

Supporting Information

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The RSPO

Founded in 2004, the RSPO is a global multistakeholder organization that consists of voting members from industry and civil society, including plantation companies, processors and traders, consumer goods manufacturers and retailers, financial institutions, and non-governmental organizations. The RSPO offers a certification program based on oversight by independent third-party accredited auditors who assess performance against the RSPO P&C, a set of legal, environmental, economic, and social guidelines.

By joining the RSPO, oil palm grower members commit to eventually certify all their mills and supply bases. Each member constructs a time-bound plan to certification that lists the mills (or estates not yet associated with mills) held by the company and a proposed date for certification of each estate or mill. This time-bound plan must be published as part of the first annual progress report after the company joins the RSPO. Subsequently, members report progress against their time-bound plans. While the code of conduct for RSPO members requires that companies commit to production of sustainable palm oil, certification mandates that individual mills abide by specific provisions in the RSPO P&C and includes annual third-party audits.

Data Sources

Certified and Noncertified Plantation Boundaries and Attributes. We compiled a dataset of RSPO-certified supply bases and non-certified oil palm concession leases in Indonesia. A supply base consists of all lands that produce or support the production of palm oil processed at an RSPO-certified mill, and may include planted palm, nurseries, riparian buffers, HCV set-asides, palm oil mills and supporting infrastructure, certified smallholder oil palm lands, and roads. A concession is granted by the Indonesian government to an oil palm company for a limited period, and is defined by boundaries negotiated between the government, the company, and resident communities. Concessions may contain lands that support the production of palm oil. However, in some cases, these concessions could be undeveloped (i.e., not planted to oil palm).

For certified supply bases, we first compiled a list of all grower and group certifications conferred by the RSPO. As of March 30, 2017, about 400 palm oil mills and 20 smallholders' groups had been certified by the RSPO globally. The RSPO secretariat supplied polygon vector data outlining the boundaries of 134 certified supply bases. We digitized additional polygons from maps available from audit reports hosted on the RSPO website, supplemented by spatial data on plantation boundaries provided by companies as part of the 2014 RSPO ACOPs, as well as plantations identified from Greenpeace (1) and Sawit Watch* concession datasets. We compiled ancillary data from audit reports, including the dates of RSPO certification, LOIs notifying stakeholders of the intent to pursue RSPO certification, and initial oil palm planting. When the initial oil palm planting date was not available, we inferred a date by inspecting our planted oil palm spatial database.

For noncertified concessions, we used oil palm concession leases compiled by Greenpeace (1) and Sawit Watch*. Greenpeace maps are based on agricultural plantation maps provided by the Indonesian Ministry of Forestry Planning Department in 2010, and were updated with province-level data from select provinces and corporate submissions to the RSPO. Sawit Watch maps were compiled from the Indonesian National Land Agency, the Indonesian Ministry of Environment and Forestry,

and district and provincial estate agencies. These datasets include the polygon locations of concessions and typically identify company names. We supplemented these datasets with RSPO member-held, yet noncertified, supply bases available from the 2014 RSPO ACOPs.

From this noncertified dataset, we removed all polygons with >50% area overlapping with a certified polygon and then erased remaining noncertified regions intersecting with the certified dataset. Next, we manually altered edges of noncertified polygons so that there was no overlap between polygons; we gave precedence to polygons that maximized consistency with adjacent plantations or 2010 planted oil palm area (2, 3). Often, multiple polygons with the same name occurred in these databases. When these polygons were <10 km apart, we combined them to represent a single concession.

To identify concessions held by RSPO members, we compared concession company names with companies listed in time-bound plans provided in ACOPs and audit reports, as well as companies that had submitted NPP documents to the RSPO, names provided in 2014 company annual shareholder reports, and subsidiaries available on RSPO member website pages. When available, we identified the date of any LOIs for these noncertified concessions.

Smallholder groups were not considered in our analysis because of the small sample size of group certifications and lack of comparable noncertified smallholder datasets. Therefore, we removed polygons in the noncertified dataset that had company names incorporating the following words and phrases: *kelompok* (group), *koperasi* (cooperative), *plasma*, *masyarakat* (community), *yayasan* (foundation), *petani* (farmer), *kebun swadaya* (independent garden), and *rakyat* (people). We also removed any polygon <1 km². Due to our focus on large-scale industrial plantations, we refer to the final combined dataset consisting of certified supply bases and noncertified concessions as certified and noncertified "plantations."

Final plantation area permitted may be less than the proposed area due to negotiations with communities, other companies, and environmental restrictions that limit lands that may be committed to palm oil production. We compared plantation areas to assess similarity between our digitized boundaries and those provided by the government. On average, certified plantations were larger than noncertified plantations (Table S1).

Oil palm plantation age was derived by binning oil palm area by initial planting year (certified plantations) or by lagging Indonesian oil palm harvested area as reported by the Food and Agriculture Organization Corporate Statistical Database (4) by 3 y to account for time from planting to harvest (all plantations).

Planted Oil Palm. Locations of planted oil palm in 2000 in Indonesia were derived from Gunarso et al. (2). We supplemented this dataset with year 2000 Kalimantan-wide planted oil palm maps (5). These datasets were developed through visual interpretation and manual digitization of plantations from Landsat and other satellite remote-sensing data.

Forest Loss. The RSPO P&C, national laws, and international agreements such as Reduced Emissions from Deforestation and Forest Degradation (REDD+) rely upon multiple definitions of deforestation, which affect estimates of deforestation rates (6). Here, we briefly review two definitions of forest that apply to these three types of policy instruments, and evaluate the degree to which canopy cover loss is a proxy for deforestation under these definitions:

*Sawit Watch (2013) Palm oil concessions in Indonesia.

- i) RSPO: The RSPO P&C strictly prohibit clearing of “primary forest,” defined as forest that has never been logged and has developed naturally or is used by local communities (7). The P&C also require protection of HCV areas, which are biological, ecological, social, or cultural values considered to be outstandingly significant or critically important (8).
- ii) Indonesia: For the purposes of REDD+, the government of Indonesia defines forest as an area of >0.25 ha with trees >5 m and canopy cover >30% (9). This includes logged, disturbed, and planted (e.g., pulp and paper) forest. Lands that are predominantly under urban or agricultural uses, such as rubber and oil palm, are not considered forest.

Fallow lands, tree plantations, logged forests, and agroforests are often indistinguishable from primary forest based on tree canopy cover (3, 10), and HCV areas cannot be delineated using remote sensing alone. Therefore, only the REDD+ (Kyoto Protocol) definitions can be applied directly to remotely sensed canopy cover to derive forest maps.

Given the impossibility of determining compliance with the RSPO P&C using changes in canopy cover alone, we evaluated land use change using several forest cover definitions. Remote sensing cannot provide forest maps that are exactly equivalent to the on-the-ground assessments required by the RSPO P&C, and so our analysis should not be considered an evaluation of compliance. We used Hansen et al. (11) year 2000 percentage tree cover maps derived from Landsat, along with their 2001–2015 deforestation estimates, defined as a stand-replacement disturbance or the complete removal of tree cover canopy at the Landsat pixel scale, to assess forest cover loss within oil palm plantations. In addition, we analyzed change in Margono et al. (12) primary forest, defined as mature natural forest of ≥ 5 ha retaining natural composition and structure that has not been completely cleared and replanted in recent history. This includes primary degraded forest that has suffered partial canopy loss (e.g., via logging), and which therefore has altered composition and structure (12). To assess the degree to which certified plantations are located on peatlands and cleared peatland forests, we used the peatland layer created by Wahyunto et al. (13–15). In all cases, we excluded forest areas identified as planted oil palm or other plantation, including rubber, timber, mixed tree crops, or crop plantation (2, 5).

Fire Activity. We used the Moderate Resolution Imaging Spectroradiometer (MODIS) global monthly fire location product (MOD14 v6) to identify locations of fire (16). This product detects fires within 1-km pixels that are burning at the same time as satellite overpass under relatively cloud- and smoke-free conditions. The product includes detections from both the Aqua and Terra satellites, which were launched in 1999 and 2002, respectively. Since only the Terra sensor was actively collecting data from 2000 onward, the rate of fire detection from 2000 and 2001 is likely lower than in the rest of our time series. As a result, we limited our fire analyses to the 2002–2015 period. For each year, we summed the total number of fires occurring within plantations, and then divided by plantation area to generate a fire rate (fire detections per square kilometer per year).

Empirical Analysis

Our analysis sought to identify the impact of RSPO participation on deforestation and fire activity in Indonesia. Due to voluntary self-selection into the certification treatment, naive comparisons of treated versus nontreated plantations would be subject to significant bias due to selection effects (17, 18). To address this bias, we used quasiexperimental methods to generate a rigorous counterfactual for our impact assessment. To the best of our knowledge, only three previous studies have used rigorous counterfactuals to quantify the impacts of sustainability certification on deforestation (19–21), and none have looked at the

impact of the RSPO. We used a combination of propensity score matching and panel methods. Such a two-stage estimation strategy is less susceptible to model misspecification (22) and has been shown to best replicate experimental results (23).

Units of Analysis and Treatment Specification

We conducted our analysis at the plantation level to match the scale at which many plantation management decisions occur. For certified plantations, we defined the beginning of treatment as the LOI date. The LOI defines the scope of the certification and planned assessment dates, and invites interested parties to submit comments. Since plantation managers are likely to anticipate certification, we felt that this lead time would better represent the beginning of the certification process than the date certification was granted. We refer to this event as “certification initiation.” For 11% of certified plantations in our database, no LOI was available. For these plantations, we substituted the date certification was granted for the LOI date. Our treatment dataset included all oil palm plantations that had issued an LOI by January 30, 2017, while our control dataset included all other plantations. Thirteen noncertified member-held supply bases have issued LOIs but have not yet received certification. Of these, just one supply base is associated with an LOI published before 2014.

Outcomes

We considered four environmental outcomes (deforestation, primary forest clearing, peatland forest clearing, and fire activity) since these have been identified by civil society and the global research community as critically important barriers to sustainability in the palm oil sector (3, 6, 24–26). Moreover, standardized remote-sensing time series for these outcomes are available at Indonesia-wide scales.

Our main outcome variable of interest was the rate of deforestation ($\% \text{ y}^{-1}$). Using 2000-era forest cover maps (11) and working in Google Earth Engine, we identified pixels within each plantation i with >90% tree cover ($f_{i,2000}$). We chose this threshold in an effort to exclude nonprimary forests and plantations from our deforestation metrics (10). This is particularly important in Indonesia, where agroforests, forest-like fallows, jungle rubber, pulp and paper, and oil palm have high canopy cover but are not targeted for conservation under the RSPO P&C or other major national and international policies (27). For each of the following $t = 14$ y, we calculated the area of pixels that were cleared according to the Hansen et al. (11) forest loss data products ($d_{i,t}$). We focused our attention on forest clearing and, as a result, did not include forest regrowth in our analysis. The deforestation rate is defined as:

$$r_{i,t} = \frac{d_{i,t}}{f_{i,t-1}} \quad [S1]$$

for each plantation i and year t . We also evaluated forest cover loss in primary (12) and peatland forest, and tested the robustness of our results to alternate definitions of tree canopy cover (>30% or >60% canopy cover in 2000). To do so, we changed the initial map of forest cover in 2000, and then repeated the same analysis as outlined above and below. We also examined fire incidence (fire detections per square kilometer per year). Using annual active fire counts from MODIS, for each of t years from 2002 to 2015, we calculated the number of fires ($b_{i,t}$) per hectare for each plantation i .

Fixed Effects Poisson Model

Since our four outcome variables were all nonnegative, include zero, and not overdispersed, we used a Poisson model to assess the impact of certification on deforestation and fire activity. We leveraged our longitudinal dataset to control for unobservable,

time-invariant differences between treated and control plantations. In our fixed effects model (Eq. S2), i indexes each plantation, t indexes the 14 y in our study period, $Y_{i,t}$ represents different outcomes (*Outcomes*), ω_i represents plantation fixed effects, γ_t represents year fixed effects, and $X'_{i,t}$ is a matrix of time-varying covariates (Eq. S2). $D'_{i,t}$ is a matrix of binary variables indicating the treatment (certification) and temporal lags to treatment. In its simplest form, this matrix is a single variable indicating whether a plantation i has declared certification intent in period t . In alternate specifications, we included lagged indicator variables to test for temporal trends in treatment effects, or for anticipatory behavior (*Synthetic Controls for Data Visualization*). The vector of coefficients β yields estimates of the treatment effect and temporal lags:

$$Y_{i,t} = \exp\left(D'_{i,t}\beta + X'_{i,t}\alpha + \omega_i + \gamma_t\right). \quad [\text{S2}]$$

We accounted for spatial and temporal correlation of errors by clustering our SEs within each *kabupaten* (district). Although our base model included 83 district-level clusters, several alternate specifications included fewer clusters (e.g., the peatland forest loss model using within-district matching included 36 clusters). To account for the possibility that we might overreject the null hypothesis due to the finite number of clusters, we assessed the statistical significance of all our model results using critical values derived from a T(G – 1) distribution, where G is the number of districts.

Alternate Model Specifications

We confirmed the robustness of our results to alternate model specifications by running linear and negative binomial models (Table S4). In response to concerns that the conditional likelihood estimation procedure commonly implemented in statistical software fails to control for time-invariant, unobserved variables, we chose to estimate the negative binomial through unconditional likelihood estimation. To do so, we explicitly included plantation-level dummy variables in the model. We also examined how different definitions of forest (30%, 60%, or 90% tree canopy cover) as well as differences across Indonesian regions (Kalimantan or Sumatra) affected outcomes (Table S4).

Matching and Subsetting

The fixed effects Poisson models control for time-varying, observable differences between treated and control plantations (e.g., local variations in temperature or precipitation) through the inclusion of $X_{i,t}$, time-varying shocks due to annual events (e.g., El Niño) through annual fixed effects (γ_t), and time-invariant differences across plantations (e.g., property ownership) through the inclusion of plantation fixed effects (ω_i). Preprocessing data through matching methods can further improve quasiexperimental impact assessment accuracy (23). Matching attempts to reduce selection bias, which occurs when differences in outcomes are correlated with characteristics that influence selection for treatment. To reduce such bias, matching mimics randomization by creating a control (nontreated) sample with similar observed covariates to the treated sample. In this sample, each treated unit is matched to one or more control units based on a propensity score, which represents the modeled probability that a unit received treatment. We developed three models that matched treated plantations to similar control plantations using propensity score matching (Table S2). In all deforestation matched models, we excluded plantations with less than 1 km² of forest cover in 2000, or greater than 99% coverage by timber, rubber, oil palm, or other plantations in 2000, under the assumption that these “fully developed” plantations would not provide relevant information on deforestation. This restriction eliminated the single certified plantation outside of Sumatra and Kalimantan.

In our base-matched model, which we used to generate the results presented in the main text, we estimated propensity scores using the covariates described in *Covariates*. Given the large number of noncertified plantations, we used a 1:10 matching algorithm to improve the precision of our coefficient estimates. To avoid poor matches and reduce bias, we used a caliper that is one-fifth of an SD of the estimated propensity score (28). Since our fixed effects model is designed to estimate the average treatment effect on the treated sample, we trimmed our treated sample to the set of properties with propensity scores falling within the support created by the control properties. To account for unobserved political and economic differences, we limited matches to occur within the same island (Kalimantan or Sumatra).

Our second matched model sought to further account for spatial and political effects that were not included in our matching variables. We used propensity score estimates from the base model, but restricted matches to plantations falling within the same district. We chose to match within districts because Indonesia’s decentralized form of government devolves most land allocation decisions to the district level (29). This restriction limited the number of potential matches for each certified plantation. To avoid dropping certified plantations that had no close within-district matches, we expanded our caliper to 1 SD of the estimated propensity score. We trimmed our treated sample to the common support, thereby losing certified plantations from districts without similar noncertified plantations.

In our third matched model, we sought to control for differences in corporate management. Here, matched pairs represented different plantations associated with the same RSPO member company. We again expanded our caliper to 1 SD of the estimated propensity score. Trimming to the common support led to the loss of any certified plantation whose associated company had certified all their plantations, meaning that these results should be interpreted with caution. Although this model may reduce bias for the included plantations, its results are less general and only represent the effect of certification on the remaining sample (30).

Given the limitations in observed characteristics of the plantations, it is possible that our matching procedures did not fully control for differences between certified and noncertified plantations. To further test the robustness of our results, we explored models based on subsets of our full dataset (Table S2). The most constrained specification included only the plantations that initiated certification during our study period, identifying the treatment effect using within-plantation changes in outcomes after certification. A further specification expanded the sample pool of plantations to all plantations belonging to RSPO member companies. Since RSPO members commit to the eventual certification of all their plantations, each of these plantations should, in theory, be certified in the future. As a result, it is possible that this subset would remove some of the unobservable differences between certified and noncertified plantations that simultaneously drive the adoption of certification, as well as differences in trends in outcome variables.

Synthetic Controls for Data Visualization

To visually depict data trends in certified and noncertified plantations in figures, we created a database of synthetic controls. For each of i certified plantations, we selected the $n \leq 10$ noncertified controls that had been identified as matches based on the method described in *Matching and Subsetting*. We then calculated the mean value of each variable of interest across this matched group of n control plantations, yielding i synthetic control plantations. The mean of these synthetic controls is equal to a weighted average of the full control sample, weighted by their propensity score weights. By calculating a specific synthetic control for each treatment plantation, we could more clearly compare trends as a function of the time to certification of the treated plantation.

Covariates

In selecting covariates, we consulted previous studies on deforestation drivers (31) and certification adoption (32) to identify variables that might be related to both outcomes, and erred on the side of inclusiveness over parsimony (30). Our covariates included biophysical, climatic, economic, and geographic attributes of plantations. Specifically, we incorporated elevation (33), variability in slope (33), total plantation area (1, 34)*, distance to the nearest port (35), distance to the nearest road (36), population density (37), area of peat soils (13–15), past forest area (11), past peatland forest area (11, 13–15), past primary forest area (11, 12), past fire rates (16), past deforestation rates (11), mean annual precipitation (38), and mean annual temperature (39). Data sources for these covariates and pre- and postmatching summary statistics are provided in Table S1.

For time-varying covariates, we ran alternate specifications that matched on data through 2003 and 2008 so as to avoid complications that might arise if certification adoption influenced these variables. In our base matching procedure, we matched through 2008, the year before the first certification, to ensure the best alignment in pre-treatment trends in outcome variables. This matching procedure produced a strong correlation in precertification deforestation rates between treatment and controls (Fig. 3C). However, given that this period may have included anticipatory behavior after the development of the RSPO standard in 2004, we ran alternate specifications of the model that only matched through the year 2003. In addition to inclusion in propensity score models, time-varying climatic variables (i.e., temperature, precipitation) were used as covariates in our fixed effects models.

Temporal Effects and Parallel Trends

In the base model specification, our matrix of treatment indicators ($D_{i,t}$) was a single vector indicating whether a plantation i had announced its intent for certification in year t . The corresponding coefficient can thus be interpreted as estimating the mean annual impact of certification. However, treatment effects may vary across time (e.g., plantation managers might accelerate clearing in years before certification). We explored this possibility through alternate specifications with lagged indicators of time to certification intent. Since we sought to identify anticipatory behavior, we ran these models using the matching specification that matched on covariates through the year 2003 (Tables S5 and S6).

In our annual temporal effects models, the matrix $D_{i,t}$ was composed of individual dummy variables $\delta_{i,t}^y$. Each vector $\delta_{i,t}^y$ indicated whether plantation i , at time t , initiated certification y years ago. For example, in a plantation that initiated certification in 2010, $\delta^{y=2}$ would equal 1 in 2012, but 0 in all other years. In our first annual temporal effects specification, we estimated this model with dummies for ≥ 10 y before certification initiation, each of the 9 y before certification initiation, and each of the 6 y after certification initiation. To ease interpretation of coefficients and reduce conflation of cohort, plantation, and temporal effects, this model did not include plantation-specific fixed effects. As a result, each lagged coefficient can be interpreted as the difference between certified and non-certified plantations y years from announcement of certification intent. Our second lagged specification reintroduced plantation-level fixed effects. Given the 15 y of observations within our panel dataset, we limited ourselves to estimating 14 temporal effects in addition to plantation-specific fixed effects. As a result, we estimated temporal treatment effects for each of the 7 y before certification, the year of certification, and the 6 y after certification. In both temporal effects models, changes in treatment effects after certification capture temporal changes in the impacts of certification, while significant precertification treatment effects might indicate anticipation. For example, if plantation managers increased deforestation in preparation for certification initiation, the coefficients on the vectors $\delta^{y < 0}$ would be significantly positive.

Our temporal effects models (Table S5) indicated that accelerated deforestation occurred 4–8 y before certification initiation. In response, we developed one more model specification to test for aggregated precertification dynamics (Table S6). In this aggregated precertification model, we included the standard treatment effect that indicated whether a plantation had already submitted its LOI, as well as a dummy variable that indicated when the plantation was 4–8 y from submitting its LOI.

We tested the assumption of parallel trends through an alternate model specification in which we included plantation-specific parametric time trends in addition to plantation-specific fixed effects (40). To avoid estimation of separate time trends for each plantation, we followed the Frisch–Waugh–Lovell theorem and estimated a transformed model. First, we removed plantation-level time trends from each time-varying variable (41). We then estimated linear models in which we replaced each time-varying variable with its detrended variant. We used linear models because the detrended outcome variables included negative values. In these detrended models, we found statistically significant negative impacts of certification on deforestation, primary forest clearing, and peat clearing, reinforcing our view that the assumption of parallel trends is sound in the case of deforestation (Table S3). In contrast, our detrended model of fire rates yielded a precisely estimated null treatment effect of certification on fire rates. These results cast doubt upon any causal claims that certification reduced fire rates.

Simulations

We estimated avoided deforestation from certification using Monte Carlo simulations of retrospective scenarios. Our two scenarios differed in assumed past rates and locations of certification:

- i) Observed baseline: Certification adoption was identical to observed historical rates and locations of certification.
- ii) No certification counterfactual: We assumed that no plantations were certified during the study period. Compared with the other scenario, this counterfactual allowed us to calculate avoided deforestation from certification.

For both scenarios, we used the fixed effects Poisson model presented in *Fixed Effects Poisson Model* to predict distributions of deforestation rates for every year and plantation. We then ran a Monte Carlo simulation in which we randomly drew deforestation rates from these distributions. Using the observed forest area in each plantation in 2000, we then applied the predicted deforestation rates for each scenario (s) to predict the forest area ($f_{s,i,y}$) in each plantation (i), for each year (y) until 2015.

We defined “avoided deforestation” as the difference in total deforestation in the scenario with certification ($s = a$) from the no certification counterfactual ($s = b$), and calculated avoided deforestation (A_s) using Eq. S3:

$$A_s = \sum_{i=1}^n (f_{a,i,2000} - f_{a,i,2015}) - \sum_{i=1}^n (f_{b,i,2000} - f_{b,i,2015}) \quad [\text{S3}]$$

Average Treatment Effect on the Treated, Average Treatment Effect on the Nontreated, and Average Treatment Effect

Since the focus of our analysis was to understand the past impacts of RSPO certification, we designed our matching procedure to estimate the average treatment effect on the treated (ATET) rather than the average treatment effect (ATE). However, the ATET might provide an inaccurate prediction of the potential impacts of certification on noncertified properties since these properties differ systematically from properties that had received certification. To explore the potential impacts of certification on noncertified

properties, we estimated the average treatment effect on the non-treated (ATENT) through a separate model in which we reversed the base-matching procedure discussed in *Matching and Subsetting*. This reverse model identified multiple certified “control” plantations for each noncertified “treatment.” We trimmed the noncertified sample to the common support defined by the certified plantations. We then used the same fixed effects Poisson model discussed in *Fixed Effects Poisson Model* to estimate the ATENT. We present the ATENT coefficient estimates in Table S4.

Uncertainties and Limitations

Data Uncertainties and Limitations. Our noncertified dataset contains substantial inaccuracies. These include errors in commission, areas not developed for oil palm production during our study period. About 78% of plantation polygons in the noncertified database contained no planted oil palm in 2010. As a result, our combined certified and noncertified plantation area of 187,567 km² is substantially greater than Indonesia’s 2014 oil palm harvested area [74,288 km² (4)]. These areas may never be developed for plantations, or they may be only partially planted due to overlapping claims and negotiations with local actors (42). The noncertified dataset also contains omission errors. In 2000, 17,948 km² of our combined plantation database in Sumatra and Kalimantan was planted to oil palm, near Indonesia’s oil palm harvested area of 20,140 km² (4). By 2010, 40,262 km² of our plantations contained planted oil palm, whereas the Indonesian harvested area was 57,800 km². This recent divergence suggests that newly established plantations, which are expected to contain most ongoing land-clearing activities, were also most likely to be omitted from our noncertified dataset. Our understanding of RSPO member-held yet noncertified plantations was also incomplete. Based on our analysis of RSPO member-controlled companies in Indonesia, at least 269 supply bases held by RSPO members (57% of all known member-held supply bases in Indonesia) were not yet certified in March 2017. In comparison, our spatial noncertified dataset contains 228 plantations identified as belonging to RSPO members. Finally, we assumed that 100% of certified plantation polygons fell under the certificate issued by the RSPO. Especially for plantations identified from sources other than audit reports and ACOPs [i.e., Greenpeace (1) and Sawit Watch* concession datasets], lands not covered by the certificate may be included in our analysis.

Remote-Sensing Uncertainties and Limitations. From a remote-sensing perspective, our results are limited in two important ways. First, while we attempted to exclude planted oil palm and other plantations from this analysis using year 2000 plantation maps, it is possible that inaccuracies in these datasets led to some inclusion of planted oil palm and other tree plantation areas in areas considered to be forest. Thus, it is possible that some “deforestation” was loss of nonforest vegetation with high canopy cover, including replanting of oil palm or conversion of another plantation type with dense canopy cover (e.g., rubber). Second, fires are less likely to be detected under forest canopies with high leaf area index (43), potentially leading to underdetection of fire in densely forested plantation areas, and (falsely) skewing fire activity toward plantations containing low canopy cover.

Econometric Uncertainties and Limitations. Our econometric models sought to control for selection bias through matching and panel methods. However, our matching technique only controlled for time-varying observable covariates in the years before treatment, and the panel techniques only controlled for time-invariant characteristics of each plantation. As a result, our estimates might be biased if systematic changes in the characteristics of treated plantations are correlated with the application of treatment. An example of when such dynamic selection bias would pose a problem is if new, more environmentally conscious cor-

porate managers decided to actively pursue both certification as well as unrelated reforms that reduced deforestation. In such a case, our models would overestimate the causal effect of certification in driving changes in deforestation. Our within-company matching model provides a robustness test that begins to address this concern (*Matching and Subsetting*) by comparing only plantations owned by the same company, but the analysis may still be subject to within-company dynamic selection. Our tests of parallel trends (*Synthetic Controls for Data Visualization*) provide further robustness checks to partially address this concern.

Our time series of deforestation also enabled robust matching. In our base models, we reduced the likelihood that differential stages of plantation development would bias our results by matching on forest areas and deforestation rates from 2001 to 2008. These rich temporal data also illustrated the degree to which cohorts of plantations were well matched. Visual inspection of remaining forests and deforestation rates (Fig. S4) suggested that we matched plantations in similar stages of development, increasing our confidence that the postcertification reduction in deforestation was not due to a temporal mismatch in plantation development time lines.

Nevertheless, we found that RSPO-certified areas tend to have less forests than noncertified plantations at the time of certification. If we did not fully eliminate this bias, and if lower deforestation rates are positively related to increasing forest area, our finding that RSPO certification reduced deforestation could simply be a result of not fully eliminating this selection bias. We tested for this possibility by examining the relationship between deforestation rate (percentage per year) or total forest loss (square kilometers per year) and forest remaining (square kilometers per year). We found that both deforestation rate and forest loss were negatively correlated with forest area. Thus, even if we did not fully eliminate selection bias related to total forest area remaining in plantations, it is unlikely that reduced deforestation rates are a spurious outcome of a poorly matched sample. In fact, this relationship suggests that plantations with less forests should have higher deforestation rates, which would reduce the apparent effect of certification on deforestation.

Our econometric analysis sought to quantify the impact of the RSPO on plantations participating in the RSPO. Thus, we may overlook broader impacts of the RSPO on nonmember plantations. Such spillovers might include leakage of deforestation to nonparticipating plantations or broader improvements in oil palm management practices across the industry. Our inability to measure leakage becomes particularly important when interpreting our simulated measurements of avoided deforestation. In this simulation, we only measure the avoided deforestation within participating plantations and ignore the possibility that deforestation pressure may shift to noncertified plantations. Thus, our avoided deforestation estimates may be viewed as an optimistic measure of the effect of certification.

Finally, the RSPO itself may be influencing which plantations are slated to become certified. For instance, RSPO member companies or companies intending to become members may purchase and develop plantations with land cover unlikely to be off limits under the RSPO P&C. While this is an important concern, in the current set of properties certified by the RSPO, about 91% of plantations were cleared before the founding of the RSPO in 2004, and 100% of them initiated clearing before certification. As a result, it is unlikely that the RSPO significantly influenced plantation establishment in our sample of certified plantations. As the RSPO matures, this effect is likely to become more important, and future assessments may require explicit consideration of the impacts of the RSPO on corporate decisions regarding where to purchase and develop plantations. Finally, our matching procedure, which included matching on area of peat, primary forest, oil palm, and total plantation area, provided additional controls on any potentially confounding effects of pre-certification selection of plantation areas.

- Greenpeace (2016) Palm oil concessions. Available at www.greenpeace.org/seasia/id/Global/seasia/Indonesia/Code/Forest-Map/en/index.html. Accessed January 30, 2017.
- Gunarso P, Hartoyo ME, Agus F, Killen TJ (2013) Oil palm and land use change in Indonesia, Malaysia, and Papua New Guinea. *Reports from the Technical Panels of the Second Greenhouse Gas Working Group of the Roundtable on Sustainable Palm Oil*, eds Killen TJ, Goon J (Roundtable on Sustainable Palm Oil, Kuala Lumpur, Malaysia), pp 29–63.
- Carlson KM, et al. (2012) Committed carbon emissions, deforestation, and community land conversion from oil palm plantation expansion in West Kalimantan, Indonesia. *Proc Natl Acad Sci USA* 109:7559–7564.
- Food and Agriculture Organization of the United Nations (2017) FAOSTAT online statistical service. Available at www.fao.org/faostat/en/#home. Accessed October 16, 2017.
- Carlson KM, et al. (2013) Carbon emissions from forest conversion by Kalimantan oil palm plantations. *Nat Clim Chang* 3:283–287.
- Sexton JO, et al. (2016) Conservation policy and the measurement of forests. *Nat Clim Chang* 6:192–196.
- Roundtable on Sustainable Palm Oil (RSPO) (2013) Principles and Criteria for the Production of Sustainable Palm Oil. Available at www.rspo.org. Accessed October 16, 2017.
- High Conservation Value Resource Network (2017) HCV Resource Network. Available at www.hcvnetwork.org. Accessed October 16, 2017.
- Ministry of Environment and Forestry (2016) *National Forest Reference Emission Level for Deforestation and Forest Degradation: In the Context of Decision 1/CP.16 para 70 UNFCCC (Encourages Developing Country Parties to Contribute to Mitigation Actions in the Forest Sector)* (Directorate General of Climate Change, The Ministry of Environment and Forestry, Indonesia, Jakarta).
- Tropik R, et al. (2014) Comment on “High-resolution global maps of 21st-century forest cover change”. *Science* 344:981.
- Hansen MC, et al. (2013) High-resolution global maps of 21st-century forest cover change. *Science* 342:850–853.
- Margono BA, Potapov PV, Turubanova S, Stolle F, Hansen M (2014) Primary forest cover loss in Indonesia over 2000–2012. *Nat Clim Chang* 4:730–735.
- Wahyunto S, Ritung, Subagio H (2003) *Maps of Area of Peatland Distribution and Carbon Content in Sumatera, 1990-2002* (Wetlands International–Indonesia Programme & Wildlife Habitat Canada, Bogor, Indonesia).
- Wahyunto BH, Bekti H, Widiastuti F (2006) *Maps of Peatland Distribution, Area, and Carbon Content in Papua 2000-2001* (Wetlands International–Indonesia Programme & Wildlife Habitat Canada, Bogor, Indonesia).
- Wahyunto S, Ritung, Subagio H (2004) *Maps of Area of Peatland Distribution and Carbon Content in Kalimantan, 2000-2002* (Wetlands International–Indonesia Programme & Wildlife Habitat Canada, Bogor, Indonesia).
- Giglio L, Schroeder W, Justice CO (2016) The collection 6 MODIS active fire detection algorithm and fire products. *Remote Sens Environ* 178:31–41.
- Blackman A, Rivera J (2011) Producer-level benefits of sustainability certification. *Conserv Biol* 25:1176–1185.
- Imbens GM, Wooldridge JM (2009) Recent developments in the econometrics of program evaluation. *J Econ Lit* 47:5–86.
- Miteva DA, Loucks CJ, Pattanayak SK (2015) Social and environmental impacts of forest management certification in Indonesia. *PLoS One* 10:e0129675.
- Heilmayr R, Lambin EF (2016) Impacts of nonstate, market-driven governance on Chilean forests. *Proc Natl Acad Sci USA* 113:2910–2915.
- Blackman A, Goff L, Planter MR (2015) *Does Eco-Certification Stem Tropical Deforestation?* (Resources for the Future, Washington, DC).
- Ho DE, Imai K, King G, Stuart EA (2007) Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. *Polit Anal* 15:199–236.
- Ferraro PJ, Miranda JJ (2014) The performance of non-experimental designs in the evaluation of environmental programs: A design-replication study using a large-scale randomized experiment as a benchmark. *J Econ Behav Organ* 107:344–365.
- Koh LP, Miettinen J, Liew SC, Ghazoul J (2011) Remotely sensed evidence of tropical peatland conversion to oil palm. *Proc Natl Acad Sci USA* 108:5127–5132.
- Curran LM, et al. (2004) Lowland forest loss in protected areas of Indonesian Borneo. *Science* 303:1000–1003.
- Marlier ME, et al. (2015) Fire emissions and regional air quality impacts from fires in oil palm, timber, and logging concessions in Indonesia. *Environ Res Lett* 10:085005.
- Garrett RD, Carlson KM, Rueda X, Noojipady P (2016) Assessing the potential additionality of certification by the Round Table on Responsible Soybeans and the Roundtable on Sustainable Palm Oil. *Environ Res Lett* 11:045003.
- Austin PC (2011) Optimal caliper widths for propensity-score matching when estimating differences in means and differences in proportions in observational studies. *Pharm Stat* 10:150–161.
- Purwanto SA (2013) Forest resource management and self-governance in regional autonomy Indonesia. *Regionalism in Post-Suharto Indonesia*, eds Erb M, Faucher C, Sulistiyano P (Routledge, New York).
- Caliendo M, Kopeinig S (2008) Some practical guidance for the implementation of propensity score matching. *J Econ Surv* 22:31–72.
- Lambin EF, et al. (2001) The causes of land-use and land-cover change: Moving beyond the myths. *Glob Environ Change* 11:261–269.
- Auld G (2014) *Constructing Private Governance: The Rise and Evolution of Forest, Coffee, and Fisheries Certification* (Yale Univ Press, New Haven, CT).
- Jarvis A, Reuter HI, Nelson A, Guevara E (2008) Hole-filled SRTM for the globe, Version 4. Available at srtm.csi.cgiar.org. Accessed May 15, 2016.
- Roundtable on Sustainable Palm Oil (RSPO) (2013) RSPO concessions. Available at commodities.globalforestwatch.org/. Accessed January 30, 2017.
- National Geospatial Intelligence Agency (2016) *World Port Index, Publication 150* (National Geospatial Intelligence Agency, Springfield, VA), 25th Ed.
- CIESIN; ITOS (2013) *Global Roads Open Access Data Set, Version 1 (gROADSv1)* (NASA Socioeconomic Data and Applications Center, Palisades, NY).
- CIESIN; CIAT (2005) *Gridded Population of the World, Version 3 (GPWv3) Data Collection* (Center for International Earth Science Information Network, Columbia University, Palisades, NY).
- NASA; JAXA Tropical Rainfall Measuring Mission. Available at <https://pmm.nasa.gov/TRMM>. Accessed May 15, 2016.
- NASA (2016) MODIS land surface temperature (MOD11A2). Available at <https://modis-land.gsfc.nasa.gov/temp.html>. Accessed May 15, 2016.
- Besley T, Burgess R (2004) Can labor regulation hinder economic performance? Evidence from India. *Q J Econ* 119:91–134.
- Greene WH (2011) *Econometric Analysis* (Prentice Hall, Boston).
- McCarthy JF, Vel JA, Affif S (2012) Trajectories of land acquisition and enclosure: Development schemes, virtual land grabs, and green acquisitions in Indonesia's Outer Islands. *J Peasant Stud* 39:521–549.
- Roy DP, Boschetti L, Justice CO, Ju J (2008) The collection 5 MODIS burned area product—Global evaluation by comparison with the MODIS active fire product. *Remote Sens Environ* 112:3690–3707.

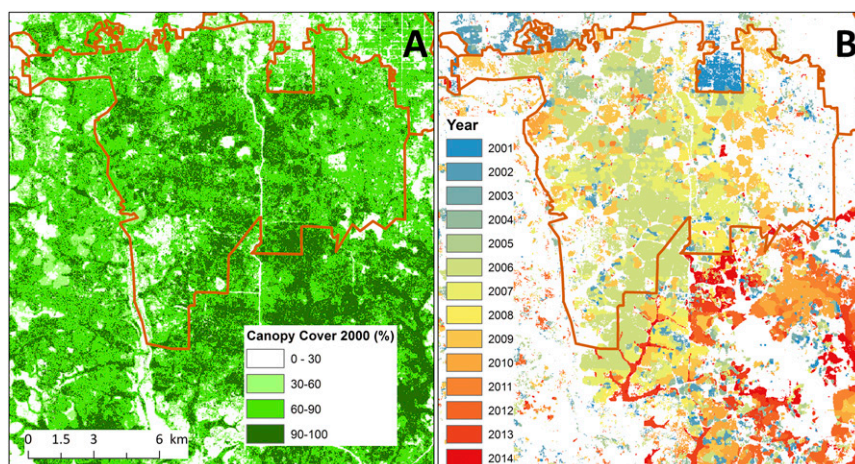


Fig. S1. Example of land cover change within an RSPO-certified oil palm plantation in Indonesia. (A) Year 2000 canopy cover (%). (B) Annual 2001–2014 tree cover loss (11).

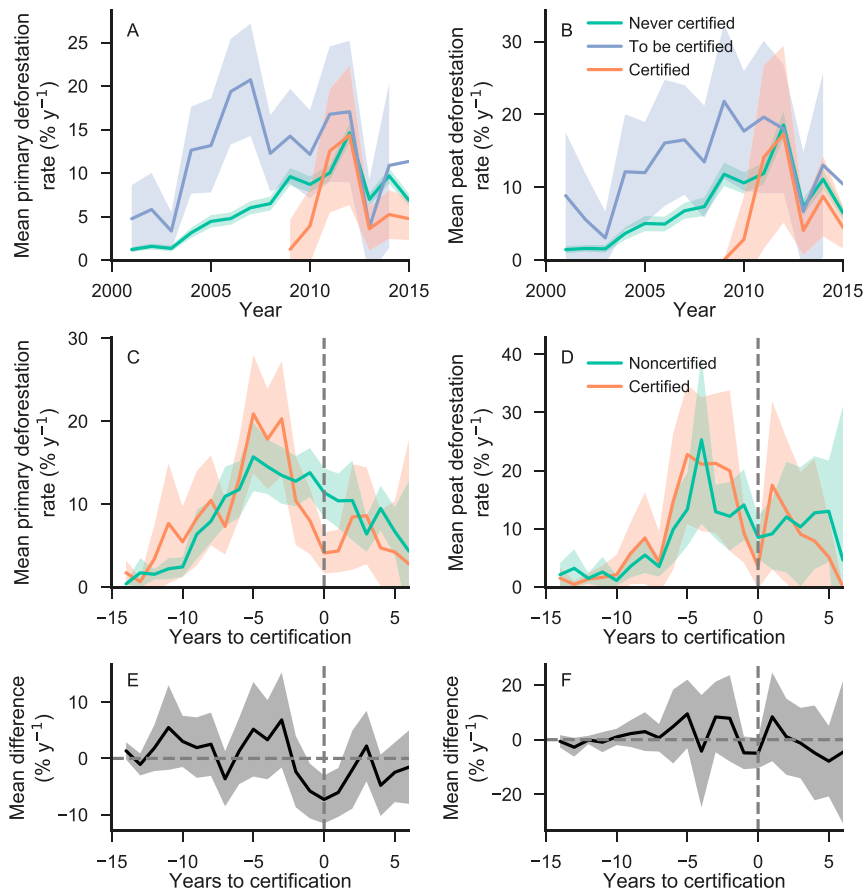


Fig. 52. Temporal trends in primary forest and peatland deforestation within Indonesian oil palm plantations. (A and B) Unmatched rates of primary forest and peat clearing in RSPO-certified, to be certified (RSPO member-held), and noncertified (not held by RSPO members) plantations. (C and D) Matched rates of primary forest and peat clearing in RSPO-certified, to be certified, and noncertified plantations. (E and F) Mean difference in deforestation or fire between RSPO-certified and noncertified plantations. The vertical dashed line represents initiation of RSPO certification, and shading indicates the 95% confidence interval. Rates are per plantation, averaged across all plantations in the group. Matched figures in C–F represent samples from simple matching through 2008 (*Matching and Subsetting*). Noncertified statistics in matched figures in C–F were calculated using synthetic control plantations (*Synthetic Controls for Data Visualization*).

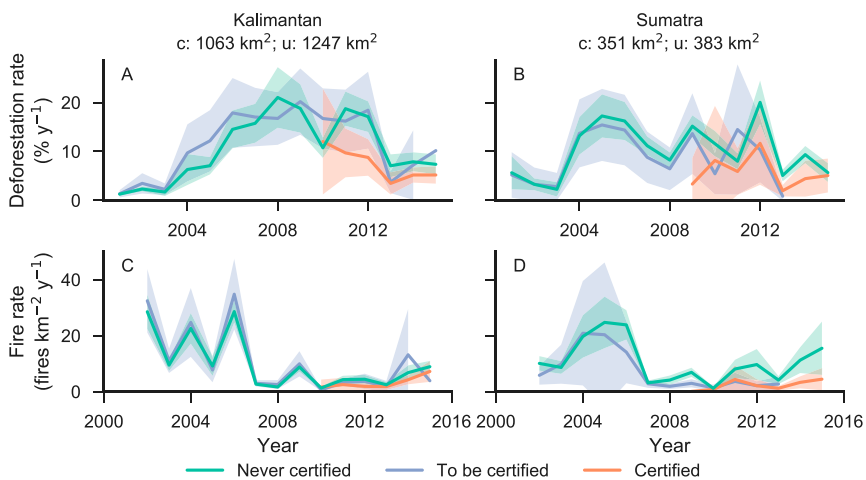


Fig. 53. Temporal trends in deforestation and fire in oil palm plantations in Indonesian regions of Sumatra and Kalimantan (Indonesian Borneo) from 2001 to 2015. Deforestation (A and B) and fire (C and D) rates in RSPO-certified, to be certified (RSPO member-held), and noncertified (not held by RSPO members) plantations are shown. Forest is defined as having $\geq 90\%$ tree canopy cover (11). Rates are per plantation, averaged across all plantations in the group. Shading indicates the 95% confidence interval. Figures represent samples from simple matching through 2008 (*Matching and Subsetting*). Noncertified statistics were calculated using synthetic control plantations (*Synthetic Controls for Data Visualization*).

Table S2. Robustness of models assessing the impact of RSPO certification on environmental outcomes in Indonesia to matching specification and data subsets

Outcome variable	Model component	Metric				I		D		C	
			NM	NC	NR	2003	2008	2003	2008	2003	2008
Deforestation	Certification	Coef	-0.83***	-0.29*	-0.71***	-0.33*	-0.40**	-0.43**	-0.27*	-0.83***	-0.36
		P	<0.001	0.084	<0.001	0.090	0.028	0.046	0.079	0.0064	0.10
	Temperature	Coef	0.0097***	0.0076***	0.0097***	0.011***	0.010***	0.010***	0.0091***	0.0090***	0.0068**
		P	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.012
	Precipitation	Coef	1.2**	4.5***	2.5***	3.1***	3.9***	3.1***	2.9***	3.4**	-0.12
		P	0.017	<0.001	0.0038	<0.001	<0.001	0.0030	0.0038	0.036	0.94
	Constant	Coef	-149***	-117***	-148***	-164***	-160***	-153***	-140***	-140***	-107***
		P	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.0093
		N, control	1473	0	173	395	262	295	223	55	43
		N, treatment	89	89	89	73	71	64	50	44	28
	N, districts (clusters)	133	34	71	91	83	29	25	40	34	
Primary forest clearing	Certification	Coef	-0.95***	-0.38*	-0.85***	-0.75***	-0.45*	-0.71***	-0.58**	-1.3***	-0.94***
		P	<0.001	0.060	<0.001	0.0023	0.053	0.0013	0.047	<0.001	0.0084
	Temperature	Coef	0.010***	0.0093***	0.0099***	0.012***	0.012***	0.011***	0.011***	0.010***	0.0086***
		P	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.0013
	Precipitation	Coef	1.1	6.6***	2.8**	2.9***	4.3***	3.1**	2.2	3.0	0.28
		P	0.10	<0.001	0.024	0.0067	<0.001	0.027	0.10	0.13	0.87
	Constant	Coef	-155***	-144***	-153***	-186***	-180***	-166***	-174***	-157***	-133***
		P	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.0010	0.0010
		N, control	1236	0	148	295	218	225	156	48	41
		N, treatment	71	71	71	56	55	46	35	30	27
	N, districts (clusters)	125	30	63	78	72	25	18	34	31	
Peat forest clearing	Certification	Coef	-0.78***	-0.44	-0.76***	-1.1***	-0.26	-0.84***	-0.75	-1.8***	-1.6***
		P	0.0021	0.13	0.0071	<0.001	0.50	0.0075	0.19	<0.001	<0.001
	Temperature	Coef	0.0094***	0.0044	0.0072***	0.0088***	0.0053**	0.0078***	0.0071***	0.0084**	0.0072*
		P	<0.001	0.18	<0.001	<0.001	0.029	<0.001	<0.001	0.011	0.076
	Precipitation	Coef	1.7**	6.2***	3.0**	2.7**	4.3**	2.9*	2.5	3.2	-1.4
		P	0.032	0.0059	0.038	0.037	0.037	0.084	0.21	0.27	0.70
	Constant	Coef	-145***	-71	-113***	-136***	-84**	-121***	-110***	-130***	-111*
		P	<0.001	0.16	<0.001	<0.001	0.021	<0.001	<0.001	0.0090	0.068
		N, control	597	0	70	132	86	112	78	14	10
		N, treatment	33	33	33	20	17	23	14	9	6
	N, districts (clusters)	79	19	42	44	36	16	10	13	11	
Fire rates	Certification	Coef	-0.69***	0.23	-0.50***	-0.25	-0.33*	-0.27*	-0.13	-0.29	-0.30
		P	<0.001	0.41	0.0060	0.15	0.082	0.088	0.47	0.38	0.55
	Temperature	Coef	0.0095***	0.011***	0.0090***	0.011***	0.011***	0.011***	0.0095***	0.0095***	0.0090***
		P	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
	Precipitation	Coef	-2.5***	-3.5**	-1.7	-3.5***	-3.2**	-3.4***	-3.5***	-0.35	-1.9
		P	<0.001	0.025	0.28	<0.001	0.015	<0.001	<0.001	0.87	0.27
	Constant	Coef	-144***	-166***	-136***	-166***	-163***	-163***	-142***	-142***	-135***
		P	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
		N, control	1473	0	173	395	262	295	223	55	43
		N, treatment	89	89	89	73	71	64	50	44	28
	N, districts (clusters)	133	34	71	91	83	29	25	40	34	

For each outcome variable, columns compare models estimated on differently matched subsets of the dataset. For models using matched samples, matching was conducted with temporally varying covariates through 2003 and 2008. A full description of matching and subsampling methods is provided in *Empirical Analysis*. We present the coefficients of certification (Coef), the *P* value associated with the certification coefficient, and number (N) of controls, treatments, and administrative districts. Three models use unmatched samples: NM, no matching; NC, no matching, restricted to certified plantations; and NR, no matching, restricted to RSPO member plantations. Models using matched samples through either 2003 or 2008 include: I, simple matching within island; D, matching within district; and C, matching within RSPO member company. Asterisks indicate degree of coefficient significance (**P* < 0.10; ***P* < 0.05; ****P* < 0.01).

Table S3. Validity of results assessing the impact of RSPO certification on deforestation in Indonesia to the parallel trends assumption

Model component	Metric	Deforestation	Primary forest clearing	Peatland forest clearing	Fire rate
Certification	Coef	-0.018**	-0.024**	-0.065***	0.0058
	<i>P</i>	0.029	0.038	<0.001	0.54
Temperature	Coef	0.0012***	0.0014***	0.0011***	0.0019***
	<i>P</i>	<0.001	<0.001	<0.001	<0.001
Precipitation	Coef	0.28***	0.21**	0.24*	-0.17*
	<i>P</i>	<0.001	0.045	0.098	0.081
Constant	Coef	-0.036***	-0.038***	-0.034**	0.063
	<i>P</i>	<0.001	<0.001	0.030	0.11
N, control		395	295	132	395
N, treatment		73	56	20	73
N, districts (clusters)		91	78	44	91

In addition to plantation-level fixed effects, these models account for the effect of plantation-specific time trends as described in *Temporal Effects and Parallel Trends*. Models use samples from simple matching through 2003. We present the coefficients of certification (Coef), the *P* value associated with the certification coefficient, and the number (N) of controls, treatments, and administrative districts. Asterisks indicate degree of coefficient significance (**P* < 0.10; ***P* < 0.05; ****P* < 0.01).

Table S5. Tests of temporal variations in treatment effects of RSPO certification on deforestation in Indonesian oil palm plantations

Model component	Metric	Deforestation				Primary forest clearing				Peatland forest clearing				Fire rate			
		No	Yes	2003	2008	No	Yes	2003	2008	No	Yes	2003	2008	No	Yes	2003	2008
≤10	Coef	0.0059		0.28													
	P	0.986		0.41													
-9	Coef	0.328		0.048													
	P	0.214		0.89													
-8	Coef	0.58***		0.11													
	P	0.0069		0.71													
-7	Coef	0.47**	0.39**	-0.0052	0.10	-0.082	-0.36										
	P	0.014	0.012	0.98	0.53	0.68	0.12										
-6	Coef	0.40**	0.34**	0.30	0.11	0.23	-0.00015										
	P	0.016	0.022	0.17	0.54	0.27	1.0										
-5	Coef	0.61***	0.55***	0.67***	0.31**	0.61***	0.39										
	P	<0.001	<0.001	0.0017	0.016	0.0035	0.11										
-4	Coef	0.29**	0.24*	0.23	0.061	0.19	0.13										
	P	0.022	0.051	0.12	0.64	0.21	0.38										
-3	Coef	0.24	0.20	0.26	0.082	0.23	0.27										
	P	0.23	0.27	0.17	0.65	0.20	0.15										
-2	Coef	0.035	0.013	-0.089	-0.20	-0.11	-0.30										
	P	0.88	0.95	0.73	0.41	0.67	0.25										
-1	Coef	-0.056	-0.071	-0.35	-0.29	-0.36	-0.44										
	P	0.75	0.68	0.28	0.15	0.27	0.14										
Certification	Coef	-0.45**	-0.47**	-1.1***	-0.52**	-1.1***	-0.88***										
	P	0.024	0.019	0.0075	0.024	0.0071	0.0056										
1	Coef	-0.12	-0.13	-0.93***	-0.41*	-0.93***	-0.89***										
	P	0.59	0.57	0.0028	0.060	0.0027	0.0034										
2	Coef	-0.20	-0.21	-0.39	-0.44*	-0.39	-0.15										
	P	0.40	0.39	0.31	0.080	0.30	0.66										
3	Coef	-0.16	-0.16	0.054	-0.48*	0.052	0.201										
	P	0.55	0.54	0.89	0.082	0.90	0.58										
4	Coef	-0.046	-0.049	-1.0**	-0.68**	-1.0**	-0.36										
	P	0.86	0.85	0.014	0.029	0.014	0.41										
5	Coef	-0.32	-0.32	-0.43	-0.43	-0.43	-0.63										
	P	0.31	0.31	0.40	0.26	0.40	0.31										
6	Coef	-0.55	-0.55	-1.3**	-1.2*	-1.3**	-0.81***										
	P	0.28	0.28	0.023	0.063	0.022	0.0053										
Temperature	Coef	0.0053***	0.0054***	0.0067***	0.0042***	0.0068***	0.0076***										
	P	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001										
Precipitation	Coef	0.093	0.14	-0.38	0.28	-0.34	0.66										
	P	0.92	0.87	0.65	0.76	0.68	0.56										
Constant	Coef	-84***	-84***	-105***	-67***	-106***	-118***										
	P	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001										
N, control		395	395	295	262	295	218										
N, treatment		73	73	56	71	56	55										
N, districts (clusters)		91	91	78	83	78	72										

Annual effects models estimate coefficients on annual leads and lags from the year of certification for response variables of deforestation, primary forest clearing, peatland forest clearing, and fire rate. A full description of the models is provided in *Temporal Effects and Parallel Trends*. Each column represents the coefficients of certification (Coef), the P value associated with the certification coefficient, and the number (N) of controls, treatments, and administrative districts. Models use matched samples through either 2003 or 2008. Some models use plantation-level fixed effects ("yes") while others do not ("no"). All results were generated from within-island matched samples (*Matching and Subsetting*). Asterisks indicate degree of coefficient significance (*P < 0.10; **P < 0.05; ***P < 0.01).

Table S6. Tests of anticipatory behavior on environmental outcomes in Indonesian oil palm plantations 4–8 y before certification by the RSPO

Outcome variable	Model Component	Metric	NM	NC	NR	I	D	C
Deforestation	Certification	Coef	−0.64***	−0.27	−0.57***	−0.22	−0.30	−0.64**
		P	<0.001	0.11	0.0016	0.29	0.18	0.024
	Precertification	Coef	0.41***	0.25	0.39**	0.31**	0.37***	0.62***
		P	0.0041	0.12	0.015	0.020	0.0018	0.0041
	Temperature	Coef	0.0096***	0.0073***	0.0093***	0.010***	0.0098***	0.0085***
		P	<0.001	0.0010	<0.001	<0.001	<0.001	<0.001
	Precipitation	Coef	1.1**	4.2***	2.3***	3.0***	3.0***	2.9*
		P	0.021	<0.001	0.0068	<0.001	0.0036	0.069
	Constant	Coef	−147***	−112***	−142***	−161***	−150***	−133***
		P	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
	N, control			1473	0	173	395	295
			89	89	89	73	64	44
N, districts (clusters)			133	34	71	91	29	40
Primary Forest Clearing	Certification	Coef	−0.81***	−0.37*	−0.76***	−0.67***	−0.64**	−1.1***
		P	<0.001	0.069	<0.001	0.0054	0.011	<0.001
	Precertification	Coef	0.30	0.12	0.29	0.24	0.25	0.50
		P	0.11	0.54	0.15	0.22	0.29	0.13
	Temperature	Coef	0.0099***	0.0092***	0.0097***	0.012***	0.011***	0.0099***
		P	<0.001	<0.001	<0.001	<0.001	<0.001	0.0024
	Precipitation	Coef	1.12	6.4***	2.7**	2.8**	2.9**	2.7
		P	0.11	<0.001	0.038	0.013	0.041	0.21
	Constant	Coef	−154***	−141***	−148***	−184***	−163***	−153***
		P	<0.001	<0.001	<0.001	<0.001	<0.001	0.0019
	N, control			1236	0	148	295	225
			71	71	71	56	46	30
N, districts (clusters)			125	30	63	78	25	34
Peatland Forest Clearing	Certification	Coef	−0.68***	−0.43	−0.67**	−0.97***	−0.69**	−1.5***
		P	0.0054	0.15	0.012	<0.001	0.026	<0.001
	Precertification	Coef	0.22	0.17	0.26	0.47	0.48*	0.98***
		P	0.25	0.50	0.19	0.15	0.094	0.0023
	Temperature	Coef	0.0094***	0.0041	0.0070***	0.0086***	0.0075***	0.0090***
		P	<0.001	0.24	<0.001	<0.001	<0.001	0.0027
	Precipitation	Coef	1.7**	5.9***	2.8*	2.5*	2.6	2.8
		P	0.035	0.010	0.057	0.052	0.11	0.41
	Constant	Coef	−144***	−66	−110***	−134***	−117***	−140***
		P	<0.001	0.20	<0.001	<0.001	<0.001	0.0021
	N, control			597	0	70	132	112
			33	33	33	20	23	9
N, districts (clusters)			79	19	42	44	16	13
Fire Rate	Certification	Coef	−0.80***	0.10	−0.61***	−0.39**	−0.38***	−0.51*
		P	<0.001	0.71	<0.001	0.017	0.010	0.099
	Precertification	Coef	−0.21	−0.27	−0.21	−0.26	−0.22	−0.49
		P	0.12	0.13	0.16	0.11	0.26	0.11
	Temperature	Coef	0.0095***	0.011***	0.0091***	0.011***	0.011***	0.0097***
		P	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
	Precipitation	Coef	−2.5***	−3.3**	−1.6	−3.4***	−3.3***	0.097
		P	<0.001	0.023	0.30	<0.001	<0.001	0.96
	Constant	Coef	−144***	−170***	−138***	−169***	−164***	−147***
		P	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
	N, control			1473	0	173	395	295
			89	89	89	73	64	44
N, districts (clusters)			133	34	71	91	29	40

The anticipatory model is described in *Temporal Effects and Parallel Trends*. A full description of matching and subsampling methods is provided in *SI Text, Matching and Subsetting*. For each outcome variable, columns compare models estimated on differently matched subsets of the dataset. We present coefficients of certification (Coef), the *P* value associated with the certification coefficient, and the number (N) of controls, treatments, and administrative districts. Three models use unmatched samples: NM, no matching; NC, no matching, restricted to certified plantations; and NR, no matching, restricted to RSPO member plantations. Models using matched samples through 2003 include: I, simple matching within island; D, matching within district; and C, matching within RSPO member company. Asterisks indicate degree of coefficient significance (**P* < 0.10, ***P* < 0.05, ****P* < 0.01).