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

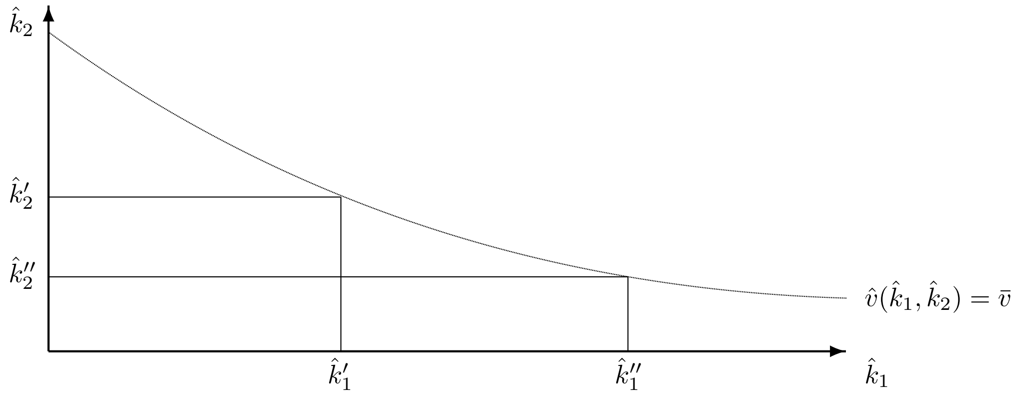


Figure 1: Illustration of an isoquant where the inputs exhibit a high degree of substitution in production and a low marginal rate of technical substitution.

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.

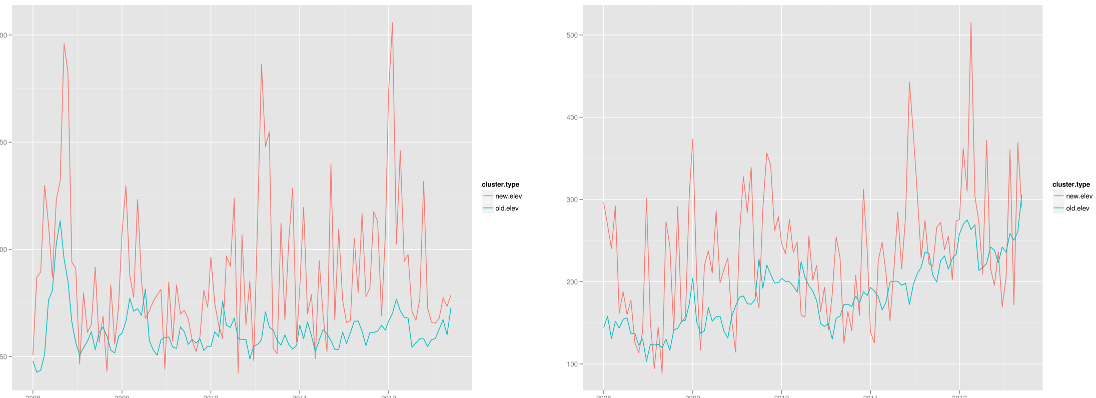
$$\frac{\partial G(\mathbf{K},\mathbf{0})/\partial \mathbf{K}_1}{\partial G(\mathbf{K},\mathbf{0})/\partial \mathbf{K}_2} = \frac{\partial G(\mathbf{K},\mathbf{0})/\partial \mathbf{I}_1}{\partial G(\mathbf{K},\mathbf{0})/\partial \mathbf{I}_2} \tag{3}$$

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 (1) 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 (1) 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.[1]

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.

[1] 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.



(a) Elevation for Indonesian land clearing   (b) Elevation for Malaysian land clearing

Figure 2: Elevation of land clearing for different cluster types over time.

Empirical rates of substitution

Data

The foundational data for this study is an original data set of deforestation for each 500-meter in the humid tropics. The data set, described in Hammer, *et al.* (2012), reports forest clearing activity for each 16-day interval between January 1, 2008 and September 23, 2012. Forest clearing activity is reported as a normalized measure of clearing intensity, based on composited, daily images from NASA's Moderate Resolution Image Spectrometer (MODIS) sensor aboard the Terra satellite. A pixel is flagged for clearing activity if the measure registers above 0.50. Only pixels that are in Malaysian or Indonesian Borneo and that were forested in January 2000 are considered in the study.[2] These data constitute a panel with $N = 2,384,095$ pixels and $T = 109$ time intervals, a total of about 260 million records. By September 2012, $207,578$ pixels in the sample area were tagged with forest clearing activity, indicating that approximately 8.71% of the study area has been subject to clearing activity since February 2000.[3]

Figure 3a reports the overall rate of deforestation for Malaysian and Indonesian Borneo. The The time series indicates the level of clearing activity for each 16-day interval, measured in the number of 500m pixels. 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 existing clusters of deforestation, and (2) pixels that constitute a new, emerging cluster. Consider, for example, the illustration in Figure 4. The black pixels represent existing cleared land, while the red, labeled pixels indicate newly cleared areas. The five newly identified pixels are grouped according to their distance to the nearest, existing cluster. We employ a distance threshold equal to twice the resolution of the pixel, or approximately 1000m, in order to identify distinct clusters. For example in Figure 4, pixels **A**, **B**, and **C** would be grouped into one cluster, while pixels **D** and **E** would be grouped into another. The distance is measured between pixel centroids. The threshold is arbitrary, but it is notable that the results of this paper are robust for many different thresholds to define clusters.

The decision to invest in cleared land, a capital input to agricultural production, is determined by agricultural prices and characteristics of the land that will effect both the cost of clear-

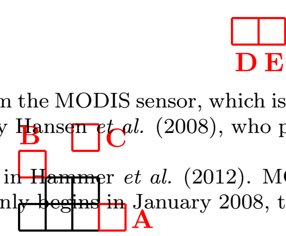
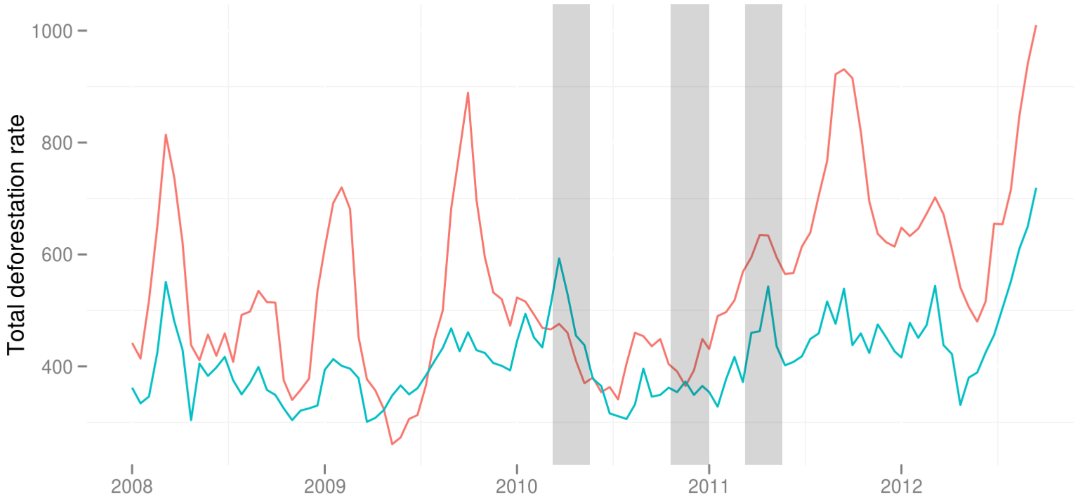


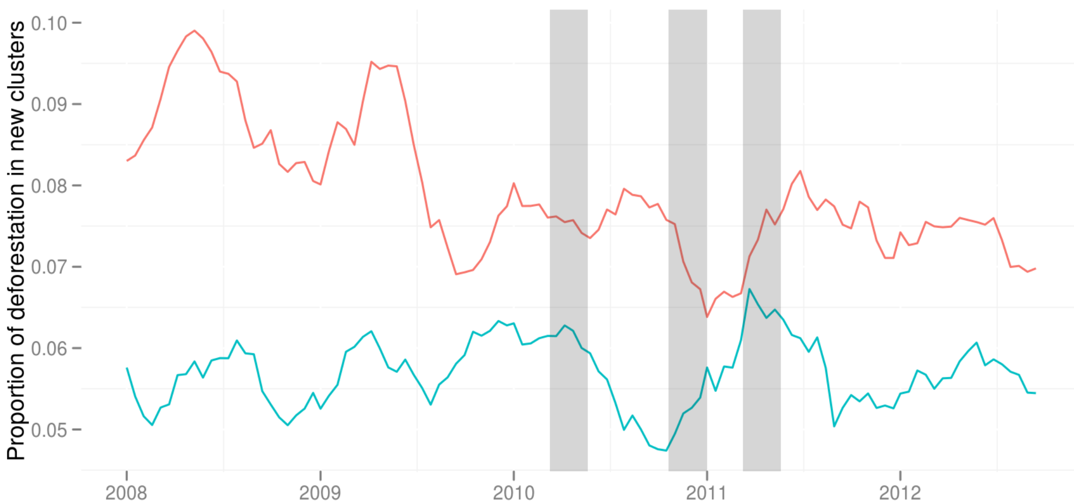
Figure 4: Illustration of clusters

[2]The definition of forest is based on the Vegetation Continuous Field (VCF) index from the MODIS sensor, which is consistent with many other publications in remote sensing. Most notably, this definition is used by Hansen *et al.* (2008), who provide the training data set for the our algorithm.

[3]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 3: 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.

ing. These factors effectively determine components of the firm's profit function. We utilize data on agricultural prices, and specifically global palm oil prices, collapsed from daily prices to 16-day averages. The trend in Figure 5 shadows the global, aggregated commodity price index — and many individual palm oil subsititutes. This argues against an endogenous price shift, even though the moratorium was coincident with a price spike in palm oil and that Indonesia accounts for about 40% of global production. In the broader agricultural oil market, Indonesia is still a relatively small player, given a high degree of substitutability. We consider the near-term price evolution of palm oil to be exogenous to Indonesia's production.

Figure 5: Palm oil price. Shaded regions indicate the three stages of the moratorium.

We also utilize elevation data from the Shuttle Radar Topography Mission (SRTM) to derive a host of physical characteristics of the landscape. The SRTM is reported at 90m, significantly higher resolution than the 500m deforestation pixels. We can therefore create a derived data set of slope, terrain roughness (variance in slope), and water accummulation at the MODIS 500m resolution. These static characteristics help specify the cost structure of investment. In addition, the deforestation data rely on spectral imagery, collected on a daily basis, along with NOAA data on precipitation and other dynamic data sets, which are detailed in Hammer *et al.* (2012).

Empirical strategy

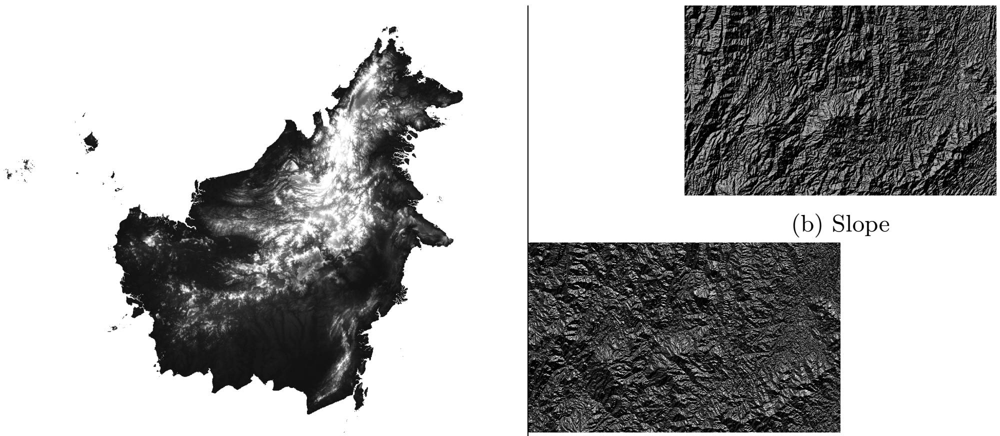
Our goal is to identify the impact of the moratorium on the spatiotemporal patterns of deforestation in Indonesia. Specifically, we attempt to identify the impact on

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 7. 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

[4]This fact will be shown in forthcoming versions of this paper by rigorously comparing the raster images in Figure 6



(a) Elevation (b) Slope (c) Drop

Figure 6: 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.

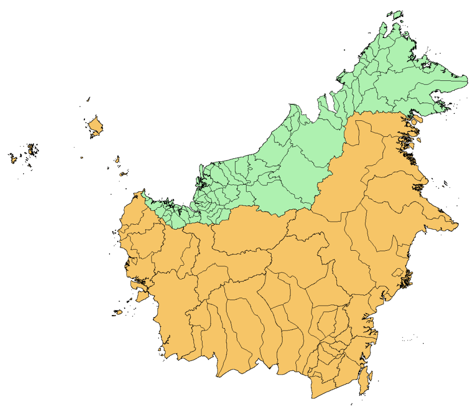


Figure 7: Sample area, Malaysia in green and Indonesia in orange. Borders indicate subprovinces.

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

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

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 3a. 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:

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

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

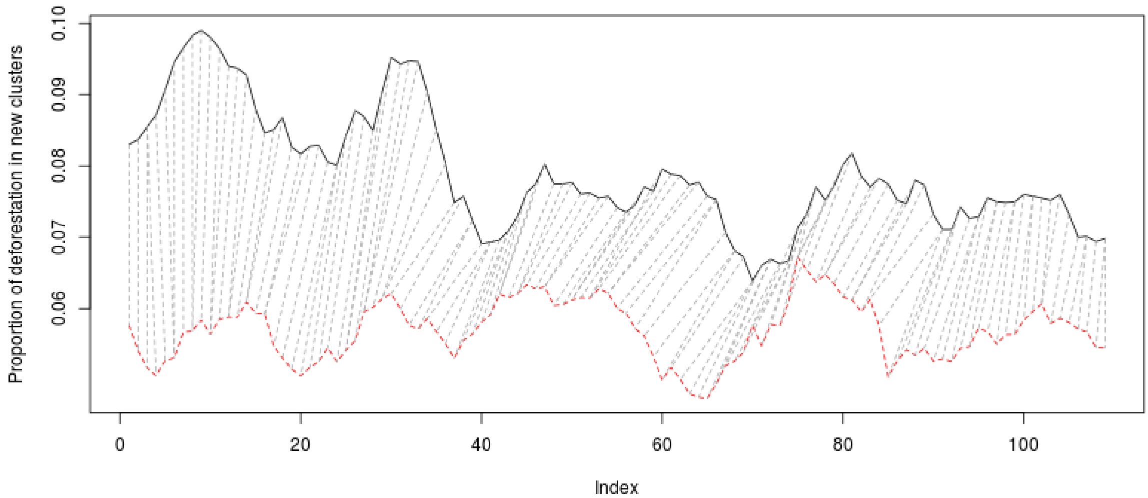


Figure 8: Dynamic time warping of the Indonesian (black, solid) series and the Malaysian (red, dashed) series. The gray matching lines match similar values across the two series, based on a set of matching penalties. The dates are replaced with index values.

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 8. A standard, uncorrected difference-in-differences estimator relies on a perfectly vertical comparison of observations. In other words, the dashed matching lines in Figure 8 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 8 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 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

	(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

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 3b 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, 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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