Planting Trees in Oil Palm Plantations: Results from a Randomized Controlled Trial

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Abstract:

Palm oil expansion in Indonesia is associated with both a reduction in biodiversity and ecosystem services, and livelihood improvements for smallholder farmers. While this dichotomy highlights the importance of sustainable management options, empirical evidence on which policies are effective in stimulating biodiversity-friendly plantation management is relatively scarce. This paper addresses this gap by presenting results from a Randomized Controlled Trial implemented in Jambi province, Sumatra, in 2016. We focus on tree nuclei planting in oil palm plantations as one sustainable management option. To test whether information and input provision affect smallholders' tree enrichment activities, two treatments were designed: the first provided information about tree planting in oil palm, while the second combined information and input delivery. We model adoption in a double-hurdle framework where farmers first decide whether to adopt or not and then how many trees they plant per hectare. Our results suggest that both interventions are effective in stimulating tree planting in oil palm. While input provision in combination with information leads to a higher probability of adoption, farmers plant on average relatively few trees per hectare. In contrast, in the informational treatment, few farmers enrich but they plant more trees per hectare than farmers who received saplings.

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1. Introduction

Since 2008, Indonesia has been the world's largest producer of palm oil (Fitzherbert et al. 2008). From 1961 on, the area of palm oil production has increased 106 fold reaching 7,428,752 ha in 2014 (FAO 2017). Further production expansions are likely (Coordinating Ministry for Economic Affairs 2011). While the cultivation of oil palm is associated with income gains for many smallholder farmers who are increasingly engaged in its farming (Rist et al. 2010; Euler et al. 2016), it is also related to deforestation and degradation in biodiversity and ecosystem services (Wilcove, Koh 2010). This highlights the importance of sustainable policy options that combine an enhancement of ecosystem services with economic development opportunities. Since only few forest patches remain in Indonesia, strategies that try to protect biodiversity at the plantation level and allow for scaling effects at the landscape level appear to be most promising. Tree nuclei planting in oil palm has been proposed as one such management practice (Koh et al. 2009; Teuscher et al. 2016).

The present study addresses the question of how the adoption of native tree planting can be promoted among small-scale oil palm farmers in Sumatra, Indonesia. While there is some experimental evidence on the effectiveness of policy options for the uptake of fertilizer and improved seeds (Carter et al. 2013; Duflo et al. 2011), relatively little is known about what instruments are appropriate to induce biodiversity-friendly land uses (Jack et al. 2013). However, enrichment planting is different from other technologies in many regards. First, there is a relatively large time horizon for reaping economic benefits of fruit and timber trees. Second, while standard technologies such as fertilizer utilization aim directly at raising yields, tree planting is intended to diversify income sources and to improve biodiversity, which might be linked to non-use values for farmers. Therefore, policies need to be particularly effective in creating awareness for the necessity of enrichment planting.

In order to test which policy interventions can increase farmers' tree planting activities in oil palm plantations, a Randomized Controlled Trial (RCT) was implemented in Jambi province, Sumatra, in 2016. Drawing on the technology adoption literature (Knowler, Bradshaw 2007; Shiferaw et al. 2008) we hypothesize that both a lack of knowledge as well as structural problems such as missing seed markets represent barriers to enrichment planting. Therefore, we test for the effect of both a video-based information treatment and gratis sapling provision on farmers' enrichment activities in oil palm. In a double-hurdle (DH) framework, the probability of farmers to plant saplings in oil palm and their planting intensity, measured as the number of trees planted per hectare, are analyzed.

The structure of the paper is as follows. Section 2 provides background information about palm oil expansion, its consequences in Indonesia and policy options to sustain biodiversity. Section 3 describes the experimental design, the interventions and the data collection process. In addition, the estimation strategy is explained. Results are presented in Section 4. Section 5 concludes.

2. Background

2.1. Palm oil expansion in Indonesia and its social and ecological consequences

In Indonesia, the development of the palm oil sector was initiated and supported by the government (McCarthy 2010). Combining rural development plans with the idea of strengthening national identity, the estate transmigrant program started in 1986. Within its framework, poor farmers were relocated from the overpopulated islands of Java and Bali to less populated ones, mostly to Sumatra (Euler et al. 2016). These new settlers received two to three hectare of land for palm oil cultivation which were located in close proximity to a state-supported company and a palm oil mill (Gatto et al. 2017). The latter were responsible for the provision of agricultural extension and inputs for the plantation management. The initial Nucleus-estate scheme (NES) was supplemented by contract-based cooperation between private companies and smallholders in the 1990s (McCarthy 2010).

Since the phasing out of the NES-scheme, the importance of independent farmers who grow oil palm without contractual arrangement with companies has been increasing. Besides transmigrant farmers, whose contract with companies ended, these smallholders comprise local farmers and spontaneous migrants from other parts of Sumatra (Krishna et al. 2017). Together, they manage more than 40% of all oil palm area (Directorate General of Estate Crops 2015; Euler et al. 2016). These independent smallholders do not represent a homogenous entity. Especially differences between transmigrant and local farmers are pronounced; local farmers' plantations appear to be more heterogeneous with regard to management intensity and palm age (Teuscher et al. 2015).

While the inclusion of local smallholders has generated livelihood improvements for big parts of the local population (Krishna et al. 2017), environmental threats of oil palm expansion appear to be high. Between 2000 and 2012, the primary forest cover loss is estimated to amount to 6.02 million ha in Indonesia (Margono et al. 2014). It is widely acknowledged that palm oil has contributed to this deforestation, even though the extent of direct and indirect channels of how the conversion of forest area into plantations could have happened is still debated in the literature (Fitzherbert et al. 2008; Obidzinski et al. 2012). Besides concerns over climatic impacts (Dislich et al. 2017; van Straaten et al. 2015) and reduced water and other regulatory ecosystem services (Merten et al. 2016; Obidzinski et al. 2012), especially threats to biodiversity appear to be high (Wilcove, Koh 2010; Edwards et al. 2014; Teuscher et al. 2015). This is because Indonesia represents a habitat for numerous endemic or endangered species many of which are dependent on forest area (Koh, Wilcove 2008). However, due to its reduced complexity, oil palm plantations harbor less animal and plant species. Moreover, invasive species are common (Dislich et al. 2017; Savilaakso et al. 2014). Given these detected environmental consequences, sustainable management practices are needed that reconcile environmental protection with economic development opportunities for the local community.

2.2. Sustainable management options and related policies

In order to enhance biodiversity in oil palm dominated areas, increasing landscape heterogeneity can be identified as key requirement (Foster et al. 2011; Azhar et al. 2011).

While especially the importance of preserving forest catchments has been stressed (Fitzherbert et al. 2008), only little forest remnants remain in high production areas (Teuscher et al. 2016). Therefore, diversification at the local level might be of high importance. Agroforestry-like systems have been shown to support a wider species diversity than pure monoculture crops (Teuscher et al. 2015; Bhagwat, Willis 2008; Azhar et al. 2011). When linking forest or conservation area patches, they might additionally protect forest-dependent species (Koh et al. 2009). Consequently, planting native tree nuclei into oil palm plantations, thereby restoring habitat heterogeneity, appears to be a promising approach to support biodiversity (Teuscher et al. 2016). Initial results from a biodiversity enrichment experiment that is conducted in Sumatra support a positive effect on species richness already one year after implementation (Teuscher et al. 2016).

As oil palm is a very water and light dependent crop (Corley et al. 2003), enriching plantations with trees might result in negative yield effects. The empirical literature shows mixed results and also indicate that the impact might be highly dependent on tree species and age (Teuscher et al. 2015; Gérard et al. 2017; Amoah et al. 1995). Even though possible negative yield effects for oil palm might reduce the private incentives farmers have for planting trees, especially smallholder plantations often contain native trees (Azhar et al. 2011; Teuscher et al. 2015). This suggests that the benefits of having trees can outweigh the costs because of the economic and social benefits generated by trees. Timber or fruit tree species present an additional income source for the farmers that can reduce the dependence on a single crop. Hence, negative income shocks due to pests or diseases, climate impacts as well as changing global palm oil prices can be mitigated (Makate et al. 2016; Gérard et al. 2017; Lin 2011). In addition, diversifying plantations with fruit trees might positively impact farmers' food security (Tscharntke et al. 2012).

In order to identify barriers to tree planting in Jambi province, focus group discussions were held in June 2015. Farmers referred to a lack of knowledge about the management and benefits of trees. Additionally, external factors such as missing seed markets appeared to hinder enrichment. From a policy perspective, this suggests that information and sapling provision represent promising policy instruments to strengthen tree planting in oil palm plantations.

3. Study Design, Data and Estimation Strategy

3.1. Study area and sampling strategy

As part of the CRC 990, *Ecological and Socioeconomic Functions of Tropical Lowland Rainforest Transformation Systems (Sumatra, Indonesia)*[1], our study took place in Jambi province, Indonesia (cf. Figure 1). We focus on five districts that represent the lowland area of Jambi which has been mainly affected by rainforest transformation into oil palm and rubber plantations (Gatto et al. 2015).

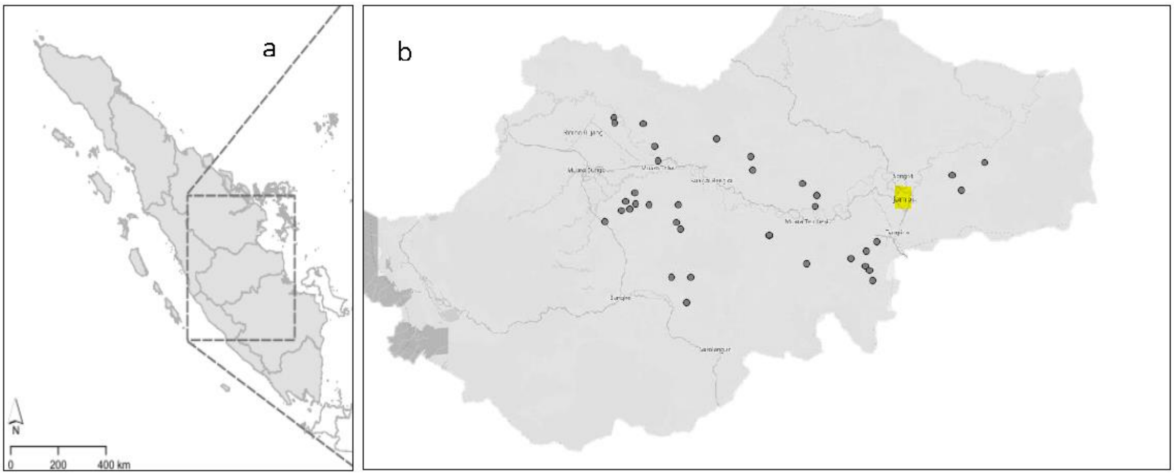

Figure 1: a) location of Jambi in Sumatra b) location of sample villages (dots) and Jambi city (yellow) in Jambi province. Adapted from Teuscher et al. (2015).

In total, 36 oil palm growing villages were selected. Given the different management intensities between transmigrant and local farmers (see above) that might affect tree planting both village types were part of the sample. A random sample of 24 villages was drawn from an assembled list of all transmigrant villages in the study area where over 70% of the dwellers report palm oil production as main occupation. The threshold was lowered to 30% for autochthonous villages because many local farmers are still engaged in rubber cultivation in Jambi (Euler et al. 2016). Nine local villages fitting this criterion could be identified in the study area and were included in the sample. Village level data was taken from the Village Potential Statistics (PODES) census dataset collected in 2008 by the Indonesian Central Bureau of Statistics. The data was complemented by a village survey in September 2015. Within each of the villages, we randomly selected 20 to 22 households of independent oil palm farmers. This led to a total sample of 817 farmers. We conducted a baseline survey in the villages from October until December 2015 to gather information on the number, the

[1] The CRC 990 is a collaboration between the universities of Goettingen (Germany) and Bogor, Palu and Jambi (Indonesia) and is funded by the German Research Foundation.

species and the location of trees planted and cut in the last 12 months, as well as household descriptives. Follow-up data was collected from October till December 2016. Approx. 91% of all farmers could be interviewed again leading to a sample of 738 farmers in the follow-up.

3.2. Randomization approach and description of treatments

Random assignment was done at village level. Villages were allocated to two treatment and one control arm with help of a stratified randomization technique. As stratification variables, we used the migration status of the village (trans- or local[2]), whether or not a village had access to sapling markets (Yes/No) and the share of oil palm growing households in the village (above or below 73.5%). Within each of the generated six strata, an equal number of villages were assigned to the three experimental arms with help of a random number generator. In the end, each arm contained twelve villages.

Table 4 in the Appendix presents baseline descriptives of the sample. In order to test whether randomization was successful in creating balance between groups, we conduct 45 tests of mean difference. The number of farmers that cut trees in oil palm in 2015 and the household size was statistically different between the treatment groups at the 1% and 5% level respectively. However, as some imbalance can occur by chance (Morgan, Rubin 2012), we assume that the randomization was successful. The relevance of the significant covariates will be discussed further in Section 4.

To test the effect of two policy options on tree planting in oil palm, an informational (T1) and a structural intervention (T2) were designed. In both treatments, we provided information about tree enrichment while farmers assigned to T2 additionally received six native saplings for free. The interventions were carried out in February 2016 such that the farmers could plant the trees before start of the dry period.

Information was delivered through a video and an illustrative manual. In an eleven minute movie, a professor from the University of Jambi discussed benefits and risks associated with enriching oil palm plantations with native trees. Moreover, information on species choice and how to plant and manage the saplings was given. In order to stimulate cognitive and emotional activity of the audience (Bernard et al. 2015), a role model approach was implemented by inviting three farmers to participate in the video. The interviewees described their experience with tree planting. The movie was complemented by an illustrative manual

[2] By local village, we mean villages in which mostly people local to Jambi live. Transmigrant villages refer to the villages that were founded as part of the transmigration program.

which provided information on environmental and economic outcomes of tree enrichment and was distributed to the farmers to be taken home.

Since missing markets were identified as one obstacle to tree planting in focus groups, saplings of six multipurpose trees, which are native from Jambi and known to the farmers (Gérard et al. 2017), were distributed for free to each farmer in T2. The selected species[3] included three fruit trees (*Archidendron pauciflorum* (Fabaceae); *Durio zibethinus* (Malvaceae); *Parkia speciosa* (Fabaceae)), one natural latex (*Dyera costulata* (Apocynaceae)), and two timber trees (*Peronema canescens* (Verbenaceae); *Shorea leprosula* (Dipterocarpaceae)). Each farmer in T2 received one of each species leading to a total of six saplings per persons. Saplings were distributed to the farmers after end of the video screening.

In total, 70.8% of all farmers assigned to the two treatment arms attended the video screening. For the informational intervention (T1), this share was 67.5%, for the structural (T2) it amounts to 74.0%. The difference between both groups is not statistically significant (p-value: 0.164).[4]

3.3. *Econometric specification*

Our main interest lies in the intention-to-treat (ITT) effect of the interventions on the expected number of trees planted per hectare[5]. Per hectare numbers are chosen as outcome variable because they might be more closely related to the expected environmental outcome than the total number of trees planted. The planting decision of the farmers is analyzed with help of a DH-model (Cragg 1971). Therefore, adoption is modelled as a two part decision. In a first step, farmers decide about whether to grow trees in their oil palm plantations or not. In the second, the intensity of adoption which is the number of trees planted per hectare is determined. The original model by Cragg (1971) assumes independence between both decisions.

The DH-model represents a general version of the Tobit model. In contrast to the latter, it does not assume that both the adoption and the intensity decision are generated by the same stochastic process (Salmon, Tanguy 2016; Tambo, Abdoulaye 2012). Therefore, the treatment

[3] Scientific name in italics and family in parentheses.
[4] Test for significance was done in a linear regression framework with the sample of treatment villages only. Attendance to movie was regressed on a dummy for T2. The p-value for the received estimate is 0.164. Standard errors are clustered at village level.
[5] By trees we understand tall wood trees that have a clear developed stem and do not have branches at the basis (Roloff, Bärtels 2014). Therefore, other palm species, banana plants and shrubs were not considered for the analysis.

and other control variables can affect the adoption decision differently than the intensity decision (Wooldridge 2010; Cragg 1971). The DH-model is especially appealing in cases where imperfect markets hinder adoption due e.g. to restricted access to seed markets (Shiferaw et al. 2008), or where people abstain from adoption due to e.g. social norms (Salmon, Tanguy 2016). While the Tobit model assumes that each zero quantity observation represents the result of a utility maximization given market prices and income, the DH-model introduces additional flexibility and allows for a different process that explains non-adoption. Some authors also use a Heckman selection model to estimate data with a high prevalence of zero amount observations (Olwande et al. 2015). However, since we are interested in actual and not potential outcomes, the DH-model is preferred (Madden 2008; Dow, Norton 2003). To further statistically support the use of the DH-model, we run a Heckman Selection model and test for independence between the participation and intensity decision. The corresponding Wald test of independence suggests that we cannot reject the independence assumption (p-value: 0.29) which strengthens the DH-approach.[6]

In case of normally distributed residuals, the intensity decision can be modelled with help a truncated normal estimation (Cragg 1971; Salmon, Tanguy 2016). Due to the highly right skewed distribution of the strictly positive per hectare number of trees planted (cf. Figure 2 in the Appendix) we use a more flexible Generalized linear model (GLM) approach with log-link to estimate the effect of the treatments on the conditional intensity decision (Manning, Mullahy 2001; Deb et al. 2014). The use of the link function is tested with help of a Pregibon test (Deb et al. 2014). This approach is superior to applying a logarithmic transformation to the skewed outcome variable in case of heteroscedasticity in the residuals at the logarithmic scale (Manning, Mullahy 2001). We use a modified White test (Wooldridge 2010) to test for heteroscedasticity in the regression of the logarithmized per hectare number of trees planted on the explanatory variables. The Chi-square test statistic suggests that heteroscedasticity is present in the data (p-value of 0.05). This supports the use of the GLM approach.

Following Belotti et al. (2015), the adoption decision can be described as:

$$\Pr(y > 0|x) = F(x\delta) \qquad (1)$$

[6] We assume that the possession of a home garden affects the planting decision but is not a relevant predictor for the number of trees planted. Consequently, this represents a valid exclusion restriction and overcomes collinearity problems (Dow, Norton 2003). This idea is further supported by the insignificance of the coefficient of home garden in the conditional expected value estimation in Table 6 in the Appendix.

where y is our outcome variable of interest, x is a set of explanatory variables, δ the coefficient of the adoption decision and F a cumulative distributional function of the error term.

The conditional intensity decision is expressed as:

$$E(y|y > 0, x) = g^{-1}(x\beta) \qquad (2)$$

where g is the respective link function of the GLM approach, x the covariates for the intensity decision and β the estimated coefficients. For the log-link case, (2) can be written as:

$$\ln(E(y|x)) = x\beta \quad \Rightarrow \quad E(y|x) = \exp(x\beta) \qquad (3)$$

Inferences about the unconditional expected value which is the overall mean can be made by combining the probability of adoption and the intensity decision:

$$E(y|x) = Pr(y>0|x)*E(y|x, y>0). \qquad (4)$$

In order to test for the correct family of distribution for the GLM error term, we use a modified Park test (Salmon, Tanguy 2016; Manning, Mullahy 2001).

For both the adoption and quantity decision, ITT models are estimated. The linear model underlying both equations can be expressed as:

$$Y_{ij} = \beta_o + \beta_1 T_{1j} + \beta_2 T_{2j} + \beta_3 S_j + \beta_4 X_{ij} + e_{ij} \qquad (5)$$

where Y_{ij} is our outcome variable of interest, the per hectare number of trees planted in oil palm. T_{1j} takes the value 1 if village j was assigned to T1, T_{2j} equals 1 if the village was assigned to T2. S_j controls for the stratification variables and the vector X_{ij} contains baseline characteristics of the farmers. e_{ijt} is an individual-specific error term that is clustered at the village level.

4. Results

In total, 375 farmers (50.8%) planted trees between October 2015 and October 2016. From these, 71.2% (267 farmers) planted in their home garden, 38.9% (146 farmers) in oil palm and 7.2% (27 farmers) either on fallow land or in other plots.[7] In total, 7,401 trees were planted, 48.8% in oil palm and 51.2% in other locations. In the following, we only focus on trees that

[7] As farmers could plant in several locations at the same time, the sum of the percentages is greater than 100%.

have been planted in oil palm since the informational campaign focused on tree enrichment in oil palm. Descriptives of our outcome variables are reported in Table 1.

4.1. Adoption decision

Table 1: Descriptives of outcome variables

	Total	Control	T1	T2
Number of farmers who planted in OP	0.20 (0.399)	0.05 (0.210)	0.11 (0.106) T1=C*	0.43 (0.496) T2=C *** T1=T2***
N	737	239	245	253
Number of trees planted per hectare	1.07 (5.561)	0.13 (0.826)	1.13 (6.581) T1=C **	1.902 (6.801) T2=C ***
N	736	239	244	253
Number of trees planted per hectare by adopters	5.44 (11.571)	2.90 (2.718)	11.04 (18.014) T1=C*	4.42 (9.836)
N	145	11	25	109

Standard deviation reported in parentheses. Test for mean difference conducted with a linear regression of the outcome variables on the treatment dummies with clustered standard errors. In vertical order, p-values for T1 = Control are 0.073, 0.048 and 0.071 for the three outcome variables respectively. For T2 = Control, p-values are 0.000, 0.013 and 0.347, for T1= T2 0.000, 0.358 and 0.150.
** p < 0.1, ** p < 0.05, *** p < 0.01*

Two model specifications are tested. The first only controls for the treatment dummies and the stratification variables. In the second, we additionally include the baseline characteristics that turn out to be imbalanced between groups (cf. Table 4 in the Appendix) as well as education and total oil palm area managed as a proxy for income since both variables have been proven to be important for technology adoption (Knowler, Bradshaw 2007). To control for the already existing tree density in oil palm plantations, the per hectare number of trees in the baseline is included in the model.[8] Moreover, we control for the existence of a home garden on a smallholding with a dummy variable. As gardens appear to be the preferred location to plant trees (see above), it is likely that farmers who have a garden are less likely to plant in oil palm.[9] We can detect one important outlier in our data who planted 167 trees per hectare for an intercropping system which is over nine times the standard deviation away from the mean of the farmers who planted in oil palm. The number of trees per hectare of this farmer is

[8] Since this distribution is highly right skewed, the variable is winsorized. The top 1% of the distribution is replaced with the 99 percentile.
[9] Because of multicollinearity concerns, we did not include age of the plantation, age of the household head and the asset index in the regression even though these variables possibly could explain adoption. This choice is supported by the joint insignificance of the three variables (p-value of F-test: 0.3442) as well as the decrease in the Akaike information criterion (AIC) from 1283.4 for the full model to 1280.1.

replaced with the observation of the farmer who planted the second highest number of trees per hectare.

Results of the modified Park-test for the distributional family (Manning, Mullahy 2001) cannot reject the use of the gamma distribution (p-value: 0.7977). In order to test whether the correct link function was specified, we additionally run a Pregibon link test (Deb et al. 2014). The use of a log-link function cannot be rejected (p-value: 0.552).[10] Manning, Mullahy (2001) highlight substantial increases in standard errors of GLM in comparison to OLS if the log-scaled residuals are heavily tailed. However, the kurtosis of the estimated log-residuals from our preferred GLM is 2.93 and hence below that of a normal distribution. Therefore, precision losses are likely to be small.

Table 2: Intention-to-treat effects of interventions

	Adoption decision		*Unconditional expected values*		*Conditional expected values*	
	(1) Pr(Y>0|X)	(2) Pr(Y>0|X)	(3) E(Y|X)	(4) E(Y|X)	(5) E(Y|X, Y>0)	(6) E(Y|X, Y>0)
T1	0.061*	0.070**	0.924**	1.077**	7.202***	7.188**
	(0.034)	(0.030)	(0.375)	(0.421)	(2.216)	(2.797)
T2	0.384***	0.404***	1.666***	1.912***	0.913	0.872
	(0.029)	(0.027)	(0.348)	(0.499)	(0.968)	(1.491)
N	737	737	736[2]	736[2]	145	145
Controls[1]	No	Yes	No	Yes	No	Yes

Clustered standard errors in parentheses.
Columns (1) and (2) report AME for the adoption decision. Based on the AIC the logit model specification was chosen instead of the probit (610.7 vs. 611.5 for model (1) and 602.3 vs. 602.5 for model (2)). Columns (3) and (4) show unconditional AME. AME for the intensity equation are reported in columns (5) and (6). A GLM with log-link and gamma distribution was used for estimation. Stratification variables are included in all model specifications. The odd numbers include additional controls. Delta method used to estimate standard errors.
[1]*Baseline controls include education, total area of oil palm managed, number of household members, whether a farmer cut trees in OP in 2015, the tree density in oil palm and whether he or she had a home garden.*
[2]*Different sample size due to the fact that one farmer could not remember how many trees he planted in his oil palm plantation.*
P-values of t-test for T1=T2: 0.000 (1), 0.000 (2), 0.129 (3), 0.193 (4), 0.006 (5), 0.045 (6).
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The ITT results for the two DH-model specifications explained above are reported in Table 2. In the first two columns, average marginal effects (AME)[11] of the treatments on the farmers'

[10] We additionally run a Pregibon-test for the identity link function. The Pregibon-test suggests a model misspecification (p-value: 0.015). Also the AIC and the BIC are lower when the log-link instead of the identity-link is used.
[11] In order to compute AME, predictions for the outcome variable are made based on the ITT estimates. To estimate AME for T1, farmers in T1 and the control group are is treated as belonging to T1. In a next step, the

decision to plant trees are displayed (eqn. 1 in Section 3.3). Columns (3) and (4) show AME of the interventions on the unconditional expected number of trees per hectare (eqn. 4). Conditional AME of the intensity decision for the subsample of the tree planting individuals only are reported in columns (5) and (6) (eqn. 2).

Both treatments have a positive and significant effect on farmers' decision to plant trees in oil palm. Assignment to T1 on average increases the probability that smallholders adopt by approx. 6 percentage points. The effect of T2 is significantly greater than of T1[12]; the provision of saplings and information increases the probability of planting by approx. 39 percentage points on average.

When looking at the AME of the unconditional expected number of trees per hectare in columns (3) and (4), one can see that both treatments are effective in stimulating higher tree planting intensities. On average, farmers in T1 plant approx. one tree per hectare more than farmers in the control group. In T2, on average 1.8 trees per hectare are planted more. Even though the effect size does not differ significantly between T1 and T2, the effect of T2 seems to be more pronounced as highly significant. If we restrict our sample to the tree planting individuals (columns (5) and (6)), farmers in T2 do not plant significantly more than those farmers who enrich their plantations in the control group. In contrast, the farmers that plant in T1 grow significantly more trees per hectare than in the control group and in T2. One possible reason for the significant difference between T1 and T2 is that the number of saplings provided in T2 influences the number of trees planted and due to the very high correlation between per hectare and total number of trees planted (Pearson correlation coefficient of 0.84) also the per hectare number. To further examine this idea, we focus on the distribution of the total number of trees planted per farmer. This allows us to differentiate between farmers in T2 who planted a maximum amount of six trees in oil palm and hence only the trees that were provided for free and the farmers in T2 who did an extra effort in tree planting and planted more than six trees[13]. In T2, 30.56% of the adopters plant exactly six trees in oil palm plantations, 76.85% plant six or less trees. These numbers amount to 16% and 48% of the

treatment status for these farmers is changed to the control group. The difference between both predictions can thus be attributable to the treatment status. The same approach can be taken for T2. This method is preferable to estimating marginal effects at means if discrete variables are present as a mean status of farmers in T1 and the control would uninformative number and amount to 0.5.

[12] P-values for the test of mean equality of T1 and T2 for the adoption, the intensity and the unconditional predicted value are reported below Table 2.

[13] Since the total area of oil palm managed differs between farmers, it is not possible to differentiate between these farmers with help of the per hectare distribution.

adopting farmers in T1. The share of farmers with more than six trees planted is significantly higher in T1 (p-value: 0.074)[14].

Even though these results need to be interpreted against a limited number of observations in the control group who enrich, they suggest that the significant and positive AME of the treatments on the unconditional expected number of trees in T2 is driven by the high planting probability of farmers in T2. However, these farmers rather plant few saplings per hectare in comparison to T1. It appears to be the case that the low predicted per hectare number of trees in T2 is driven by the huge share of farmers who plant a max. amount of six trees. This suggests that the number of saplings provided might act as an anchor for the planting decision. In contrast, while the planting probability is lower in T1 than in T2, a higher share of individuals decides to plant relatively many trees. Therefore, the positive and significant effect of T1 on the unconditional predicted number of trees planted per hectare is likely to be driven by the few farmers who plant on average more than in T2.

AME for all covariates for the adoption, the intensity and the unconditional expected number of trees are reported in Tables 5-7 in the Appendix. None of the covariates that are significantly different between treatment and control groups in the baseline balance check appear significant in the model estimation. This supports the validity of the results.

4.2. Attrition

From the original 817 farmers interviewed in 2015, 738 were re-interviewed in the follow-up leading to an attrition rate of 9%. Comparing the rates of attrition between treatment and control groups shows that assignment to T2 reduces the probability of attrition by three percentage points at the 5% significance level[15]. To further test for differential attrition, we run mean comparison tests[16] for attritors who drop out of the sample in the different treatment groups (Duflo et al. 2006). The results show that attritors do not differ systematically between groups except that farmers dropping out in T2 manage statistically less area of oil palm than those that drop out in the control group (p-value: 0.084). Even though these results point to a rather small influence by attrition, we employ inverse probability weighting to test for the robustness of the results (Wooldridge 2002).

[14] We test for mean difference in a linear regression framework with clustered standard errors.
[15] Mean comparison test in a linear regression framework with clustered standard errors. Only the dummy for T2 is significant (p-value: 0.056).
[16] Mean comparison test in a linear regression framework with clustered standard errors.

Drawing on Fitzgerald et al. (1998) weights are constructed with help of auxiliary variables that determine selection in the follow-up sample while being of minor importance for the outcome analysis. Dummies for the interviewer in the baseline as a proxy for the quality of the first contact with the farmer, age and gender of the household head as well as whether a farmer grows other crops are used as auxiliary variables. Results of regression with and without auxiliary variables are reported in Table 8 in the Appendix. The Pseudo-R^2 reveals that only 5% of selection in the sample can be explained by the estimation which supports the idea of mostly random attrition.

Table 3: Weighted ITT effects of interventions

	Adoption decision		*Unconditional expected values*		*Conditional expected values*	
	(1) Pr(Y>0|X)	(2) Pr(Y>0|X)	(3) E(Y|X)	(4) E(Y|X)	(5) E(Y|X, Y>0)	(6) E(Y|X, Y>0)
T1	0.059^{*}	0.069^{**}	0.918^{**}	1.073^{**}	7.260^{***}	7.294^{***}
	(0.033)	(0.030)	(0.371)	(0.418)	(2.164)	(2.805)
T2	0.384^{***}	0.404^{***}	1.669^{***}	1.905^{***}	0.873	0.817
	(0.029)	(0.027)	(0.347)	(0.494)	(0.956)	(1.503)
N	737	737	736	736	145	145
Controls[1]	No	Yes	No	Yes	No	Yes

Village-level clustered standard errors in parentheses and estimated with Delta method.
AME are reported. Stratification variables included in all model specification. Inverse probability weights applied
[1]*Baseline controls include education, total area of oil palm managed, number of household members, whether a farmer cut trees in OP in 2015, the tree density in oil palm and whether he or she had a home garden.*
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

A comparison between Table 2 and Table 3 reveals that our results are robust to controlling for attrition on observables[17]. The introduction of attrition weights leads to only very small changes in the size of the parameters. None of the variables changes its significance level.

5. Conclusion

Results from an RCT implemented in Jambi, Indonesia, suggest that both information and input in combination with information provision are effective in stimulating tree planting among oil palm smallholders. Both treatments lead on average to a higher predicted number of trees planted per hectare in comparison to the control group, the difference between the two

[17] As with the baseline balance test, we therefore assume that individuals who do not differ in observable characteristics also do not differ in unobservables.

interventions is statistically insignificant. Input together with information provision leads to a higher probability that farmers enrich than sole extension approaches. However, farmers plant relatively few trees per hectare which might be influenced by the rather small number of saplings provided. This anchoring effect cannot be observed for farmers in the informational campaign. Here, farmers have a smaller probability of adoption, but plant on average more trees per hectare than farmers who were given saplings for free.

The drawing of policy conclusions hinges on the generated biodiversity effects from different spatial distribution of and tree densities in enriched plantations at the landscape level. If policy makers only need to focus on increasing the number of trees per hectare, extension approaches can be seen as the preferred option. The unconditional expected number of trees per hectare is not statistically different from the structural intervention, the incurred costs though likely to be smaller. However, to allow for ecological scaling effects from the local to the regional level, tree nuclei need to be spread over a large area (Koh et al. 2009). Therefore, higher biodiversity effects might be generated by more farmers with medium tree planting intensities whose plantations are dispersed over a larger area than by few farmers who plant a lot. While the environmental effects are subject to the number of trees that survive, assuming similar survival rates between treatment groups, this in contrast could rather be seen as an argument to favor input in combination with information provision. Further ecological research is therefore needed to be able to draw more informed cost-benefit-analyses. In addition, future research should focus on the question whether the willingness of farmers to plant saplings is linear in the number of saplings provided. If yes, the number of trees planted per hectare is likely to increase the more saplings are provided.

Appendix

Table 4: Baseline descriptives and mean comparison tests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Total	Control	T1	T2	C=T1	C=T2	T1=T2
	Mean estimates, standard errors in parentheses				P-values		
Household head's characteristics							
Age of HH head	49. 52 (0.59)	49.14 (1.02)	49.62 (0.77)	49.79 (1.23)	0.708	0.687	0.909
Years of education HH Head	7.53 (0.16)	7.67 (0.21)	7.42 (0.32)	7.49 (0.26)	0.510	0.604	0.850
Access to environmental education (1=Yes/0=No)	0.076 (0.02)	0.052 (0.02	0.084 (0.02)	0.092 (0.04	0.325	0.380	0.870
Gender of HH head (1=female/0=male)	0.02 (0.004)	0.03 (0.010)	0.01 (0.008)	0.01 (0.006)	0.141	0.203	0.706
Household characteristics							
Household size (No. of persons)	3.96 (0.06)	3.93 (0.11)	3.83 (0.09)	4.13 (0.11)	0.502	0.209	0.047**
Value of assets (in 1,000 IDR)	49,745.24 (16749.47)	32,778.05 (3473.89)	84,134.21 (48120.35)	32,011.06 (3661.573	0.295	0.880	0.288
Other crops cultivated (1=Yes/0=No)	0.28 (0.04)	0.29 (0.07)	0.26 (0.07)	0.29 (0.08)	0.732	0.997	0.754
Total land owned (in ha)	5.69 (0.29)	5.68 (0.38)	5.81 (0.62)	5.58 (0.48)	0.863	0.865	0.771
Home garden (1=Yes/0=No)	0.91 (0.03)	0.833 (0.08)	0.91 (0.03)	0.96 (0.01)	0.324	0.113	0.139
Farms' oil palm characteristics							
Total ha oil palm managed	4.47 (0.24)	4.42 (0.23)	4.63 (0.62)	4.29 (0.27)	0.750	0.714	0.616
Share of plots with systematic certificate	0.684 (0.05)	0.695 (0.09)	0.661 (0.06)	0.698 (0.09)	0.752	0.983	0.741
Plot age (in years)	14.83 (0.74)	15.52 (1.16)	14.40 (6.26)	14.59 (1.48)	0.501	0.626	0.920
Mean number of trees per ha in OP	3.43 (0.95)	5.07 (2.57)	2.62 (0.60)	2.63 (0.90)	0.360	0.377	0.992
Trees planted in OP in last 12 months (1=Yes/0=No)	0.01 (0.00)	0.003 (0.003)	0.007 (0.005)	0.01 (0.006)	0.554	0.279	0.619
Trees cut in OP in last 12 months (1=Yes/0=No)	0.034 (0.01)	0.033 (0.01)	0.06 (0.01)	0.01 (0.01)	0.169	0.127	0.004***
N	817	270	274	273			

*Columns (1) to (4) show mean estimates and corresponding standard errors. Columns (5) to (7) report p-values for a test of mean difference based on a linear regression model. Stars refer to * 0.10 ** 0.05 and *** 0.01 significance level. All standard errors are clustered at village level.*

Figure 2: Distribution of strictly positive tree planting quantities

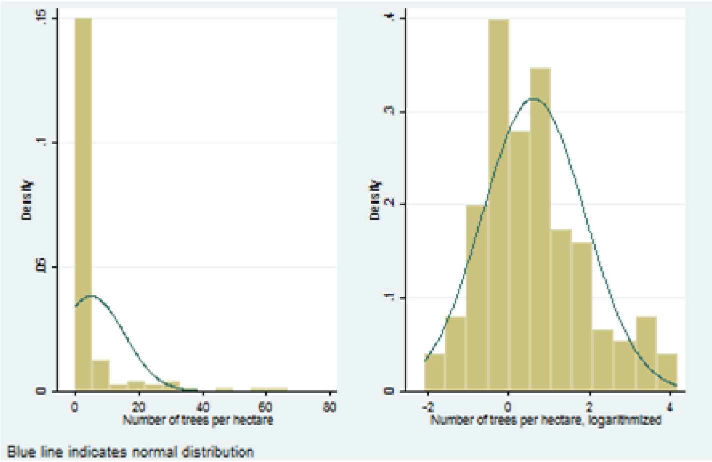

Table 5: Intention-to-treat estimates for the adoption decision

	(1) Planting in OP	(2) Planting in OP
T1	0.061*	0.070**
	(0.034)	(0.030)
T2	0.384***	0.404***
	(0.029)	(0.027)
Access to seeds	-0.026	-0.027
	(0.029)	(0.028)
Autochthonous	-0.033	-0.043
	(0.038)	(0.037)
Oil palm share > 73.5%	-0.035	-0.039**
	(0.025)	(0.019)
Number HH members		0.004
		(0.009)
Trees cut in OP		-0.019
		(0.110)
Years of education		0.009**
		(0.004)
Trees per hectare		0.003**
		(0.002)
Home garden		-0.165***
		(0.053)
Total hectare OP managed		-0.001
		(0.002)
N	737	737

Village-level clustered standard errors in parentheses. Delta method used to estimate standard errors.
AME of a logit regression.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Intention-to-treat estimates for intensity decision

	(1) Trees planted per hectare	(2) Trees planted per hectare
T1	7.202***	7.188**
	(2.216)	(2.797)
T2	0.913	0.872
	(0.968)	(1.491)
Access to seeds	-1.526	-0.724
	(1.789)	(1.821)
Autochthonous	1.898	3.953
	(2.159)	(2.732)
Oil palm share > 73.5%	-5.252***	-4.877**
	(1.620)	(1.961)
Number HH members		-0.106
		(0.491)
Trees cut in OP		4.192
		(3.835)
Years of education		0.077
		(0.094)
Trees per hectare		0.085
		(0.078)
Home garden		-1.724
		(2.324)
Total hectare OP managed		-0.916***
		(0.178)
N	145	145

Village-level clustered standard errors in parentheses. Delta method used to estimate standard errors.
AME from a GLM-model with log-link and gamma distribution of error terms.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Intention-to-treat effects on the unconditional predicted number of trees planted per hectare

	(1) Trees planted per hectare	(2) Trees planted per hectare
T1	0.924**	1.077**
	(0.375)	(0.421)
T2	1.666***	1.912***
	(0.348)	(0.499)
Access to seeds	-0.426	-0.283
	(0.404)	(0.413)
Autochthonous	0.169	0.532
	(0.486)	(0.621)
Oil palm share > 73.5%	-1.252***	-1.242***
	(0.384)	(0.440)
Number HH members		0.001
		(0.113)
Trees cut in OP		0.767
		(1.038)
Years of education		0.074**
		(0.034)
Trees per hectare		0.036*
		(0.020)
Home garden		-1.354**
		(0.591)
Total hectare OP managed		-0.201***
		(0.048)
N	736	736

Village-level clustered standard errors in parentheses. Delta method used to estimate standard errors.
AME for the unconditional expected number of trees per hectare.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Determinants of selection in follow-up

	(1) selection	(2) selection
T1	0.020	0.003
	(0.129)	(0.131)
T2	0.206	0.161
	(0.128)	(0.123)
Years of education	0.023*	0.006
	(0.014)	(0.016)
Trees planted in OP	-0.265	-0.497
	(0.614)	(0.595)
Total hectare oil palm managed	-0.011	-0.011
	(0.008)	(0.008)
Environmental extension received	0.040	-0.032
	(0.266)	(0.276)
Home garden	0.228*	0.323**
	(0.131)	(0.146)
Autochthonous	0.159	0.198
	(0.157)	(0.169)
Oil palm share > 73.5%	0.006	-0.038
	(0.121)	(0.146)
Access to seeds	0.091	0.085
	(0.126)	(0.126)
Number HH members		0.0003
		(0.041)
Age		-0.012***
		(0.007)
Gender		-0.903**
		(0.389)
Trees cut in OP		0.133
		(0.207)
Year of planting		-0.011
		(0.009)
Other crops		-0.137
		(0.124)

Mean estimate for eleven assistants[1]		-.329
		(0.261)
Constant	0.801***	24.74
	(0.215)	(18.63)
N	817	817
Pseudo R^2	0.017	0.057

[1]:Out of eleven dummy variables for the assistants collecting the baseline data, only two are statistically significant at the 10% level.
Probit model employed. Standard errors in parentheses are clustered at village level. Model 2 includes additional auxiliary covariates.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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