Effects of information and seedling provision on tree planting and survival in smallholder oil palm plantations

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Abstract: Oil palm expansion in Indonesia is associated with a reduction in biodiversity and ecosystem services, as well as 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 native tree planting in oil palm plantations as one sustainable management option. To test whether information and input provision affect the number of trees planted by smallholders two treatments were designed: the first provided information about tree planting in oil palm, while the second combined information and seedling 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. Seedling provision in combination with information leads to a higher probability of adoption, but farmers plant on average relatively few trees per hectare. In contrast, in the informational treatment, few farmers adopt, but they plant more trees per hectare than farmers who received seedlings. Furthermore, we observe that the survival rate of trees planted is lower for farmers who received seedlings in comparison to farmers who only received information. Since we cannot find evidence for farmer and plot selection effects, it is likely that species choice and seedling quality are the underlying drivers of this difference. (JEL Codes: Q12, Q16, Q57, D04, C9)

Keywords: technology adoption; randomized control trial; double-hurdle model; policy analysis; tree survival; video-based extension

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Effects of information and seedling provision on tree planting and survival in smallholder oil palm plantations

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Oil palm expansion in Indonesia is associated with a reduction in biodiversity and ecosystem services, as well as 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 native tree planting in oil palm plantations as one sustainable management option. To test whether information and input provision affect the number of trees planted by smallholders two treatments were designed: the first provided information about tree planting in oil palm, while the second combined information and seedling 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. Seedling provision in combination with information leads to a higher probability of adoption, but farmers plant on average relatively few trees per hectare. In contrast, in the informational treatment, few farmers adopt, but they plant more trees per hectare than farmers who received seedlings. Furthermore, we observe that the survival rate of trees planted is lower for farmers who received seedlings in comparison to farmers who only received information. Since we cannot find evidence for farmer and plot selection effects, it is likely that species choice and seedling quality are the underlying drivers of this difference. (JEL Codes**:** Q12, Q16, Q57, D04, C9)

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1. Introduction

During the last decades, oil palm monocultures have expanded rapidly in many tropical regions, responding to high demand for palm oil in international markets. Between 1961 and 2013, the world's production of palm oil has increased 43 fold to a total amount of approximately 53 Mio. tons and growth rates are predicted to remain positive in the coming years (FAO 2018, 2019). Over 80% of palm oil production comes from South-East Asia (FAO 2019), with Indonesia being the biggest producer of palm oil since 2008 (Gatto et al. 2015). While the cultivation of oil palm is associated with income gains for many smallholder farmers, who are increasingly engaged in its farming (Euler et al. 2016b), it has also contributed to deforestation. Between 2000 and 2012, the primary forest cover loss was estimated to amount to 6.02 million ha in Indonesia (Margono et al. 2014). Besides concerns over climate impacts and reduced water and other regulatory ecosystem services (Dislich et al. 2017), especially threats to biodiversity appear to be high (Teuscher et al. 2015). This is because Indonesia represents a biodiversity hotspot providing habitat for numerous endemic or endangered species, many of which are dependent on forest area and cannot live in oil palm plantations due to their reduced vegetation complexity (Koh et al. 2009). Therefore, sustainable policy options are needed that combine the protection of habitat for biodiversity with economic development opportunities. Since often only few forest patches remain in high production areas, 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 island planting in oil palm has been proposed as one such sustainable management practice (Koh et al. 2009; Teuscher et al. 2016): Positive effects on species richness can be generated by increased plant diversity at the plantation level (Azhar et al. 2011), while fruit and timber trees represent additional income sources for farmers (Gérard et al. 2017).

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. Because of the positive relationship between the number of trees planted per hectare and invertebrate and bird diversity and abundance (Teuscher et al. 2015; Teuscher et al. 2016), we specifically analyze the intensity of adoption, which is not restricted to the binary adoption decision of the farmers, but considers how the number of trees planted can be increased. Relatively little is known about what instruments are suitable to induce biodiversity-friendly land uses such as agroforestry. Most studies focusing on agroforestry-like practices or tree planting analyze the effects of existing Payments for Ecosystem Services (PES) contracts that compensate adopters financially for their planting efforts (Pagiola et al. 2007; Wunder and Albán 2008). Relatively few studies compare different policy designs with regard to their effectiveness to induce tree planting. Exceptions are Jack (2013b) who compares a lottery and an auction PES contract design for tree planting and Jack et al. (2015) who analyze the effect of varying levels of seedling subsidies and reward payments on tree planting and survival. However, none of the studies test whether tree planting can also be promoted by other policies but monetary payments, despite their possible advantages such as lower costs.

The focus on financial rewards can be motivated by limited private benefits and by the positive externalities generated through tree planting (Jack et al. 2015). Nonetheless, in particular in developing countries, market inefficiencies that hinder technology adoption can stem from several sources and individuals might face constraints simultaneously in several dimensions (Jack 2013a; Knowler and Bradshaw 2007; Foster and Rosenzweig 2010). Among others, lack of information and missing access to input markets have been identified to impede the uptake of agroforestry and other agricultural technologies (Shiferaw et al. 2008;

Shiferaw et al. 2015; Noordwijk et al. 2008; Meijer et al. 2015). Awareness of the existence of a technology, as well as knowledge about its implementation and expected benefits can be considered pre-conditions for adoption. In addition, even if farmers are willing to use a technology, high transaction costs related to accessing markets can prevent adoption. The relevance of both factors has also been supported by focus group discussions held prior to data collection in our study area. Despite their importance, these potential barriers have so far received little attention in the literature analyzing policy incentives for tree planting.

To overcome these barriers, information and input provision appear to be promising approaches. Information provision can be successful to spur technology adoption in rural settings in developing countries (Aker 2011). However, farmers might be reluctant to adopt a production technology, which is not primarily intended to increase income or productivity, but rather to diversify income and production patterns, and in particular aims at improving regional and global environmental conditions. While there is ample evidence that farmers' land use choices are also affected by environmental and social motives (Narloch et al. 2012; Greiner and Gregg 2011), rigorous evaluations of the effect of information provision on land management decisions with primarily environmental motives are scarce. Most studies focus on possible productivity improvements by increasing soil fertility (Kondylis et al. 2017; Benyishay and Mobarak 2018), fertilizer applications (Duflo et al. 2006b) or generally improved management practices (Cole and Fernando 2016; van Campenhout et al. 2017b).

Studies on agroforestry adoption support the relevance of knowledge and extension approaches, however, these are mostly cross-sectional studies with relatively small sample size, such that a clear identification of the effect of information provision is difficult (Matata et al. 2010). Several studies have analyzed the effect of information provision on a broad set of pro-environmental behaviors and find mixed results (Steg and Vlek 2009; Abrahamse et al. 2005; Bolderdijk et al. 2013). This highlights the relevance of contextual and socio-economic factors as well as the way in which the information is provided. Some studies suggest that especially role model approaches might be a promising way to deliver information which could be, if combined with videos or other information and communication technologies, also cost-effective in rural settings (Steg and Vlek 2009; Bernard et al. 2015; Aker 2011). While there is evidence that videos can be an effective tool to increase knowledge or stimulate behavioral change in rural settings (van Campenhout et al. 2017a; Zossou et al. 2009), until now only few studies allow for a clear identification of the effect of video-based information provision on agricultural land use decisions (Gandhi et al. 2009; van Campenhout et al. 2017b).

If information provision is successful in convincing farmers of the relevance of adoption, it may suffice to significantly increase adoption rates. However, if structural barriers such as missing access to seedling markets or high transaction costs prevail, adoption might not occur, even if intentions are there (Shiferaw et al. 2015; Steg and Vlek 2009). In the presence of multiple constraints, a comprehensive approach combining e.g. information with input or subsidy provision is likely needed that aims at overcoming several barriers at the same time. Previous studies that have looked at such combined approaches often do not allow disentangling the pure information effect from the effect of structural incentives (e.g. Brauw et al. 2018; Duflo et al. 2006b; Jack et al. 2015). In an earlier contribution, we find that structural interventions can significantly increase the probability of tree adoption compared to pure information interventions (Romero et al. 2019). However, Romero et al. (2019) focus on the psychological mechanisms – changes in perceptions and intentions – explaining changes in the binary adoption decision, but do not provide evidence on the impacts on adoption intensity and tree survival, which are critical determinants of ecological outcomes. We aim to address these research gaps by testing the effects of a pure information intervention and an approach combining information with seedling provision on tree planting intensity and survival in oil palm plantations. To be able to draw causal inferences, a Randomized Controlled Trial (RCT) was implemented in Jambi Province, Indonesia, in 2016. Our information intervention is based on a video that includes testimonies of farmer role models, and thus adds to the scarce literature evaluating video-based extension. The combined intervention allows us to identify whether adding a structural component that aims to overcome restricted access to seed markets significantly increases farmers' tree planting activities in oil palm, compared to the pure information intervention. While farmers can plant trees also in other locations, e.g. their home gardens, we specifically consider tree planting in oil palm plantations. This choice is motivated by the fact that to restore biodiversity at the landscape level large tree islands need to be planted within the oil palm monoculture structure and not only in proximity to households as it would be the case for home gardens. We focus on smallholder farmers due to their growing importance in the oil palm sector (Rist et al. 2010; Euler et al. 2016b). Hence, they can be identified as key addressees of policies promoting sustainable plantation management. In a double-hurdle framework, the probability of farmers to plant seedlings in oil palm and their planting intensity, measured as the number of trees planted per hectare, are analyzed. Since ecological effects of tree planting are subject to tree survival, we additionally analyze the effect of the interventions as well as other drivers on tree survival.

The structure of the paper is as follows. Section 2 provides background information about tree planting as a biodiversity-enhancing management option. Section 3 describes the experimental design, the interventions, the data collection process, as well as the estimation strategy. Results are presented in section 4, and section 5 concludes.

2. Biodiversity-enhancing oil palm management

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, 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; 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 islands 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 bird and invertebrate 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 indicates that the impact might be highly dependent on tree species and age (Teuscher et al. 2015; Gérard et al. 2017). Teuscher et al. (2015) analyze the effects of trees on yields in oil palm smallholdings in Sumatra. They detect a negative effect which is decreasing in the number of trees. Having 40 trees in a one hectare plantation approximately reduces yields by two tons[1]. Results from the biodiversity enrichment experiment in Sumatra do not support a negative effect of trees on oil palm yields two years after planting (Gérard et al. 2017). Previous research has also shown that intercropping oil palm with cacao does not affect oil palm yields, and cacao yields can even increase if optimal spacing is applied (Corley et al. 2003).

Even though possible negative yield effects for oil palm might reduce the private incentives farmers have for planting trees, 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 for smallholder farmers. Per hectare revenues of valuable fruit trees such as Durian, Jengkol or Petai can be important and might even be comparable to oil palm revenues.[2] Timber trees represent additional income sources. Hence, trees can reduce the dependence on a single crop and mitigate negative income shocks due to pests or diseases, climate impacts as well as fluctuations in global palm oil prices (Teuscher et al. 2015). Besides direct income effects, increased plant and species diversity can also raise farmers' income indirectly through improved soil fertility, pollination and pest management (Foster et al. 2011).

3. Study Design, Data and Estimation Strategy

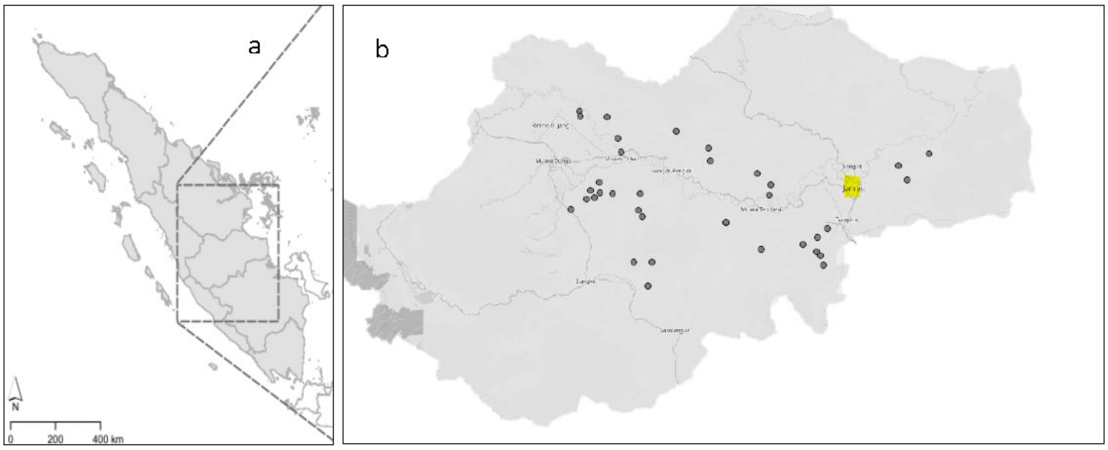
3.1. Study area and sampling strategy

Our study took place in Jambi Province, Indonesia (cf. Figure 1), one of the hotspots of oil palm cultivation in Indonesia (Krishna et al. 2017). Oil palm was introduced in Jambi in the 1980s through a government program which supported the expansion of oil palm. Within this so-called transmigration program, poor farming households were relocated from the overpopulated islands of Java and Bali to less populated ones, mostly to Sumatra (Euler et al. 2016b). These new settlers received two to three hectare of land for oil palm cultivation as well as extension services and inputs for oil palm cultivation.

We focus on five districts in Jambi– Muaro Jambi, Batanghari, Sarolangun, Tebo and Bungo – 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). In total, 36 oil palm growing villages were selected, 75% of which are transmigrant villages and 25% local villages.[3] A random sample of 27 villages was drawn from an assembled list of 90 transmigration 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 local villages, because local farmers are still mainly engaged in rubber cultivation in Jambi (Euler et al. 2016b).

[1] For comparison, average per hectare yields of smallholder plantations in Indonesia are approx. eleven tons (Euler et al. 2016a).
[2] Calculation based on Center for Agricultural Data and Information System 2016 and BPS-Statistics Indonesia 2017. Oil palm revenues taken from Euler et al.(2016a).
[3] By transmigration (local) villages, we understand villages in which mostly transmigration (local) farmers live. Local farmers belong to the Melayu ethnic group while transmigrant farmers are mostly Javanese. Since especially local Melayu farmers, who are more and more switching from rubber to oil palm cultivation, will drive the further expansion of oil palm, we opted to include both village types in the sample.

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).



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 which gathered additional information on access to seedling markets, extension services received and other village-specific information. Lists with all oil palm growing households were provided by the village employees.

Contract-farming arrangements between oil palm smallholders and companies are common in the study region and were in particular promoted at the beginning of the oil palm expansion (Gatto et al. 2015). As farmers who are under contract with companies do not have full autonomy over management decisions, which could impact the results of our interventions, we restrict our sample to independent smallholders who grow oil palm without contractual arrangements. Within each of the villages, we randomly selected 22 to 24 households of independent oil palm farmers. In total, 817 farmers were part of the sample. We conducted a baseline survey in the villages from October until December 2015 to collect information on the number, the species and the location of trees planted and cut in the last 12 months, as well as household descriptives. The interviews were carried out by twelve local assistants who were students from the Indonesian universities of Jambi (UNJA) and Bogor Agricultural University (IPB). After pre-testing the questionnaire in four villages, the assistants were trained intensively in the classroom and in the field. Follow-up data was collected from October till December 2016. 90% of all farmers could be interviewed again resulting in a sample of 737 farmers in the follow-up.

3.2. Randomization approach and description of treatments

In order to reduce the risk of spill-over effects, 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 (transmigration or local), whether or not a village had access to seedling 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 A1 in the Appendix presents baseline descriptives of the sample. In order to test whether randomization was successful in creating balance between groups, we conduct 54 tests of mean difference. Only the number of farmers that cut trees in oil palm in 2015 and the household size are statistically different between the treatment groups at the 1% and 5% level respectively. Given that some imbalance can occur by chance (Morgan and Rubin 2012), the randomization can be considered 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. Farmers assigned to T2 additionally received six native seedlings for free.

Information was delivered through a video and an illustrative manual. In an eleven minute movie, a lecturer from UNJA 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 seedlings 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 from Jambi to participate in the video. The interviewees described their experience with tree planting. The movie was complemented by an illustrative manual designed by a local artist. The manual additionally provided information on environmental and economic outcomes of tree enrichment and was distributed to the farmers to be taken home.[4]

Since focus groups identified missing markets as one obstacle to tree planting , seedlings of six multipurpose trees native to Jambi were distributed for free to each farmer in T2. The selected species[5] included three fruit trees (*Archidendron pauciflorum* ‘Jengkol’; *Durio zibethinus* ‘Durian’; *Parkia speciosa* ‘Petai’), one natural latex (*Dyera costulata* ‘Jelutung’), and two timber trees (*Peronema canescens* ‘Sungkai’; *Shorea leprosula* ‘Meranti’). Tree choice was made because the trees are native to Jambi, known to farmers and provide economic benefits (Gérard et al. 2017). Each farmer in T2 received one of each species leading to a total of six seedlings per person after the end of the video screening. Measured in local prices in Jambi city, the six seedlings are worth approx. 37,500 Indonesian Rupiah (IDR)[6]. In total, 1458 seedlings were distributed.

The interventions were carried out in February 2016 such that the farmers could plant the trees before the start of the dry period. Five local assistants helped with the implementation. The video screening took place in the village office. Farmers were invited to the video session by the village staff via an official letter three days prior to screening. A reminder text message was sent one day before. The attendance of the assigned farmers was controlled with help of an attendance sheet.

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

[4] Due to the different supply systems in the villages, contact information of traders or similar were not provided. However, in case farmers asked about where to buy seedlings, the tree nursery of UNJA was mentioned.

[5] Scientific name in italics and local name in quotation marks. Two of the three fruit trees provided are leguminous plants such that they fix nitrogen in the soil which provides additional nutrients to the oil palms.

[6] This amounts to 2.8 USD using the average exchange rate between IDR and USD at the time of the interventions. Because of transportation costs it is likely that the prices in the villages are higher.

intervention (T2) it was 74.0%. The difference between both groups is not statistically significant (p-value: 0.164).[7] Farmers who did not attend the video screening were visited at their houses at a later moment to complete a short mid-term survey. At this occasion, the farmers were also provided with the manual and, if assigned to T2, with the seedlings. The survey was also conducted in the control group. 26.3% of farmers in T1 received only the manual. Seedlings and the manual alone were given to 22.0% in T2. Accordingly, 5.8% in T1 and 4.0% in T2 did not receive any of the interventions. Additional non-compliance can occur if other external institutions are present in the study region and provide information and seedlings to the control group. Our results show that around 5% of all farmers in the sample received tree related extension approaches from other sources while approx. 9% of the farmers got seedlings for free from other sources. Since both the number of farmers who got either other extension approaches or seedlings, and the number of trees provided for free are balanced between treatment and control groups, this is unlikely to threaten the internal validity of the results [8].

In order to reduce possible experimental effects that could undermine the internal and external validity of the results (Simons et al. 2017), farmers were not told that they participated in an experiment.[9] However, we cannot rule out that due to the frequent visiting of the farmers, questions related to tree planting in oil palm might have become more salient to the interviewees (Zwane et al. 2011). Since both treatment and control groups were visited with the same frequency, the effect should be similar across groups, and therefore, should not bias the estimates. Additionally, we keep track of information exchange between farmers in the control and treatment villages in order to be able to control for possible spill-over effects. We do not find evidence that information between treatment and control villages about tree planting has happened at a broad scale.[10]

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[11]. We estimate the following model:

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

where Y_{ij} is the outcome variable of interest, i.e., 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 is a vector of stratification variables and the vector X_{ij} contains baseline

[7] 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.

[8] Mostly farmers get seedlings for free from their neighbors. Controlling for the external interventions does not change the results presented in section 4.

[9] Examples are the Hawthorne effect where individuals in the treatment group work harder knowing that they participate in an experiment and are selected to be part of the treatment group or the John Henry effect where the control group tries to overcome possible disadvantages due to not having been assigned to the treatment group by working harder.

[10] In our sample, we can detect only twelve cases of information exchange between farmers in treatment and control villages. Out of the twelve, only six state that the topic of tree planting was discussed. It is therefore unlikely that spillover effects threaten the internal validity of our results.

[11] By trees we understand tall wood trees that have a clearly developed stem and do not have branches at the basis (Roloff and Bärtels 2014). Therefore, other palm species, banana plants and shrubs were not considered in the analysis.

characteristics of farmers. e_{ij} is an individual-specific error term that is clustered at the village level. Two model specifications are tested. The first one only controls for the treatment dummies and the stratification variables. In the second one, we additionally include the baseline characteristics that are imbalanced between groups (cf. Table A1 in the Appendix) and the remaining control variables in Table A1 to increase the precision of our estimates[12].

We analyze the planting decision of the farmers using a Double-hurdle (DH) model (Cragg 1971). Therefore, adoption is modelled as a two stage process. 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. This assumption finds statistical support in our data.[13]

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 and Tanguy 2016). Therefore, the treatment 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, e.g. due to restricted access to seed markets (Shiferaw et al. 2008), or where people abstain from adoption, e.g. due to social norms and beliefs (Salmon and Tanguy 2016). As shown in the focus group discussions, both aspects appear to be relevant in our context. 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. To further support the use of the DH-model, a Vuong test is conducted (Shiferaw et al. 2008). The test results suggest that the DH-model is closer to the true data generating process than the Tobit model (p-value 0.000).

In case of normally distributed residuals, but if negative predicted outcome variables should be prevented, the intensity decision can be estimated with help of a truncated normal distribution (Cragg 1971; Salmon and Tanguy 2016). Due to the highly right skewed distribution of the strictly positive per hectare number of trees planted (cf. Figure A1 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 and Mullahy 2001). The use of the link function is tested with help of a Pregibon test (Belotti et al. 2015). The log-link cannot be rejected (p-value: 0.331).[14] In order to test for the correct family of distribution for the GLM error term, we use a modified Park test (Salmon and Tanguy 2016; Manning and Mullahy 2001). We cannot reject the use of the gamma-distribution for the error term (p-value: 0.801).

The GLM-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 and Mullahy 2001). We use a modified White test (Wooldridge 2010) to test for

[12] Because of multicollinearity concerns, we did not include age of the plantation, age of the household head the asset index, the share of plots with systematic land titles and whether the farmer has planted trees in his or her plantation in 2015 in the regression. This choice is supported by the joint insignificance of the variables (p-value of 0.425).

[13] Test for independence done with help of a Heckman selection model. Test results and more information are provided in Table A6.

[14] We additionally run a Pregibon-test for the identity link function. The Pregibon-test suggests a model misspecification (p-value of squared prediction: 0.011). Also the AIC and the BIC are lower when the log-link instead of the identity-link is used.

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 0.04). This supports the use of the GLM approach. Manning and 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.

We assume a representative household that is maximizing its expected utility from tree planting taking into account the discussed benefits and costs of tree planting (cf. section 2).[15] In a first step, the farmer decides whether to plant or not. In case the expected utility is positive, we will observe adoption. Conditional on a positive decision to plant, the utility maximizing number of trees is determined. Following Belotti et al. (2015), the adoption decision can be described as:

$$\Pr(y > 0|x) = F(x\delta) \qquad (2)$$

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

The conditional intensity decision is expressed as:

$$E(y|y > 0, x) = g^{-1}(x\beta) \qquad (3)$$

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:

$$\ln\big(E(y|y > 0, x)\big) = x\beta \Rightarrow \mathrm{E}(y|y > 0, x) = \exp(x\beta) \qquad (4)$$

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

$$E(y|x) = \Pr(y > 0|x) * E(y|y > 0, x) \qquad (5)$$

[15] See Mercer and Pattanayak 2003 for a theoretical discussion of agroforestry adoption.

4. Results

Table 1. Descriptives of outcome variables

	Total	Control	T1	T2
Share of farmers who planted in oil palm plots	0.20 (0.398)	0.05 (0.210)	0.10 (0.303) T1=C*	0.43 (0.496) T2=C*** T1=T2***
N	737	239	245[1]	253
Number of trees planted per hectare	1.07 (5.561)	0.13 (0.826)	1.13 (6.581) T1=C**	1.90 (6.801) T2=C***
N	736	239	244[1]	253
Number of trees planted per hectare by adopters	5.47 (11.608)	2.90 (2.718)	11.48 (18.268) T1=C*	4.40 (9.839)
N	144	11	24	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 0.082, 0.049 and 0.060 for the three outcome variables respectively. For T2 = Control, p-values are 0.000, 0.013 and 0.351, for T1= T2 0.000, 0.358 and 0.128.
$* p < 0.1$, $** p < 0.05$, $*** p < 0.01$
[1]Different sample size due to the fact that one farmer could not remember how many trees he planted in his oil palm plantation.

During the one-year period between baseline and follow-up survey, 145 farmers (19.7%) planted a total number of 3,591 trees in oil palm plantations.[16] To see which economic benefits farmers can derive from the trees planted, we divided them into different purpose categories. 44.5% of the trees planted in oil palm are fruit, 47.4% timber, 5.2% rubber trees and 2.8% do not have a specific economic use. Descriptives of our outcome variables are reported in Table 1.

Adoption decision

The intention-to-treat (ITT) estimates are reported in Table 2. In the first two columns, average marginal effects (AME)[17] of the interventions on the unconditional expected number of trees planted per hectare (eqn. (5)) are displayed. Columns (3) and (4) show AME of the interventions on the farmers' decision to plant trees (cf. eqn. (2)). Columns (5) and (6) report conditional AME on the intensity decision for the subsample of the tree-planting individuals only[18] (eqn. (3)). Besides standard significance levels based on p-values, we also report

[16] In addition, trees were planted in home gardens (36.2% of all farmers), in other plots or on fallow land (3.7% of all farmers). 40.4% of all farmers did not plant trees at all.
[17] AME are preferred over marginal effects at the average in case of discrete variables (Ricker-Gilbert et al. 2011). They represent the average over all partial effects of the variable of interest in the sample.
[18] To allow for more flexibility in the specification of the density function, quasi maximum likelihood estimates are presented in Table A3 in the Appendix. The standard errors change only slightly, though, such that the

significance levels based on pairs cluster bootstrap-t procedure. This approach provides asymptotic refinements and has been shown to reduce problems of over-rejection in case of a limited number of clusters (Cameron et al. 2008).[19] AME of all covariates for the adoption decision, the conditional and unconditional expected number of trees are reported in Tables A2-A4 in the Appendix. None of the covariates that are significantly different between treatment and control groups in the baseline balance check are significant in the model estimation, supporting the validity of the results.

Both treatments significantly increase the unconditional expected number of trees planted per hectare (columns (1) and (2)). On the average, farmers in T1 plant 0.9 trees per hectare more than farmers in the control group. Assignment to T2 increases the number of trees planted per hectare on average by 1.7 trees in comparison to the control group. Although the effect size of T2 is slightly larger than that of T1, the difference between both treatments is not statistically significant.[20] This suggests that both interventions are similarly effective in increasing the expected number of trees per hectare. Yet, the unconditional planting intensity potentially masks underlying decision patterns that may differ under the two policy interventions. Results of the double hurdle model allow us to distinguish between extensive and intensive margins.

At the extensive margin, columns (3) and (4) show that both treatments have a positive and significant effect on farmers' decision to plant trees in oil palm, although to varying degrees. Assignment to T1 on average increases the probability that smallholders adopt by approx. 6 percentage points in comparison to the control group. The effect of T2 is significantly larger than that of T1; the provision of seedlings and information increases the probability of planting by approx. 39 percentage points on average. Although we cannot separate the individual effects of information and input provision in T2, because of the possibility of interactions between both (Ashraf et al. 2013), the results suggest that input provision is important to motivate tree planting in oil palm plantations for a large share of the farmers.

interpretation of the results is not affected by a possible misspecification of the density function in case of maximum likelihood estimation.

[19] Bootstrap-t confidence intervals are provided in the Appendix in Table A5.

[20] The results for the unconditional expected number of trees planted per hectare are supported by an OLS regression of the number of trees planted per hectare on the treatment dummies alone or on the treatment dummies in combination with the stratification variables.

Table 2. Intention-to-treat effects of interventions

	Unconditional expected values		*Adoption decision*		*Conditional expected values*	
	(1) $E(Y \mid X)$	(2) $E(Y \mid X)$	(3) $Pr(Y>0 \mid X)$	(4) $Pr(Y>0 \mid X)$	(5) $E(Y \mid X, Y>0)$	(6) $E(Y \mid X, Y>0)$
T1	$0.922^{**/a}$ (0.367)	$0.930^{**/a}$ (0.416)	$0.057^{*/c}$ (0.032)	$0.061^{**/b}$ (0.030)	$7.609^{***/a}$ (2.185)	$7.504^{**/a}$ (2.980)
T2	$1.659^{***/a}$ (0.345)	$1.728^{***/a}$ (0.467)	$0.384^{***/a}$ (0.029)	$0.400^{***/a}$ (0.028)	0.908 (0.961)	1.060 (1.545)
N	736	736	737	737	144	144
Control group[1]	0.156** (0.068)	0.149** (0.080)	0.046*** (0.017)	0.042 *** (0.015)	3.415*** (0.747)	3.454*** (1.093)
P-values of t-test for T1=T2	0.124	0.168	0.000	0.000	0.003	0.069
Controls[2]	No	Yes	No	Yes	No	Yes

Clustered standard errors in parentheses.
Columns (1) and (2) show unconditional AME. Columns (3) and (4) report AME for the adoption decision. 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]*Predicted mean for control group displayed. Significance level reported for test E(Y) = 0.*
[2]*Baseline controls include number of household members, whether a farmer cut trees in OP in 2015, education, whether he or she had a home garden, total area of oil palm managed, the tree density in oil palm, the mean oil palm price receive, whether he or she received environmental extension, the gender of the household head, whether other crops are grown by the household, the total are of land owned and the share of plots that were flooded.*
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$
[a/b/c] refer to significance level 1% ([a]), 5% ([b]) and 10% ([c]) based on bootstrap-t procedure. 1000 replications used for estimating confidence intervals.

At the intensive margin, columns (5) and (6) show that the expected number of planted trees conditional on adoption is not significantly higher in T2 compared to the control group. In contrast, T1 has a significantly positive effect on the conditional number of trees planted per hectare compared to both T2 and the control group. Accordingly, in T2 we observe large numbers of farmers planting only few trees each, whereas in T1 few farmers adopt, but each of them plants a relatively large number of trees on the average. The treatment effects on the unconditional expected number of trees are therefore driven by different underlying mechanisms: T2 particularly increases the planting probability of farmers, whereas the effect of T1 is driven by a few high-intensity adopters.

One possible reason for the difference in conditional planting intensity between T1 and T2 could be the number of seedlings provided in T2 setting a benchmark for the number of trees planted[21]. To further examine this idea, we focus on the distribution of the total number of

[21] Due to the very high correlation between per hectare and total number of trees planted (Pearson correlation coefficient of 0.88) the number of seedlings provided also influences the per hectare number.

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 planted more than six trees. In T2, 30.6% of the adopters plant exactly six trees in oil palm plantations, 76.9% of the adopters plant six or less trees. In comparison, only 17% of the adopting farmers in T1 plant exactly six trees and 50% plant less than six trees, which are significantly smaller shares.[22] It thus seems that the low predicted number of trees planted per hectare in T2 is driven by the large share of farmers who plant a maximum amount of six trees. Two interpretations for the average lower predicted number of trees planted are possible. First, in the informational campaign, the optimal number of trees to be planted per hectare in order to generate biodiversity effects with low expected yield effects for oil palm was not specified. Thus, it is possible that some farmers in T2 interpreted the number of seedlings provided as being optimal and hence did not make additional planting efforts. Second, it might be that because of the gratis provision of seedlings also farmers who derive a rather low utility from tree planting are motivated to adopt. For these farmers, the gratis input provision might act as a subsidy, such that adoption only occurs if inputs are provided for free. This interpretation is in line with findings from the experimental literature on sorting effects (DellaVigna et al. 2012). It additionally finds support in our data. In the baseline survey, farmers were asked how many trees they intent to plant. We can find a statistically significant difference in the intended number of trees to be planted between the farmers in T2 who plant a maximum amount of six trees and those that plant more than six trees (p-value: 0.060).[23] Thus, the farmers who only planted the seedlings received for free already stated a lower intention for tree planting in the baseline survey.

4.1.1. Attrition

From the original 817 farmers interviewed in 2015, 737 could be re-interviewed in the follow-up implying an attrition rate of 10%. This rate is comparable to other randomized studies collecting household data in developing countries (Molina Millan and Macours 2017). Nonetheless, if attrition is non-random across treatments, standard ITT estimates might be biased. 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[24]. To further test for differential attrition, we run mean comparison tests for attritors' characteristics who drop out of the sample in the different treatment groups (Duflo et al. 2006a)[25]. 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 (IPW) to correct for attrition on observables (Wooldridge 2002) as robustness check. In addition, we use non-parametric techniques, such as Manski and Horrowitz Bounds (Horowitz and Manski 2000) and Lee Bounds (Lee 2009), which rely on less assumptions. Results are presented in Tables A7 and A9 in the Appendix. The construction of weights is further discussed in Table A8. Both parametric and non-parametric techniques support the results presented in Table 2.

4.1.2. Outlier analysis

[22] Mean comparison test in a linear regression framework with clustered standard errors. P-value is 0.096.
[23] Standard errors are clustered at village level.
[24] Mean comparison test in a linear regression framework with clustered standard errors. Only the dummy for T2 is significant (p-value: 0.056).
[25] Mean comparison test in a linear regression framework with clustered standard errors.

Several cross-checks for the number of trees were implemented in the questionnaire to ensure the validity of the reported quantities of trees planted. Notwithstanding, as a further robustness check, we analyze the extent to which our results are driven by outliers. To this end, the distribution of the strictly positive number of trees planted per hectare is winsorized at the 99 percentile. Seven observations are replaced, four of which are farmers belonging to T1 and three belonging to T2. Results are displayed in Table 3[26].

Table 3. Intention-to-treat estimates with distribution winsorized at 99 percentile

	Unconditional expected values		*Adoption decision*		*Conditional expected values*	
	(1) E(Y|X)	(2) E(Y|X)	(3) Pr(Y>0|X)	(4) Pr(Y>0|X)	(5) E(Y|X, Y>0)	(6) E(Y|X, Y>0)
T1	0.683**	0.679**	0.057*	0.061**	5.232***	4.996**
	(0.274)	(0.297)	(0.032)	(0.030)	(1.495)	(2.374)
T2	1.426***	1.497***	0.384***	0.400***	0.517	0.618
	(0.253)	(0.351)	(0.029)	(0.028)	(0.770)	(1.408)
N	736	736	737	737	144	144
P-values of t-test for T1=T2	0.040	0.058	0.000	0.000	0.003	0.073
Control[1]	No	No	No	Yes	No	Yes

Village-level clustered standard errors in parentheses and estimated with Delta method.
Columns (1) and (2) show unconditional AME. Columns (3) and (4) report AME from a logit regression. Columns (5) and (6) report AME from a GLM with log-link and gamma distribution of the error terms. Stratification variables included in all model specification. Before estimation, distribution was winsorized at the 99 percentile.
[1] Baseline controls include number of household members, whether a farmer cut trees in OP in 2015, education, whether he or she had a home garden, total area of oil palm managed, the tree density in oil palm, the mean oil palm price receive, whether he or she received environmental extension, the gender of the household head, whether other crops are grown by the household, the total are of land owned and the share of plots that were flooded.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Comparing Table 2 and Table 3 shows that the significance levels of the estimated AME are not affected by replacing dependent values, which are greater than the 99 percentile, with the 99 percentile. While the size of the estimated coefficients decreases for the unconditional expected values, both T1 and T2 still lead to a higher expected number of trees in comparison to the control group. However, in contrast to Table 2, the unconditional expected number of trees planted per hectare is statistically greater in T2 than in T1. With respect to the conditional expected number, we can observe a decrease in the effect size for both interventions. The effect of T1 is still statistically different to the control group and T2. Therefore, the positive effect of the intervention on the expected number of trees planted is not driven by outliers. Notwithstanding, because of the decrease in the conditional expected number of trees in T1 after winsorizing the outcome variable, assignment to T1 leads to a lower unconditional expected number of trees per hectare than in T2. Hence, the generation of

[26] For completeness, also the results of the participation decision are shown even though it is not affected by winsorizing the distribution.

the same unconditional expected values of trees planted per hectare in both treatments is dependent on the 1% of farmers who plant the most. In order to increase the external validity of our results in section 4.1., it is therefore important to conduct further experiments on tree planting in oil palm to see whether also in other contexts the adopters receiving only information plant sufficiently high numbers of trees to compensate for the lower probability of planting, when only information is provided.

4.2. Tree survival

While tree planting can be seen as the first necessary step towards more biodiversity-friendly plantation management, environmental effects are only generated if trees survive. Descriptives of tree survival one year after planting for the adopting farmers and estimated coefficients from a fractional probit estimation[27] of tree survival on treatments are reported in Table 4. Even though trees can die also at a later point in time, trees are especially vulnerable and require more care during the first year after planting (Jack et al. 2015).

Results from Table 4 show that trees planted by adopters in T2 experience a significantly lower survival rate than trees planted by adopters in T1 and the control group. The survival rate in T1 is not statistically different from the control group.

We identified four different categories of factors that are likely to be correlates of tree survival rates in our context. If these factors are unbalanced between treatment groups, they can help explain the differential survival rates observed between treatment groups. First, the planting pattern might determine tree survival. Many trees planted together in clusters are more resilient and hence are likely to show higher survival rates (Goldman et al. 2007). We control for both the number of trees planted and the share planted in clusters. Second, farmers' characteristics such as experience and skills might positively influence the maintenance given to trees and thus tree survival.[28] Also, farmers who received seedlings for free may invest less effort in maintenance, due to either a lower intrinsic interest in trees or due to lower sunk costs of seedling loss (Ashraf et al. 2010; Thaler 1980). Third, the environmental conditions of the plot, including exposure to flooding and drought[29], oil palm plantation age, the number of oil palms planted per hectare and whether a river borders the plot, might affect tree survival. Fourth, the species choice might be a significant predictor for tree survival. Even though the species distributed in the experiment were chosen because they are native to Jambi and known by the farmers, they might not have been optimal species to plant with oil palms. In addition, it could be that exogenously distributed seedlings do not correspond to smallholders' preferences.

[27] Since both zero and one appear with a positive frequency in our data set, we rely on a fractional probit estimation instead of a beta regression to explain survival rates. Fractional probit estimation is preferred over OLS due to the bounded nature of the dependent variable.
[28] We proxy skills with education and wealth. Variable choice is discussed in Table A12 in the Appendix.
[29] Since we would like to analyze whether farmers in T1 and in the control group choose a more suitable environment for tree seedlings, we use variables that reflect whether a flood is prone to being flooded or affected by a drought. These variables equal one if the respective plot was affected by these conditions both in 2015 and 2016. The results do not change if we include actual flooding or drought in 2016.

Table 4. Descriptives of survival rate and fractional probit estimation results (adopters only)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Overall	Control	T1	T2	T1=C	T2=C	T1=T2
A	0.660 (0.399)	0.923 (0.140)	0.854 (0.320)	0.590 (0.408)	0.462	0.000***	0.022**
Observations	144	11	24	109			
B	Survival rate		-0.366 (0.437)	-1.196*** (0.297)			0.0402**
Observations	144						

Line A presents descriptives of the survival rate. In columns (1) to (4), standard deviations are reported in parenthesis. Columns (5) to (7) show p-values of mean difference test with clustered standard errors.
Line B displays estimated coefficients of a fractional probit estimation in columns (3) and (4). Village clustered standard errors are displayed in parenthesis. Column (7) shows p-value of test T1=T2.

Table 5. Mean comparison test of significant predictors for tree survival

	(1)	(2)	(3)	(4)
Variable	Overall	Control + T1	T2	Control +T1 = T2
Maintenance[1] (Yes=1, No= 0)	0.333 (0.473)	0.314 (0.471)	0.339 (0.476)	0.810
Experience with tree planting (Yes =1, No = 0)	0.230 (0.422)	0.286 (0.458)	0.211 (0.410)	0.539
Share of plots which border a river	0.204 (0.400)	0.118 (0.327)	0.231 (0.418)	0.156
Share of tree species provided in total trees planted	0.700 (0.439)	0.278 (0.441)	0.832 (0.346)	0.000***

In columns (1) to (3), standard deviation reported in parenthesis. Column (4) shows p-values of test for mean difference with clustered standard errors.
[1]Maintenance includes fertilizer and/or manure application and/or weeding.
Plot characteristics taken from plots where farmers plant trees on.

In order to test these hypotheses, we regress tree survival on a range of factors using a fractional probit model. Given that tree survival is conditional on prior adoption of tree planting, we only include the farmers who decided to plant trees in the estimation. Results are reported in Table A10 in the Appendix. We find ample support for the second category of factors identified above. Prior experience with tree planting in oil palm and maintenance given to the trees[30] are significant and positively associated with the probability of tree survival. Regarding the third category of factors, only the share of plots which border a river

[30] We acknowledge that reverse causality between survival rate and maintenance might be present in case seedlings die early, such that maintenance is no longer given. Yet, our informational session indicated that maintenance should be given directly after planting the trees. This reduces the risk of reverse causality in the treatment groups. In addition, it is unlikely that reverse causality is systematically linked to T2, since both treatment groups received the same set of information.

is positively and significantly correlated with tree survival in all model specifications. Trees are often planted along the river side, where light and water availability are higher. Finally, regarding the fourth category, we find that the six species which were selected to be distributed in the experiment (cf. section 3.2.) perform worse than other species. Thus, the share of these species in overall species planted is significant and negatively correlated with tree survival. To further explore the relevance of the significant predictors in explaining the lower survival rates in T2 compared to T1 and the control group, we report mean difference tests in Table 5 [31].

From the variables that exhibit a significant correlation with tree survival, only the share of tree species provided in total trees planted is significantly different between treatment groups. Thus, our species choice might be one relevant reason why we observe a lower tree survival rate in T2. In fact, a rather low survival rate of three of the species is also found in an ecological experiment in the study area (Gérard 2016)[32]. While native to Jambi, these tree species may not perform well, when planted in immediate proximity to oil palm. Regarding farmers' preferences, we do not find evidence that the stated satisfaction with the trees received significantly correlates with tree survival (see columns (3) and (6) in Table A10 in the Appendix). It is therefore unlikely that non-correspondence between tree selection and farmers' preferences drives the differences in survival rate. Finally, we cannot rule out that other factors, which are confounded with the share of our tree species in total tree species planted and which we cannot control for, are the underlying reason for the low survival rate of the distributed species and hence for the lower survival rate of trees in T2. Especially it could be the case that the age of the seedlings was not ideal for immediate planting. Moreover, since the seedlings were brought from Jambi to the respective villages, it could be that the delivered seedlings did not arrive in a good state at the farmers' houses due to poor quality roads in part of the study region. Some evidence for the former is provided by the significant and negative correlation between the distance from Jambi to the respective village and tree survival that is however small in size (columns (2) and (4) in Table A10 in the Appendix).

5. Conclusion

Results from an RCT implemented in Jambi Province, Indonesia, suggest that information and information in combination with input provision are effective in stimulating tree planting in smallholder oil palm plantations. Both treatments lead on average to a higher predicted number of trees planted per hectare in comparison to the control group, the difference in the number of trees planted per hectare between the two interventions is statistically insignificant. Input together with information provision leads to a higher probability of farmers planting than sole information provision. However, farmers plant relatively few trees per hectare, which might have been influenced by the rather small number of seedlings provided. A similar tendency cannot be observed for farmers assigned to the informational campaign only. Here, fewer farmers adopt, but those who adopt plant on average more trees per hectare than farmers who were given seedlings for free. For the assessment of the biodiversity effects generated by the two interventions, the survival rate of the planted seedlings is of importance. We can observe a significantly lower tree survival rate for farmers who planted in T2. While

[31] Adopters in T1 and in the control group are merged into one comparison group, given that their survival rates are not statistically different. The combined survival rate for adopters in the control group and T1 is 0.876. This is statistically different from the survival rate in T2, which is 0.590 (p-value: 0.004). Descriptives of the other variables are shown in Table A11 in the Appendix, for which we do not find any systematical differences between treatment groups either.

[32] The low performing species are Meranti, Durian and Jelutung.

it is unlikely that differential maintenance between treatments, farmer self-selection based on experiences and skills, or differences in the environmental conditions of the plots between treatment groups drive these differences, we find evidence that the reliance on the species distributed in the experiment is relevant for the difference in tree survival rates.

At first sight, information provision may be seen as the preferred option from a policy perspective. The unconditional expected number of trees planted per hectare is not statistically different from the combined structural intervention, the incurred costs though likely to be smaller, and the survival rate of the trees higher. However, two aspects are important to note. First, the unconditional expected number of trees planted per hectare in T1 is strongly influenced by a few high-intensity adopters. When the distribution is winsorized at the 99 percentile, the unconditional number of trees planted per hectare is significantly higher in T2. Second, to allow for ecological scaling effects from the local to the regional level, tree islands need to be spread over a large area (Koh et al. 2009). Therefore, many farmers with medium tree planting intensities whose plantations are dispersed over a larger area may generate higher biodiversity effects than few farmers who plant a lot. Such spatial coordination is more likely to be generated by a combination of seedling and information provision.

If further ecological research can support and substantiate the role of spatial coordination for different ecosystem functions, it will be particularly important to find ways of increasing the survival rate of planted trees after the structural intervention. Our results suggest that here species choice is critical and should be based on recent evidence from ecological experiments (Gérard 2016). Also, seedling quality and logistics of seed delivery are important challenges that need to be addressed, as they can otherwise jeopardize the success of the intervention. Involving local nurseries, thereby reducing transport distances, can be promising, also in terms of local value creation and strengthening capacities along the value chain. Furthermore, tree mortality is generally lower for farmers with more experience in tree planting. The integration of practical training elements into the extension approach might thus be a way to increase tree survival. Finally, further research could also experiment with the number of seedlings provided to farmers to assess how it influences their planting decision and intensity. This will generate important insights regarding the feasibility of up-scaling tree planting intensities among larger numbers of farmers.

Our results are important in order to help tackling oil palm related problems of biodiversity loss in Indonesia. Since the situation in Jambi province is very similar to other oil palm expansion areas in Indonesia, it is likely that our results can be generalized to other areas in the country experiencing a similar expansion. With regard to the external validity of our results for other countries, two aspects deserve mentioning. Many smallholders in Indonesia were previously part of an outgrower scheme or have received extension services from large-scale plantations, propagating homogeneous plantation structures. In focus group discussions held prior to data collection many farmers voiced concern over the feasibility of growing trees with oil palms. Hence, if in other contexts prior concerns are less pronounced, farmers may be even more willing to plant trees. Second, the baseline survey took place while our study region was experiencing forest fires and haze (Field et al. 2016). This might have made environmental problems more salient to the local population and thus increased their interest in tree planting. Therefore, further studies are particularly important to explore the extent to which our results can be generalized to other contexts.

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Appendix

Table A1. Baseline descriptives and mean comparison tests

	(1) Total	(2) Control	(3) T1	(4) T2	(5) C=T1	(6) C=T2	(7) T1=T2
	Mean estimates, standard errors in parentheses				P-values		
Household head characteristics							
Age of HH head (in years)	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)	0.08 (0.02)	0.05 (0.02)	0.08 (0.02)	0.09 (0.04)	0.325	0.380	0.870
Gender of HH head (1=female/0=male)	0.02 (0.00)	0.03 (0.01)	0.01 (0.01)	0.01 (0.01)	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 (48120.3 5)	32,011.06 (3661.57 3	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)	0.83 (0.08)	0.91 (0.03)	0.96 (0.01)	0.324	0.113	0.139
Farm 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 land titles	0.68 (0.05)	0.70 (0.09)	0.66 (0.06)	0.70 (0.09)	0.752	0.983	0.741
Share of plots flooded in last 12 months	0.13 (0.02)	0.10 (0.03)	0.16 (0.05)	0.15 (0.05)	0.250	0.343	0.811
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
Farmer planted trees on his/her own (1=Yes/0=No)	0.17 (0.02)	0.15 (0.03)	0.18 (0.03)	0.16 (0.03)	0.478	0.828	0.637
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	0.034 (0.01)	0.033 (0.01)	0.06 (0.01)	0.01 (0.01)	0.169	0.127	0.004***

(1=Yes/0=No)							
Mean price for FFB per kg (‘000 IDR)	1.024 (0.01)	1.025 (0.026)	0.999 (0.021)	1.048 (0.035)	0.455	0.595	0.238
Observations	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 A1. Distribution of strictly positive tree planting quantities

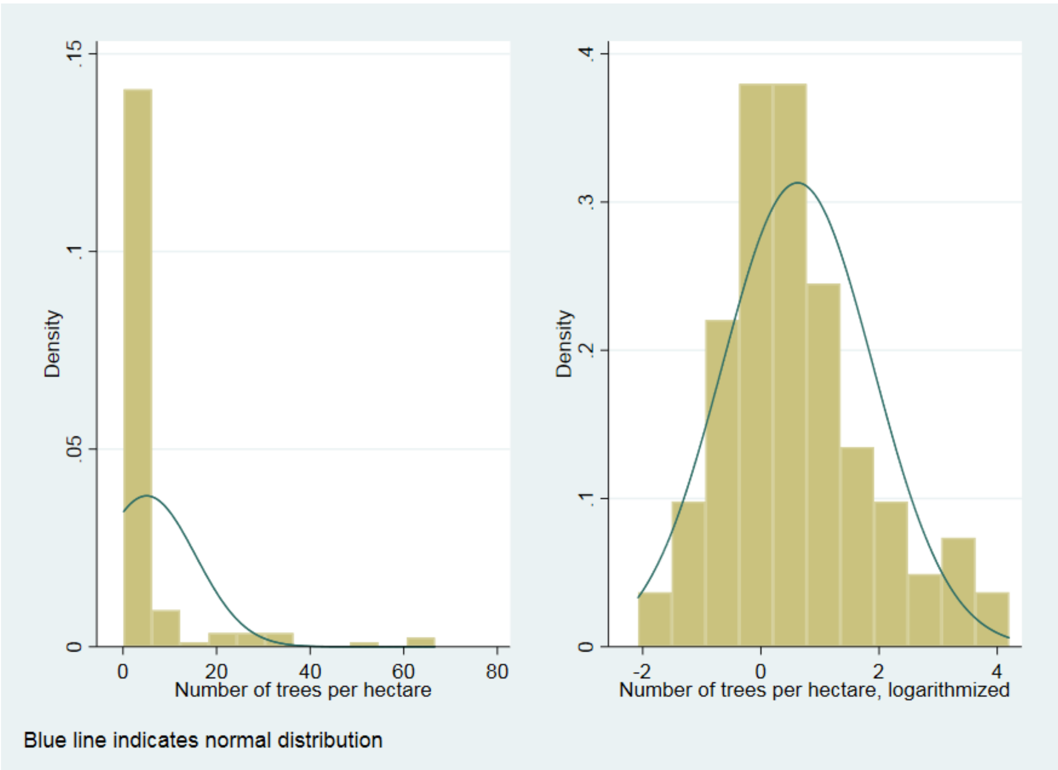

Table A2. Intention-to-treat estimates for the adoption decision

	Estimated Coefficients		*Marginal Effects*	
	(1)	(2)	(3)	(4)
	Planting in OP	Planting in OP	Planting in OP	Planting in OP
T1	0.863[*/c]	0.990[**/b]	0.0565[*/c]	0.0607[**/b]
	(0.493)	(0.478)	(0.0323)	(0.0296)
T2	2.758[***/a]	3.068[***/a]	0.384[***/a]	0.400[***/a]
	(0.406)	(0.387)	(0.0291)	(0.0281)
Access to seeds	-0.209	-0.204	-0.0268	-0.0246
	(0.221)	(0.251)	(0.0278)	(0.0300)
Local village	-0.260	-0.465	-0.0333	-0.0563
	(0.294)	(0.340)	(0.0369)	(0.0395)
Oil palm share > 73.5%	-0.292	-0.379[**]	-0.0374	-0.0458[**]
	(0.196)	(0.183)	(0.0238)	(0.0214)
Number HH members		0.0315		0.00381
		(0.0615)		(0.00737)
Trees cut in OP		-0.303		-0.0366
		(0.827)		(0.101)
Years of education		0.0728[**]		0.00880[**]
		(0.0302)		(0.00371)
Homegarden		-1.278[***]		-0.155[***]
		(0.408)		(0.0510)
total hectare OP managed		-0.107		-0.0130
		(0.0733)		(0.00874)
Trees per hectare		0.0155		0.00187
		(0.0140)		(0.00167)
FFB price per kg		-0.256		-0.0310
		(0.715)		(0.0860)
Environmental extension received		0.907[**]		0.110[***]
		(0.365)		(0.0425)
Gender		-0.591		-0.0715
		(1.120)		(0.136)
Other crops grown		-0.502		-0.0608
		(0.388)		(0.0472)
Total land owned		0.0724		0.00876
		(0.0624)		(0.00746)
Experience with tree		0.504		0.0609

planting in OP		(0.356)		(0.0427)
Share of plots flooded		0.147		0.0178
		(0.302)		(0.0363)
Constant	-2.674***	-2.093**		
	(0.383)	(0.988)		
Observations	737	737	737	737
McFadden pseudo R^2	0.187	0.230		

Logit estimation used. Columns (1) and (2) report estimated coefficients. Columns (3) and (4) derived AME. Village-level clustered standard errors in parentheses. Delta method used to estimate standard errors for AME.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
a/b/c *refer to significance level 1% (a), 5% (b) and 10% (c) based on bootstrap-t procedure. 1000 replications used for estimating confidence intervals. For the bootstrapped mode, dummies for cutting trees in oil palm in the last 12 months and the gender dummy were not included. This is because the dummy did not vary between some clusters prohibiting the estimation of the parameters in several pseudo samples. Due to computational complexity, bootstrapped confidence intervals were only computed for the treatment variables.*

Table A3. Intention-to-treat estimates for intensity decision

	Estimated Coefficients		*Marginal Effects*		*Estimated Coefficients*		*Marginal Effects*	
	(1) Trees planted per ha	(2) Trees planted per ha	(3) Trees planted per ha	(4) Trees planted per ha	(5) Trees planted per ha	(6) Trees planted per ha	(7) Trees planted per ha	(8) Trees planted per ha
T1	1.172***/b (0.257)	1.155***/b (0.379)	7.609***/a (2.185)	7.504**/a (3.377)	1.172*** (0.239)	1.154*** (0.427)	7.609*** (2.430)	7.504** (3.486)
T2	0.236 (0.254)	0.268 (0.404)	0.908 (0.961)	1.060 (1.545)	0.236 (0.225)	0.267 (0.394)	0.908 (0.872)	1.059 (1.455)
Access to seeds	-0.296 (0.334)	0.0671 (0.300)	-1.549 (1.798)	0.366 (1.660)	-0.296 (0.275)	0.0671 (0.228)	-1.549 (1.538)	0.366 (1.258)
Local village	0.372 (0.399)	0.600 (0.592)	1.946 (2.167)	3.268 (3.593)	0.372 (0.335)	0.600* (0.342)	1.946 (1.863)	3.269 (2.099)
Oil palm share > 73.5%	0.988*** (0.251)	-0.708** (0.325)	5.164*** (1.605)	3.860** (1.704)	0.988*** (0.244)	-0.708*** (0.267)	5.164*** (1.607)	-3.860** (1.621)
Number HH members		0.00931 (0.102)		0.0507 (0.551)		0.00931 (0.0785)		-0.0507 (0.425)
Trees cut in OP		0.209 (0.871)		1.139 (4.770)		0.209 (0.640)		1.137 (3.455)
Years of education		0.0149 (0.0225)		0.0815 (0.123)		0.0150 (0.0233)		0.0815 (0.126)
Home garden		-0.485 (0.391)		-2.641 (2.140)		-0.485 (0.353)		-2.641 (1.926)
total hectare OP managed		-0.0541 (0.0608)		-0.295 (0.345)		-0.0541 (0.0537)		-0.295 (0.294)
Trees per hectare		0.0153 (0.0193)		0.0834 (0.111)		0.0153 (0.0155)		0.0833 (0.0854)
FFB price per kg		0.247 (0.947)		1.346 (5.269)		0.247 (0.624)		1.346 (3.385)
Environ.extension received		0.439 (0.336)		2.394 (1.886)		0.439 (0.330)		2.393 (1.906)
Gender		-0.719 (0.515)		-3.917 (3.016)		-0.719 (0.450)		-3.919 (2.556)
Other crops grown		0.587** (0.281)		3.201* (1.753)		0.587** (0.249)		3.201** (1.545)
Total land owned		-0.0827* (0.0444)		-0.451* (0.240)		0.0827** (0.0358)		-0.451** (0.211)

Experience with tree planting in OP		0.0232 (0.323)		0.126 (1.753)		0.0234 (0.299)		0.127 (1.626)
Share of plots flooded		0.413 (0.332)		2.251 (1.736)		0.413 (0.287)		2.250 (1.572)
Constant	1.606^{***} (0.539)	1.426 (1.568)			1.606^{***} (0.398)	1.426 (0.961)		
Observations	144	144	144	144	144	144	144	144
McFadden pseudo R^2	722.6	737.0	.	.	.	.	.	.

Results presented from a GLM model with log-link and gamma distribution of error terms for the subsample of adopters only. Columns (1) to (4) based on maximum likelihood estimation. Columns (5) to (8) on quasi maximum likelihood estimation. Columns (1) and (2) as well as (5) and (6) present estimated coefficients. Columns (3) and (4) as well as (7) and (8) report derived AME. Village-level clustered standard errors in parentheses. Delta method used to estimate standard errors.

* *p < 0.1,* ** *p < 0.05,* *** *p < 0.01*

$^{a/b/c}$ *refer to significance level 1% (^{a}), 5% (^{b}) and 10% (^{c}) based on bootstrap-t procedure. 1000 replications used for estimating confidence intervals. For the bootstrapped mode, dummies for cutting trees in oil palm in the last 12 months and the gender dummy were not included. This is because the dummy did not vary between some clusters prohibiting the estimation of the parameters in several pseudo samples. Due to computational complexity, bootstrapped confidence intervals were only computed for the treatment variables.*

Table A4. Intention-to-treat effects on the unconditional predicted number of trees planted per hectare

	(1) Trees planted per ha	(2) Trees planted per ha
T1	0.922**/a	0.930**/a
	(0.367)	(0.416)
T2	1.659***/a	1.728***/a
	(0.345)	(0.467)
Access to seeds	-0.434	-0.0289
	(0.401)	(0.360)
Local village	0.174	0.305
	(0.484)	(0.726)
Oil palm share > 73.5%	-1.241***	-1.017***
	(0.378)	(0.364)
Number HH members		0.0141
		(0.115)
Trees cut in OP		0.0347
		(1.069)
Years of education		0.0687*
		(0.0354)
Homegarden		-1.353**
		(0.536)
total hectare OP managed		-0.0842
		(0.0885)
Trees per hectare		0.0267
		(0.0248)
FFB price per kg		0.139
		(1.123)
Environmental extension received		1.085**
		(0.466)
Gender		-1.163
		(0.978)
Other crops grown		0.400
		(0.419)
Total land owned		-0.0830
		(0.0676)
Experience with tree planting in OP		0.380
		(0.399)

Share of plots flooded		0.559
		(0.385)
Observations	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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
$^{a/b/c}$ *refer to significance level 1% (^{a}), 5% (^{b}) and 10% (^{c}) based on bootstrap-t procedure. 1000 replications used for estimating confidence intervals. For the bootstrapped mode, dummies for cutting trees in oil palm in the last 12 months and the gender dummy were not included. This is because the dummy did not vary between some clusters prohibiting the estimation of the parameters in several pseudo samples. Due to computational complexity, bootstrapped confidence intervals were only computed for the treatment variables.*

Table A5. Bootstrap-t confidence intervals for treatment groups

	(1)		(2)	
	T1	T2	T1	T2
Coefficients adoption decision	90%-CI [0.111; 1.558]	99%-CI [1.793;4.024]	95%-CI [0.181; 1.827]	99%-CI [2.201; 3.990]
AME adoption decision	90%-CI [0.009; 0.102]	99%-CI [0.283; 0.479]	95%-CI [0.006; 0.118]	99%-CI [0.301; 0.466]
Coefficients intensity decision	95%-CI [0.628; 1.881]	90%-CI [-0.116; 0.922]	95%-CI [0.116; 2.072]	90%-CI [-0.808; 1.004]
AME intensity decision	99%-CI [1.613; 1.613]	90%-CI [-0.538; 3.223]	99%-CI [1.013; 30.25]	90%-CI [-2.794; 2.969]
AME unconditional expected value	99%-CI [0.282; 2.748]	99%-CI [0.387; 3.948]	99%-CI [0.150; 3.211]	99%-CI [0.659; 3.970]

1000 replications are used for bootstrapping. The table shows the confidence level for the highest significance level. In case coefficients or AME is not significant at 10% level, 90% confidence intervals are displayed.
Columns (1) are estimated based on the model without covariates. Columns (2) include the same covariates as used in Tables A2-A4.

Table A6. Heckman selection model

	(1) Trees planted per ha (log.)	(2) Selection equation
T1	0.434	0.466^{**}
	(0.379)	(0.230)
T2	-0.565	1.640^{***}
	(0.409)	(0.190)
Access to seeds	-0.501^{**}	-0.0658
	(0.228)	(0.132)
Local village	0.194	-0.159
	(0.261)	(0.182)
Oil palm share > 73.5%	-0.685^{***}	-0.219^{**}
	(0.192)	(0.104)
Constant	1.968^{***}	-0.980^{***}
	(0.699)	(0.242)
Homegarden		-0.657^{***}
		(0.217)
Observations	737	737

Estimated coefficients from a Heckman selection model. Standard errors clustered at village level and reported in parenthesis.
Wald test of indep. eqns. (rho = 0): chi2(1) = 0.83 Prob > chi2 = 0.3637.
* *p < 0.1,* ** *p < 0.05,* *** *p < 0.01*

Further explanation of test for independence: *To ensure that only positive values are predicted by the quantity equation, we follow Wooldridge (2010) and apply a logarithmic transformation to the number of trees planted per hectare. We assume that the possession of a home garden affects the planting decision; as farmers with a home garden will often choose to plant trees there rather than in their oil palm plantation. At the same time, we assume that home garden is not a relevant predictor for the number of trees planted, which is supported by the insignificance of the coefficient of home garden in the conditional expected value estimation in Table A3. Consequently, the possession of a home garden represents a valid exclusion restriction and overcomes collinearity problems often encountered when conducting a Wald test of independence (Dow and Norton 2003). The test suggests that we cannot reject the independence assumption (p-value: 0.364). The validity of the test based on the significance of the inverse mills ratio (IMR) is further supported by the Variance inflation factor (VIF) of the regression of the IMR on the remaining parameters in the model. The resulting sizes of the VIF of 14.10 and 14.30 for the two model specifications tested are well below 30 which is considered the critical level for conducting this test (Madden 2008). This supports the use of the DH-model.*

Table A7. Weighted Intention-to-treat effects of interventions

	Unconditional expected values		*Adoption decision*		*Conditional expected values*	
	(1) E(Y|X)	(2) E(Y|X)	(3) Pr(Y>0|X)	(4) Pr(Y>0|X)	(5) E(Y|X, Y>0)	(6) E(Y|X, Y>0)
T1	0.916**	0.921**	0.055*	0.060**	7.660***	7.542**
	(0.363)	(0.410)	(0.032)	(0.030)	(2.127)	(3.362)
T2	1.663***	1.724***	0.384***	0.399***	0.867	1.049
	(0.345)	(0.462)	(0.029)	(0.027)	(0.949)	(1.554)
N	736	736	736	736	144	144
P-values of t-test for T1=T2	0.115	0.160	0.000	0.000	0.002	0.065
Controls[1]	No	Yes	No	Yes	No	Yes

Village-level clustered standard errors in parentheses and estimated with Delta method.
Columns (1) and (2) show unconditional AME. Columns (3) and (4) report AME from a logit regression. Columns (5) and (6) report AME from a GLM with log-link and gamma distribution of the error terms. Stratification variables included in all model specification. Inverse probability weights applied.
[1]*Baseline controls include number of household members, whether a farmer cut trees in OP in 2015, education, whether he or she had a home garden, total area of oil palm managed, the tree density in oil palm, the mean oil palm price receive, whether he or she received environmental extension, the gender of the household head, whether other crops are grown by the household, the total are of land owned and the share of plots that were flooded.*
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. Results of the Selection Equation are presented in Table A8. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A8. Determinants of selection in follow-up for the construction of Inverse Probability weights

	(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)
Local village	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
McFadden 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. In order to get unbiased estimates for the outcome variable of interest, weights are constructed by dividing (1) and (2).
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A9. Bounds estimation for Intention-to-treat estimates

	Unconditional expected values		Adoption decision			
	Lee bounds		Manski- Horowitz bounds		Lee bounds	
	Lower	Upper	Lower	Upper	Lower	Upper
T1	0.635 [-2.360; 3.630]	1.002 [0.164; 0.840]	-0.061 [-0.116; -006]	0.156 [0.103; 0.209]	0.050 [-0.020; 0.121]	0.057 [0.010; 0.104]
T2	0.632 [0.115; 1.150]	1.845 [0.960; 2.730]	0.247 [0.174; 0.320]	0.432 [0.367; 0.496]	0.360 [0.284; 0.436]	0.403 [0.330; 0.476]

Bounds presented for ITT regression without covariates. Confidence intervals in parentheses.

Manski- Horowitz bounds (MH-bounds) assume worse and best case scenarios for the attritors, i.e. farmers dropping out of the control group adopt and those dropping out of the treatment group do not (and vice versa). Since MH bounds are uninformative if applied to non-bounded outcome variables Lee (2009) they are only presented for the adoption decision.
Besides random assignment of the treatments, the Lee bounds assume that treatment status can affect selection only in one direction. Since attrition is highest in the control group, this monotonicity assumption is likely to be fulfilled. Since Lee bounds are often smaller, they are more informative. This is also why we interpret the results from the bounds as support for our previous results, despite the non-significance of T1 for the adoption decision when MH-bounds are used. However, the MH-Bounds provide a helpful indication whether the monotonicity assumption imposed by the method proposed by Lee (2009) is realistic. Lee-Bounds need to lie within the wider MH-bounds.
Since we cannot disentangle sample selection because of attrition and because of adoption for the intensity decision, we do not present bounds for the conditional expected number of trees per hectare.

Table A10. Fractional probit estimation for tree survival

	(1) tree survival per hh	(2) tree survival per hh	(3) tree survival per hh	(4) tree survival per hh, mfx	(5) tree survival per hh, mfx	(6) tree survival per hh, mfx
share of trees	0.0883	0.0228	0.0945	0.0267	0.00671	0.0284
planted in island	(0.391)	(0.389)	(0.404)	(0.118)	(0.114)	(0.121)
share of provided species in total trees planted	-0.917^{***} (0.254)	-0.689^{**} (0.290)	-0.931^{***} (0.256)	-0.277^{***} (0.0767)	-0.203^{**} (0.0882)	-0.280^{***} (0.0776)
total number of trees planted	0.000155 (0.00147)	0.000145 (0.00159)	0.000170 (0.00148)	0.0000468 (0.000444)	0.0000425 (0.000467)	0.0000512 (0.000444)
mean plot age	0.0138 (0.0192)	0.0118 (0.0171)	0.0159 (0.0193)	0.00417 (0.00574)	0.00346 (0.00497)	0.00478 (0.00571)
mean number of oil palms per ha	-0.00187 (0.00514)	-0.00429 (0.00452)	-0.00217 (0.00519)	-0.000565 (0.00154)	-0.00126 (0.00130)	-0.000651 (0.00155)
share of plots with a river bordering	0.550^{**} (0.221)	0.632^{***} (0.235)	0.504^{**} (0.217)	0.166^{***} (0.0628)	0.186^{***} (0.0645)	0.151^{**} (0.0621)
share of plots which are flood prone	-0.256 (0.544)	-0.499 (0.526)	-0.234 (0.544)	-0.0773 (0.163)	-0.147 (0.152)	-0.0705 (0.163)
share of plots which are drought prone	-0.252 (0.226)	-0.191 (0.233)	-0.272 (0.242)	-0.0760 (0.0678)	-0.0561 (0.0670)	-0.0817 (0.0720)
Years of education	0.0278 (0.0274)	0.0219 (0.0257)	0.0278 (0.0275)	0.00839 (0.00847)	0.00644 (0.00768)	0.00837 (0.00843)
Experience with tree planting in OP	0.714^{***} (0.203)	0.822^{***} (0.204)	0.751^{***} (0.202)	0.216^{***} (0.0594)	0.242^{***} (0.0570)	0.226^{***} (0.0588)
values of assets	0.00399 (0.00282)	0.00372 (0.00271)	0.00401 (0.00294)	0.00120 (0.000815)	0.00109 (0.000762)	0.00120 (0.000845)
maintenance done to trees	0.592^{***} (0.191)	0.663^{***} (0.184)	0.560^{***} (0.180)	0.179^{***} (0.0534)	0.195^{***} (0.0490)	0.168^{***} (0.0504)
Distance to asphalt road		0.0130 (0.0166)			0.00381 (0.00486)	
Distance to Jambi city		-0.00631^{*} (0.00353)			-0.00185^{*} (0.000990)	

	(1)	(2)	(3)	(4)	(5)	(6)
Other trees preferred			0.222 (0.186)			0.0667 (0.0555)
Constant	0.561 (0.913)	1.334 (0.909)	0.498 (0.909)			
Observations	141	141	141	141	141	141

Standard errors clustered at village level reported in parentheses. Columns (1) to (3) report coefficients from a fractional probit estimation. Columns (4) to (6) report derived AME To control for the ease of transport of the seedlings, we also include the distance between the villages and Jambi city and the distance to the next paved road in column (2). A precise description of the variables can be found in Table A12. The results for column (2) do not change substantially if only the subsample of farmers in T2 is taken.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A11. Descriptives of other explanatory variables

	(1)	(2)	(3)	(4)
Variable	Overall	Control + T1	T2	Control +T1 = T2
Share of trees planted in islands	0.066 (0.247)	0.086 (0.284)	0.060 (0.234)	0.622
Total number of trees planted	24.944 (91.812)	37.229 (71.062)	21 (97.502)	0.358
Mean plantation age	13.552 (7.606)	13.043 (7.413)	13.716 (7.693)	0.763
Mean number of oil palms per ha	141.091 (15.936)	139.749 (17.072)	141.509 (15.624)	0.621
Share of plots which are flood prone	0.105 (0.307)	0.147 (0.359)	0.092 (0.290)	0.584
Share of plots which are drought prone	0.608 (0.485)	0.451 (0.498)	0.657 (0 .472)	0.056*
Education	8.188 (3.861)	8.6 (4.146)	8.055 (3.776)	0.457
Asset index (in 1,000 IDR)	33.835 (58.814)	44.157 (55.326)	30.521 (59.757)	0.310
N	144	35	109	

In columns (1) to (3), standard deviation reported in parenthesis. Column (4) shows p-values of test for mean difference with clustered standard errors. Test for equality between the combined group of control and T1, and T2 done with help of a linear regression with village level clustered standard errors. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A12. Definition of explanatory variables

Intention-to-Treat Estimation	
Variable Name	Explanation
Trees planted per hectare (outcome variable)	We can detect one important outlier in our outcome variable who planted 167 trees per hectare for an intercropping system. This 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 replaced with the observation of the farmer who planted the second highest number of trees per hectare.
T1	=1 if the village was assigned to treatment one, the informational intervention = 0 otherwise
T2	= 1 if the village was assigned to Treatment two, the structural intervention
Access to seeds	= 1 if the farmers in the village have access to tree seedlings = 0 otherwise (baseline)
Local village	= 1 if mostly local Melayu farmers live in the village = 0 mostly transmigrant farmers live in the village (baseline)
Oil palm share > 73.5%	= 1 if more than 73.5% of the farmers in one village are engaged in palm oil cultivation = 0 otherwise (baseline)
Number HH members	Number of persons in a household (baseline)
Trees cut in OP	= 1 if a farmer has cut trees in his or her oil palm plantation in the last 12 months (baseline)
Years of education	Years of education (baseline)
Home garden	= 1 if a farmers has a home garden = 0 otherwise (baseline)
Trees per hectare	Average number of trees per hectare present in the oil palm plantations, per household. Since the distribution of tree density is highly right skewed, the variable is winsorized. The top 1% of the distribution is replaced with the 99 percentile. (baseline)
FFB price per kg	For prices, we use the mean prices for Fresh Fruit Bunches farmers got in 2015 for the rainy and dry season. For farmers who have not harvested their plots yet, the mean village value is used. (baseline)
Environmental extension received	= 1 if the farmer has received any environmental extension in the last 12 months (baseline) = 0 otherwise
Gender	= 1 if household head is female = 0 otherwise
Other crops grown	= 1 if a farmer grows other crops (baseline) = 0 otherwise
Total land owned	Total number of hectare a farmer owns (baseline)
Experience with tree planting in OP	= 1 if a farmer has trees in his or her own in an oil palm plantation which he or she planted on his or her own. = 0 otherwise (baseline)
Share of plots flooded	Number of plots flooded in 2015 divided by total number of plots
Tree survival equation	
Variable Name	Explanation
Preference for other trees	=1 if a farmer, who has received seedlings for free, would have preferred to receive different species = 0 if a farmer has either not received saplings for free or would have not liked to receive different species
Distance to Jambi city	Distance from village office to Jambi city based on GPS coordinates

	(in km)
Distance to asphalt road	Distance from village to next asphalt road (in km)
Maintenance done to trees	= 1 if a farmer applies fertilizer and/or manure application and/or weeding. = 0 otherwise
Values of assets	Asset index in 1,000 IDR. Assets considered for the compilation are television, motorbike, car, fridge, washing machine, cell-phone (baseline)
Experience with tree planting in OP	= 1 if a farmer has trees in his oil palm plantation which he or she planted on his or her own (baseline) = 0 otherwise
Share of plots with river bordering	Share of plots a farmer planted trees on which have a river bordering
Share of plots which are flood prone	Share of plots a farmer planted trees on which have been flooded both in 2015 and in 2016.
Mean steepness of plots	Mean steepness of plots a farmer planted trees on Variable ranges from 1 to 6. A one unit increase represents an increase in slope of 10 degrees.
Mean age of plot	Mean age of the plantation where the farmers planted trees on
Total number of trees planted	Total number of trees a farmer planted
Share of provided species in total trees planted	Number of the six species, which were chosen to be distributed in T2, divided by the total number of trees planted.
Share of trees planted in islands	Number of trees which are planted in a clustered way divided by the total number of trees planted.
Education	Years of education of household head (baseline)