Cease and Disperse: The impact of targeted conservation on the optimal development of resource pools

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Abstract

This paper examines the effect of narrowly defined conservation policy on the spatial distribution of deforestation. Specifically, we estimate the impact of the 2011 Indonesian moratorium on new forest concessions for agriculture production. The intended impact was to reduce the rate of deforestation, but instead we find that the aggregate rate of deforestation may have increased. This paper offers a possible explanation that is founded in basic optimal control and production theory. Cleared land is an input to agriculture, which can be sourced from the periphery of existing deforestation or from remote forests. We model the moratorium as a discrete increase in the input price of cleared land in remote forests. The marginal rate of technical substitution over time determines both the differentiated and aggregate rate of capital investment, or clearing activity. We argue that the marginal productivity of land in remote clusters is higher than land on the periphery of existing clusters. The implied rate of substitution between the two land types indicates that the moratorium will decrease the amount of remote land used, but increase the aggregate rate. This conclusion is supported by an empirical study based on an original data set derived from satellite imagery. Our sample area is the island of Borneo, which is bisected into Indonesia and Malaysia by a national boundary, serving as our identifying assumption for a difference-in-differences estimator. We employ a series of novel robustness checks to further validate the conclusion.

Deforestation accounts for 12% of annual carbon emissions, which is roughly equivalent to the emissions from the transportation sector. Any viable effort to mitigate climate change must therefore address deforestation. Deforestation is a distinctly economic activity. This may be a difficult proposition, however, since most deforestation occurs in tropical countries, which rely heavily on cleared land for agriculture. Indonesia, for example, is responsible for roughly 20% of annual deforestation; and its agricultural sector, broadly defined, contributed 14.3% to gross domestic product in 2012, a percentage only exceeded by India. Indonesia's rural economy relies heavily on products derived from cleared land, and there exist incentives at every level to convert standing forest to a more fiscally productive land use. 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

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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. The Indonesian government 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. Various environmental groups, however, counter that the moratorium has had no effect on aggregate clearing activity. Greenpeace claims that deforestation has actually increased since the moratorium. They claim that illegal forest clearing activity and rampant corruption has eroded the efficacy of the moratorium. These claims seem to be corroborated by local media outlets. In May 2012, the Jakarta Globe reported that 5 million hectares of Indonesia's remaining 130 million hectares of existing tree cover had been cleared during the previous yea. The state of Kalimantan on Borneo was hardest hit, losing 1.9 million hectares of forest cover. The source of this information is unclear[1] and the statistic is highly contested by the Ministry of Forestry. The Ministry claims that the deforestation has occurred outside of the boundaries of the specified conservation areas. The moratorium does not apply to concessions that had been granted before May 2011.

Independent reports of deforestation are essentially nonexistent. Satellite imagery of forests is
Satellite imagery supports the claim of accelerating deforestation, despite the moratorium. This paper tests the hypothesis that the deforestation rate in Indonesia increased *because* of the moratorium.

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 geographic "leakage" to identify the true additionality of the policy, seeking to answer the question of whether the deforestation rate was reduced or merely pushed to an unaffected country or province. They pay little attention, however, to shifting spatial patterns of deforestation *within* an affected administrative area. This is still leakage, but it is not a common 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 substitution across different types of clearing activity on the aggregate level of forest conversion, based on the net revenue structure of the cleared land.

[1] The Jakarta Globe cites Greenpeace as the source of this information, but repeated interactions with geospatial team at Greenpeace have not produced a firm estimate. It remains unclear where the statistic came from.

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 validity 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 natural 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 more 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.

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 2a 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

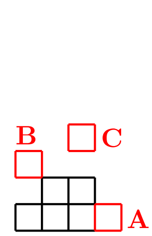


Figure 1: Illustration of clusters

[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.

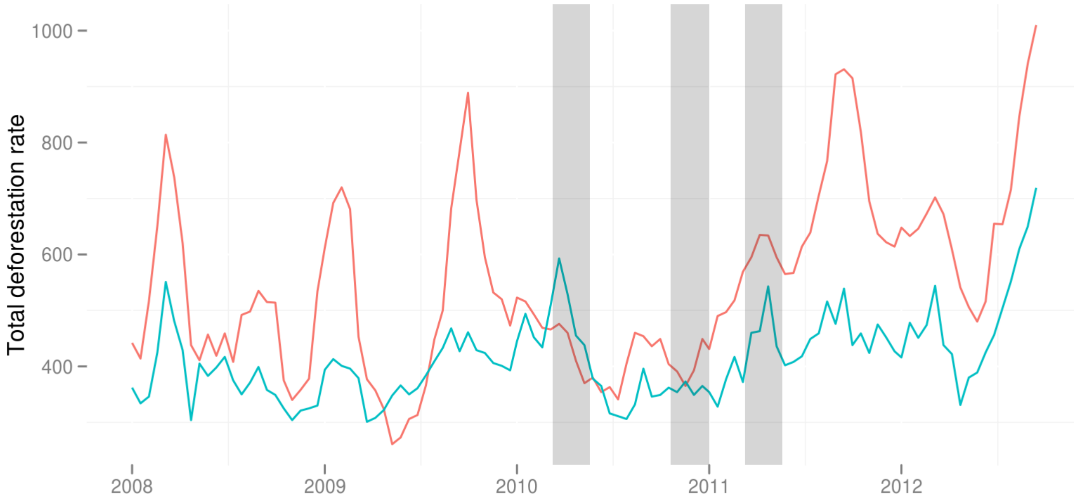
lag in the detection of clearing activity. Within each interval, the identified pixels are categorized into one of two groups: (1) pixels on the periphery of existing clusters of deforestation, and (2) pixels that constitute a new, emerging cluster. Consider, for example, the illustration in Figure 1. 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 1, 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 clearing. 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 3 shadows the global, aggregated commodity price index — and many individual palm oil substitutes. 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.

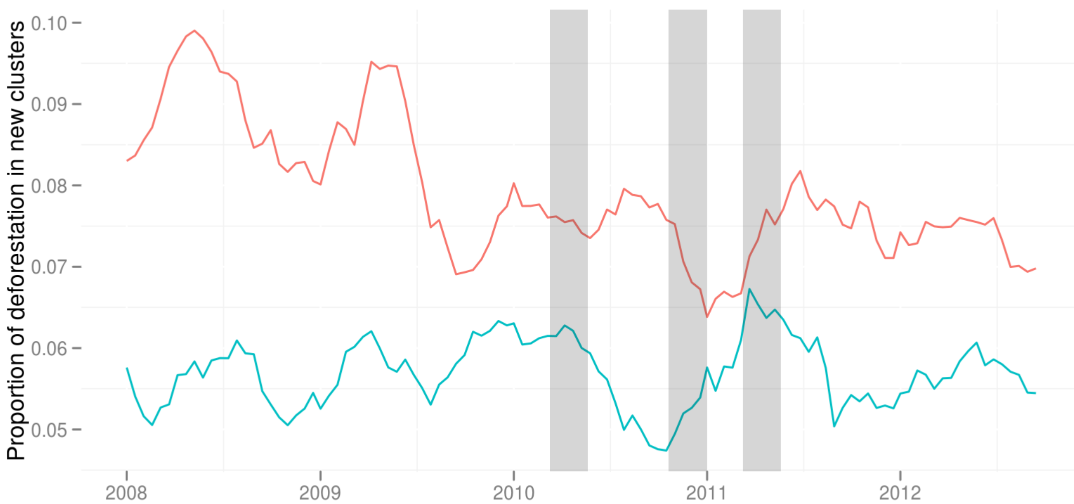
We also utilize elevation data from the Shuttle Radar Topography Mission (SRTM) to derive a host of physical characteristics of the landscape. The SRTM is reported at 90m, significantly higher resolution than the 500m deforestation pixels. We can therefore create a derived data set of slope, terrain roughness (variance in slope), and water accumulation 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).

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 revealed that the sequencing of extraction



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

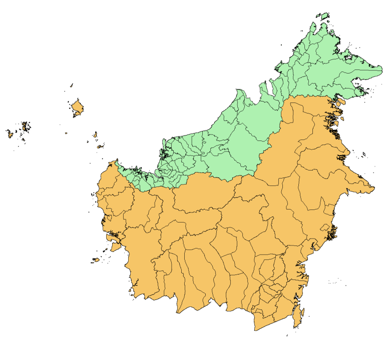


(b) Two month moving average of proportion of new clearing activity that occurs in new clusters, rather than on the periphery of old clusters of deforestation.

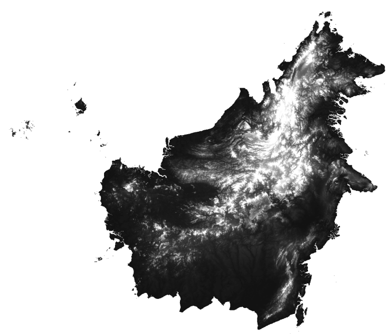
Figure 2: Time series of overall deforestation and the spatial distribution of deforestation. Indonesia is in red and Malaysia is in blue. Shaded bars indicate the three stages of the moratorium.

from different resource pools dependent on the cost structure over time, rather than just the instantaneous, marginal cost of extraction. Many extensions have been published to generalize his result and to offer specific theoretical extension. Weitzman's original models and the subsequent extensions have been overwhelmingly theoretical, since detailed information on the evolution of individual resource pools has not been available. We offer an empirical application of Weitzman's optimal control framework, using clusters of deforestation to indicate separate resource pools.

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



(a) Malaysia in green and Indonesia in orange, borders indicate subprovinces.



(b) Elevation in meters, black to white indicates low to high elevation

Figure 4: Sample Area, Borneo

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:

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

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

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 parameter ρ indicates the competitive interest rate. Define $R(\hat{\mathbf{K}})$ to be the stationary rate of capital return when optimal investment is zero. For a stationary solution to exist, there must also exist a time T such that for any $\epsilon_i > 0$ and $t > T$, the optimal solution maintains $\mathbf{I}(t) < \epsilon$. The vector $\hat{\mathbf{K}}$ is the capital input mix that satisfies the conditions for a stationary solution. The stationary rate of capital return is thus defined as

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

Equation (1) implies that the capital mix $\hat{\mathbf{K}}$ is optimal for all time, without any additional investment. Any deviation from $\hat{\mathbf{K}}$ will yield a less profitable outcome. A valid question, from the outset, is whether the stationary solution is reasonable when the capital input is cleared land. The price of cleared land within a small country in the agricultural market will not evolve with scarcity, just as the cost of labor will not evolve with scarcity in a standard two-factor production model. The derived demand for the capital input is determined by setting marginal cost equal to marginal revenue product. The substitution away from inputs with increasing costs will prevent the evolution of input price. Unlike many exhaustible resource problems, the expansion of cleared land is not driven by increasing returns, but rather by increases in agricultural prices.

The fundamental theorem of capital theory sets the stationary rate of return equal to the competitive interest rate, resulting in the the system of equations

$$R(\hat{\mathbf{K}}) = \rho \tag{2}$$

The investment mix is subject to an external valve, such that the decision to invest in each capital input will be weighed against the going interest rate. Weitzman notes that the stationary solution may never be reached, depending on the particulars of the investment schedules; but investment decisions will push the capital mix toward the stationary solution through time. An implication of Equation (2) is that, for any two inputs i and j,

$$\frac{\partial G(\mathbf{K}, \mathbf{0})/\partial \mathbf{K}_i}{\partial G(\mathbf{K}, \mathbf{0})/\partial \mathbf{I}_i} = \frac{\partial G(\mathbf{K}, \mathbf{0})/\partial \mathbf{K}_j}{\partial G(\mathbf{K}, \mathbf{0})/\partial \mathbf{I}_j} \qquad \Rightarrow \qquad \frac{\partial G(\mathbf{K}, \mathbf{0})/\partial \mathbf{K}_i}{\partial G(\mathbf{K}, \mathbf{0})/\partial \mathbf{K}_j} = \frac{\partial G(\mathbf{K}, \mathbf{0})/\partial \mathbf{I}_i}{\partial G(\mathbf{K}, \mathbf{0})/\partial \mathbf{I}_j} \tag{3}$$

These equalities hold for arbitrary investment schedules, as long as the dynamic solution tends toward a stationary input mix. The implications are not so different from the static, two-factor production model. The present value of the marginal rate of technical substitution should equal the present value of the relative investment costs at the optimum. For our study, the two factors are cleared land on the periphery of existing clusters and cleared land that would constitute a new, remote cluster. Let $\hat{\mathbf{K}}_1$ be the stationary capital usage for peripheral land, and let $\hat{\mathbf{K}}_2$ be the stationary usage of remote land. These two inputs can be combined to produce a certain level of agricultural product at a competitive market price. The associated revenue, or value to the land developer, is the gross gain Weitzman's $G(\cdot)$ function. Call this revenue function $v(\cdot)$ and the present value of the discounted revenue stream $\hat{v}(\cdot) = v(\cdot)/\rho$. At this point, the dynamic problem has been sufficiently collapsed to use the standard insight from a static two-factor production model. The derivation from the dynamic problem ensures that the subsequent insight is robust up to the dynamic considerations faced by the land developer.

Figure (5) graphically represents the present value isoquant. The two inputs, peripheral and remote cleared land, are highly substitutable in agricultural production, such that the isoquant is almost linear. Some level of complementarity, through time, may emanate from risk mitigation strategies on the part of the agriculturalist, or other dynamic considerations where exploration is optimal. Suppose that $\hat{\mathbf{K}}_1'$ and $\hat{\mathbf{K}}_2'$ satisfy Equation (3) under an initial investment schedule. If the required investment for remote land increases, then the optimum input mix will move along the isoquant to $(\hat{\mathbf{K}}_1'', \hat{\mathbf{K}}_2'')$; the price, broadly defined, to hire the input increased. This situation corresponds to the moratorium.

The moratorium differentially impacted the cost of investment in remote clusters by increasing the uncertainty surrounding the maintenance of the capital input. Given that the moratorium map is uncertain and changes every six-months, the likelihood that a concession granted after May 2011 may be revoked is nontrivial. At best, the moratorium increases the uncertainty of a stranded capital asset (cleared land), and at worst, the moratorium provides leverage to local administrators to extort money from land developers. The rate of corruption surrounding land tenure and development in Indonesia has skyrocketed since the moratorium, according to various local news reports. Either way, the requisite investment for remote clusters increased relative to peripheral clusters as a direct result of the moratorium. Figure (5) indicates that the relative intensity of remote land decreases in response to the price increase.

The effect of the moratorium on the aggregate use of cleared land depends on the average slope of the present value isoquant, which is in turn determined by the relative productivity of the two land types. The dominant use for land cleared at large-scale in Borneo is palm oil. The palm oil production process requires that the raw kernels be processed by a central facility within 24 hours of harvesting. The kernels spoil quickly, and the proportion of spoiled kernels increases in time. The time required to transport the harvested kernels to the processing facility is substantial, given a network of poor, dirt roads. Cleared land that is close to the processing facility therefore has a higher per-acre yield of processed oil than cleared land that is further away. Land on the periphery of existing clusters is, by definition, further away from the seed of the deforestation cluster than the seed itself. New clusters in remote forest landscapes therefore have a higher productivity over the course of the plantation development. Peripheral deforestation indicates that the plantation is further along in its development than remote deforestation, which indicates initial clearing activity. The argument is, in effect, a geometric argument, and reflects the diminishing productivity of a unit of land as the plantation grows.

The characteristics of the two land types support this argument. Note that the tangency of the isocost line would imply that the cost of investment tends to be higher $\hat{\mathbf{K}}_2$ than for $\hat{\mathbf{K}}_1$. It is more difficult to prepare cleared land for agriculture at higher elevations and at higher slope, all else equal. We use the elevation data from the SRTM digital elevation model to examine the characteristics of the two land types. For both Indonesia and Malaysia, the slope and elevation are significantly higher for remote deforestation than for peripheral deforestation (with p-values less than 0.001). This result is consistent with the slope of the isoquant in Figure (5).

Note that, assuming the shallow isoquant in Figure (5), an increase in the cost of investment in $\hat{\mathbf{K}}_2$ will yield an increase in the aggregate level of cleared land at the optimum, i.e.,

$$\hat{\mathbf{K}}_1' + \hat{\mathbf{K}}_2' < \hat{\mathbf{K}}_1'' + \hat{\mathbf{K}}_2'' \tag{4}$$

The decrease in $\hat{\mathbf{K}}_2$ is more than offset by the increase in $\hat{\mathbf{K}}_1$ as land developers shift agriculture to the periphery of existing clusters, despite the lower marginal production. After the dynamic investment decisions are collapsed to their stationary equivalents, there is nothing particularly deep about this structure. The empirics indicate that, indeed, more land was cleared in the aggregate after the moratorium, even with a decrease in remote clusters.

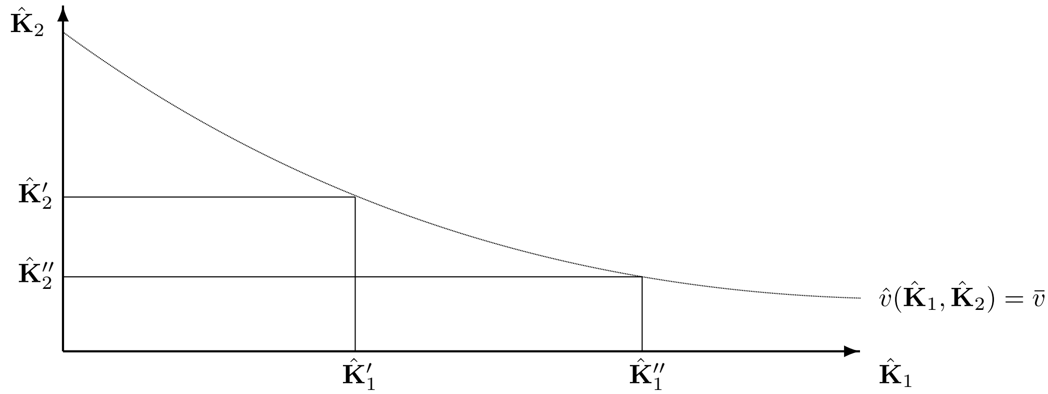


Figure 5: Illustration of an isoquant where the inputs exhibit a high degree of substitution in production and a low marginal rate of technical substitution.

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 of the moratorium on

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

Our sample is the island of Borneo, which is bisected into Indonesia (73%) and Malaysia (26%) along the central highlands, seen in Figure 4a. Forest conversion on both sides of the border is primarily driven by large-scale palm oil production. Together, Malaysia and Indonesia produce 65% of the world's oil palm, much of it coming from the island of Borneo. The climate and terrain are ideal for palm oil production. The border was established between Great Britain and the Netherlands in 1891, based on coastal trade positions. The conflict over trade routes the generated the border was independent of the land characteristics that affect palm oil production, although we acknowledge that the partition may have subsequently and differentially influenced palm oil production on either side of the border. We utilize a difference-in-differences approach to estimate the impact, with modifications introduced for robustness checks. Only the Indonesian side was directly impacted by the moratorium. Let M be a binary variable indicating the time period after the moratorium was established. We will allow the defining interval to vary in order to reflect the three-stage enactment of the moratorium. Let C be a country indicator for Indonesia. The standard difference-in-differences model for the overall rate of deforestation is given by

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

where $\mathbf{x}$ is a vector of cofactors. The identifying assumption is that in the absence of the moratorium, the time trends in R_{it} and P_{it} are stable for the control and treatment groups after controlling for relevant covariates. The relevant covariates that may affect the trends are the price of palm oil and the relative value of the Indonesian and Malaysian currency. Both measures have been shown to substantially impact the rate of deforestation, and presumably the spatial pattern of deforestation, although empirical research is lacking. The price of palm oil peaked soon after the second stage of the moratorium, as shown in Figure 2a. We argue that the price change was exogenous, and not affected by the moratorium. As a supporting illustration, consider the regression of palm oil prices on the prices of copper, silver, and salmon. Indonesia has no impact on the price of these commodities. These commodities, however, explain almost 85% of the variation in the palm oil price, and the addition of M_{it} lowers the adjusted R^2 value. It is clear that the trend in palm oil price was coincident with global commodity prices; and the spike is unlikely to have been caused by the moratorium. In fact, including the price of oats in Canada has greater explanatory power on the palm oil price than the moratorium in Indonesia. The vector $\mathbf{x}$ therefore includes the price of palm oil and the relative exchange rate of Indonesia's rupiah to the Malaysian 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 (5), except that the proportion of new deforestation in new clusters is the dependent variable:

$$P_{it} = \alpha_0 + \alpha_1 M_t + \alpha_2 C_i + \tau(M_t \cdot C_i) + \beta\mathbf{x} + \epsilon_{it} \tag{6}$$

The average effect of the moratorium in Indonesia is estimated by $\hat{\tau}$. The estimate will only be consistent if the identifying assumption holds, specifically that the outcome would have followed parallel paths over time. Abadie (2005) outlines the severe assumptions that underlie difference-in-differences estimation, especially with respect to lag structure of the response variable in the presence of unobserved shocks. Suppose, for example, that the time required to adjust the expectations in response to changes in agricultural prices is different for Indonesian and Malaysian developers. The length of time that the global price must remain high before a developer invests in a new deforestation cluster may be different, based on domestic price guarantees or other stabilization policies. This difference may be enough to induce non-parallel transformations of the outcome variable P_{it}, which would thereby render the estimate $\hat{\tau}$ inconsistent. A visual inspection of Figure **??** may support this situation, given that the superficial patterns in P_{it} for Indonesia seems to lag behind the P_{it} measure for Malaysia. Abadie proposes a semi-parametric correction based on the observables in $\mathbf{x}$ to account for non-parallel effects in the outcome variable. But even this correction assumes a constant shift between the outcome variable for the treatment and control groups. Moreover, the semi-parametric correction is based on the trends of observable characteristics, whereas there may be dynamics that are within the error that drive the shifts. Any non-parallel stretching or compressing in the outcome variable will not be addressed by the Abadie (2005) correction.

We propose a robustness check to the standard difference-in-differences approach by way of a first-stage alignment algorithm. It is beyond the scope of this empirical paper to describe in detail the non-parametric algorithm. The basic objective, however, is to uncover broad trends in the difference between the outcome variables by matching corresponding, temporal patterns in the residual variation. We employ a matching technique called dynamic time warping to "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. We present an illustration of the matching procedure in Figure 6. A standard, uncorrected difference-in-differences estimator relies on a perfectly vertical comparison of observations. In other words, for the standard difference-in-differences estimator, the dashed matching lines in Figure 6 would all be vertical, associating values within the same time period only. Time warping allows for flexible slopes. Figure 6 shows the result of the matching algorithm between the treatment and control P_{it} series. The matching procedure defines a correspondence between the two series that is based on the broad trends, rather than idiosyncratic noise.

We reconstruct the Indonesia P_{it} series based on the dynamic time warping procedure in order estimate τ using the same model in Equation (6). This new series, the aligned series, may better characterize the comparable differences between the treatment and control groups that directly result from the moratorium. 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 assumption. The dynamic time warping algorithm is only applied to Equation (6) and not Equation (5) as a robustness check. The systematic stretching and compression is much more apparent between the P_{it} series for the control and treatment groups. The application of the matching algorithm to the R_{it} does not yield any appreciable change in the results, since there does not seem to be any systematic but shifting correspondence.

Results

The results of the aggregate deforestation regression in Equation (5) 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.

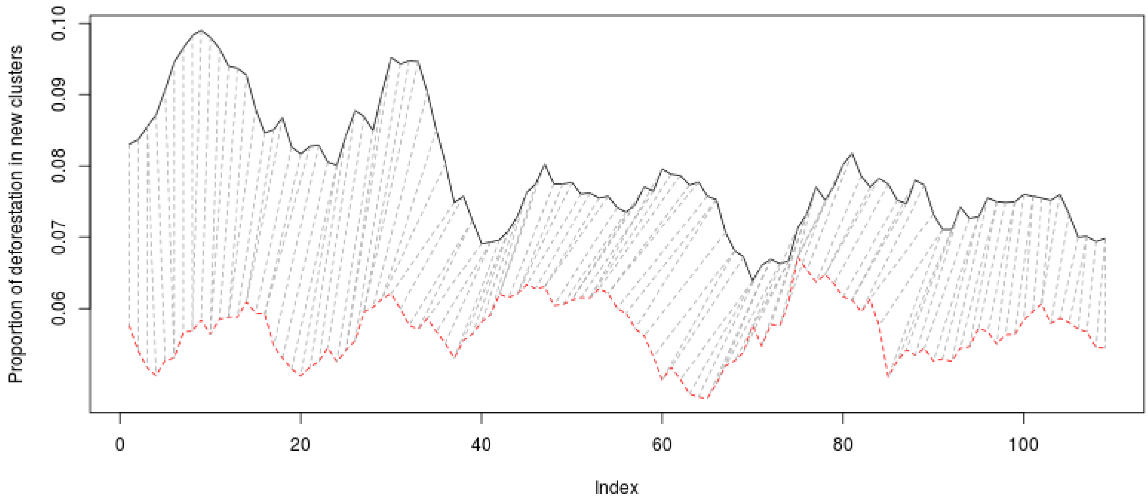


Figure 6: Dynamic time warping of the Indonesian (black, solid) series and the Malaysian (red, dashed) series. The gray matching lines match similar values across the two series, based on a set of matching penalties. The dates are replaced with index values.

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 the lagged effect of a price change, which is not accounted for in the regression.

Deforestation in Indonesian and Malaysian Borneo is highly concentrated into superclusters, clusters with more than 0.5% of total deforestation on the island. In Indonesian Borneo, for example, almost 5% of total deforestation in September 2012 was concentrated in the top 10 largest clusters of the 2,861 total clusters. A concern may be that these superclusters drive the result. However, the results in Table 1 are robust after iteratively screening out the top 10 clusters in each country. And, in fact, the results become stronger as the superclusters are removed from the analysis.

The results of the regression described by Equation 6 are reported in Table 2, and the results of the dynamically warped regression are reported in Table 3 as a robustness check. 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 to reflect the three stages of the moratorium. Given the high prices of oil palm, and the associated incentive to create new clusters of deforestation, the proportion in Indonesia *should have* increased to about 8.5%; but instead it has remained at around 7.5%, as if the price did not increase at all. The moratorium wiped out the dispersion we would expect from an increase in agricultural prices.

	(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 results in Table 2. In fact, the correction increased the magnitude of the moratorium's impact. The coefficient on `country:post`, the interaction between the country and post-moratorium indicators, is negative and highly significant in all specifications. As in the previous tables, Columns (1), (2), and (3) define the treatment period based on the three different phases of the moratorium. The magnitude of the impact decreases 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. Developers have begun to resume their involvement in remote forest landscapes. The rate of violations reported in the Jakarta Post has certainly increased dramatically, with little official response. The impact is both statistically and economically significant, indicating that the moratorium reduced dispersion of forest clearing activity.

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 2b 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. The direct and blunt policy instrument was to ban new concessions for forest conversion. In response, land developers merely shifted clearing activity away from the directly impacted areas and toward forests within existing concessions. The result was an increase in aggregate deforestation, given the relative productivity of land on the periphery of existing clusters, within existing concessions. The narrowly defined conservation policy had the unintended consequence of increasing deforestation, strictly counter to the expressed intentions.

The analysis also suggests that efforts to extend the two-year moratorium will be met with strong industry

	(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

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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