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A B S T R A C T

Native tree planting in oil palm plantations represents one management option to increase biodiversity in oil palm dominated landscapes. Using a randomized controlled trial, we test which policy options can promote tree planting. Our policy interventions include pure information provision and a combination of information and free seedling provision. Results from a double-hurdle model suggest that both interventions are effective in stimulating tree planting in oil palm plantations. While both interventions motivate a small share of farmers to make substantial planting efforts, the combined intervention additionally induces low-intensity planting among a large share of farmers. The combination of seedling and information provision is thus more likely to spread diversified plantations over a larger area and hence might generate broader biodiversity effects. Our results provide evidence that free seedling provision does not crowd out own planting effort and is more effective under seed access constraints. While cost effectiveness does not differ significantly between the two interventions, we identify potential leverage points to increase tree survival rates among farmers who received seedlings in the intervention.

1. Introduction

Agricultural expansion is a major driver of biodiversity loss, which is currently at unprecedentedly high levels, as emphasized in the recent report of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (Diaz et al., 2019). In South-East Asia, agricultural expansion during the last three decades has been mainly driven by palm oil production (Gibbs et al., 2010). Responding to high demand in international markets, the production area has increased six fold between 1990 and 2017 (FAO, 2019). The region is now the main producer of palm oil in the world, accounting for over 80% of global palm oil production (FAO, 2019). Approximately 45%–50% of the oil palm plantations are established on land

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that was formerly forest area (Vijay et al., 2016; Meijaard et al., 2018). Since tropical rainforests globally show the highest level of biodiversity (Diaz et al., 2019) and since only around 15% of the recorded species living in primary forests can be found in oil palm plantations (Fitzherbert et al., 2008), this expansion has led to a drastic decrease in local and global biodiversity.

The limited range of taxa found in oil palm plantations is in particular due to the reduced vegetation complexity within the plantations (Koh et al., 2009). One approach to increase the structural complexity is the planting of native trees inside oil palm plantations (Zemp et al., 2019a). Positive biodiversity effects of polycultural plantations, where trees and other crops are grown within oil palm plantations, in comparison to pure monocultural plantations have been shown for bird, arthropod and bat communities (Ashraf et al., 2018; Ghazali et al., 2016; Syafiq et al., 2016; Yahya et al., 2017; Teuscher et al., 2016). Most of these studies do not consider different planting intensities of trees or other crops, and therefore cannot derive empirical evidence on the relationship between the number of trees planted and biodiversity effects. One exception is Teuscher et al. (2016) analyzing biodiversity effects of native tree islands in oil palm plantations, who systematically vary tree island size,[1] but do not find a statistically significant correlation with biodiversity effects after one year of tree planting. However, in a study with smallholder oil palm farmers, Teuscher et al. (2015) show that already small increases in the number of trees planted per hectare can positively affect bird abundance and species richness in oil palm plantations.

The present study addresses the question of how native tree planting can be promoted in oil palm plantations of small-scale farmers in Sumatra, Indonesia. Small-scale farmers are increasingly engaged in oil palm cultivation, accounting for approximately 50% of the total oil palm area in Sumatra (BPS-Statistics Indonesia, 2016), and thus represent key addressees of policies promoting sustainable plantation management. Various studies have documented that smallholder farmers and their families have benefited significantly from oil palm cultivation in terms of income gains (Euler et al., 2017; Kubitza et al., 2018; Feintrenie et al., 2010). Smallholder oil palm plantations in our study area typically resemble large-scale plantations in terms of being homogeneous monocultural stands, and only few farmers maintain individual trees – usually remnants – in their plantations (Teuscher et al., 2015).[2] From a farmer's perspective, planting native trees in their oil palm plantations bears the risk of affecting oil palm yields negatively. Lower oil palm yields may result from competition for light, water and nutrients between trees and oil palms (Teuscher et al., 2015) although some studies have also reported insignificant or tentative evidence of positive yield effects (Corley and Tinker, 2003; Miccolis et al., 2019). Moreover, farmers may also derive benefits from native trees, such as fruits and timber and increased resilience through the diversification of income sources.

Relatively little is known about what instruments are suitable to induce biodiversity-friendly land uses such as native tree planting. 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 (2013) 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. 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 (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 tree planting (Romero et al., 2019) and agroforestry (Noordwijk et al., 2008; Meijer et al., 2015). Despite their importance, these potential barriers have so far received little attention in the literature analyzing policy incentives for tree planting.

More generally for the case of agricultural technologies, previous studies have shown that information provision can effectively spur adoption among small-scale farmers in developing countries (Aker, 2011). Most of these studies, however, focus on productivity-enhancing technologies such as soil fertility management (Kondylis et al., 2017; Benyishay and Mobarak, 2018), fertilizer application (Duflo et al., 2008) or generally improved management practices (Cole and Fernando, 2016; van Campenhout, 2019). However, farmers might be reluctant to adopt an agricultural technology that is not primarily intended to increase income or productivity, but rather to diversify income and production patterns, and in particular to improve regional and global environmental conditions. While there is evidence that farmers' land use choices are also affected by environmental and social motives (Greiner and Gregg, 2011), rigorous evaluations of the effect of information provision on land management decisions with primarily environmental motives are scarce.

In the presence of positive environmental externalities, additional incentives in the form of free or subsidized input provision may be justified and necessary to significantly increase technology uptake. Free or subsidized input provision can potentially relieve constraints, such as missing access to input markets or high transaction costs (Bensch and Peters, 2020; Omotilewa et al., 2019), frequently hindering technology adoption among small-scale farmers in developing countries. However, some scholars have questioned the suitability of free or heavily subsidized input provision based on two main arguments: First, free provision might reduce product use or the maintenance given to the goods in comparison to when a positive price is charged. Possible explanations are linked to the inability of the providers to differentiate between individuals deriving low and high utility from the respective technology use, so called screening effects, or to the lower sunk costs of losing the good (Ashraf et al., 2010; Thaler, 1980). In particular for long-lived goods such as trees, lack of maintenance after

[1] Tree islands refer to native trees planted in clusters within oil palm plantations. Teuscher et al. (2016) study tree islands with 6, 25, 100 and 400 trees.
[2] In our study area, around 28% of the farmers have trees in their plantations.

adoption might lead to low survival rates of the seedlings planted. Second, the one-time free or subsidized provision might negatively affect future or further acquisition of the good by setting a price benchmark too low for free market transactions (Bensch and Peters, 2020; Omotilewa et al., 2019; Dupas, 2014).

Recent empirical evidence shows that the subsidized provision of goods which are easy to use and do not generate negative side effects does not reduce product use (Dupas, 2014; Carter et al., 2013), Klicken oder tippen Sie hier, um Text einzugeben. or the willingness to pay for the good in markets (Omotilewa et al., 2019). The picture is less clear for goods that require continued care such as improved stoves, for which both positive effects of free provision on stove maintenance (Bensch and Peters, 2020) and high abandonment rates have been reported (Hanna et al., 2016). In particular, there is scarce evidence on how free input provision affects use and care for goods with limited private, but substantial public environmental benefits. In contrast to goods aiming at improved private health outcomes or increased agricultural income, the decision to adopt a technology with positive environmental externalities, such as tree planting, might also be motivated by altruistic or environmental motives. These intrinsic motivations can potentially interact with the external interventions that subsidize the respective action. As a result, tree planting activities that go beyond the subsidized material might be discouraged or farmers might stop tree planting and maintenance activities when subsidies cease (Gneezy et al., 2011).

Previous research on the effect of free or subsidized seedling provision on tree planting in general supports a positive correlation (Ruseva et al., 2015). Yet, some authors have raised concern over potential negative effects on the local seedling supply system, which could then imply negative effects on further acquisitions (Gregorio et al., 2015; Harrison et al., 2008). There is hardly any experimental literature quantifying the effect of subsidized seedlings provision on tree planting and maintenance, with the exception of Romero et al. (2019) who find that the free provision of seedlings increases the probability of tree planting, and Jack et al. (2015), who find a positive relationship between the size of the take-up subsidy and tree planting, but no significant effect on tree survival. None of these studies analyzes planting intensity – the number of trees planted – and can therefore draw insights on whether the provision of free or subsidized seedlings discourages further planting efforts.

In this study, we use a randomized controlled trial to test the effects of two distinct policy interventions on tree planting and survival. The first intervention provides information on native tree planting in oil palm plantations. The second intervention combines the provision of information with the provision of free seedlings. The combined intervention allows us to identify whether providing farmers with free seedlings in addition to information provision significantly increases farmers' tree planting activities in oil palm, compared to the pure information intervention. 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. We also assess whether the provision of free seedlings discourages tree planting beyond what is provided for free. To derive more explicit policy implications, we compare the cost effectiveness of the two interventions with respect to the total number of trees planted and survived. Finally, since the ecological effectiveness of the interventions is subject to tree survival, we analyze the drivers of farmers' performance in terms of their tree survival rates. Next, section 2 describes the experimental design, the interventions, the data collection process, as well as the estimation strategy. Results on tree planting and survival as well as cost effectiveness considerations are presented in section 3. Section 4 concludes.

2. Study design, data and estimation strategy

2.1. Study area and sampling strategy

Our study took place in Jambi Province (Fig. 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., 2016). These new settlers received two to 3 ha of land for oil palm cultivation as well as extension services and inputs for oil palm cultivation.

We focus on five regencies 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]

To construct the sampling frame, we listed all transmigration villages in the study area that have a main focus on oil palm production.[4] Out of a total of 90 transmigration villages, we randomly selected 27 villages to be included in our sample. In addition, we identified nine local villages.

With a main focus on oil palm production in the study area and included them in our sample.[5] We obtained village-level data from the Village Potential Statistics (PODES) census dataset collected in 2008 by the Indonesian Central Bureau of

[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.

[4] The criterion for inclusion was that at least 70% of the dwellers report oil palm production to be their main occupation.

[5] For local villages we had to adjust the criterion to at least 30% of the dwellers reporting oil palm production to be their main occupation, because local villages are mainly engaged in rubber production and oil palm expansion is more recent (Euler et al., 2016).

Fig. 1. Location of Jambi (shaded area) in Indonesia (left) and location of sample villages and Jambi city (shaded area) in Jambi Province (right). Control villages are indicated by dots. Blue triangles indicate T1 villages. Green rhombi indicate T2 villages. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Statistics. To complement the data, we implemented a small village survey in September 2015, which elicited information on seedling market access, extension services and other village-specific information. Lists with all oil palm growing households were provided by the village staff.

Contract-farming arrangements between oil palm smallholders and companies are common in the study region and were in particular promoted at the beginning of 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. 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 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 and Bogor Agricultural University. 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.

2.2. Randomization approach

In order to reduce the risk of spill-over effects, random assignment was done at village level. Villages were allocated to two treatment arms, Treatment 1 (T1) and Treatment 2 (T2), 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 1 presents baseline descriptives of the sample. In order to test whether randomization was successful in creating balance between groups, we conduct 60 mean difference tests. 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% level. Additionally, we find that the share of farmers who refer to problems of getting seedlings is statistically different between T1 and the control group at the 1% level. With regard to the possession of home gardens, farmers in T2 possess slightly more often a home garden than farmers in the control group, but the difference is only marginally significant (p-value: 0.094). Given that some imbalance can occur by chance (Morgan and Rubin, 2012), the randomization can be considered successful.

2.3. Description and implementation of treatments

To test the effect of two policy options on tree planting in oil palm, two interventions were designed: one provides only information (T1), while the other one combines information with the free provision of six seedlings (T2). Information was delivered through a video that we composed and filmed in collaboration with a local film-maker, and through an illustrative manual.[6] In the short movie, a lecturer from the University of Jambi introduced the concept of tree planting in oil palm plantations. He explained that planting native trees can increase local biodiversity with positive effects on pest control, and improve soil fertility, in particular in the case of nitrogen-fixing legume trees. He raised the possibility of negative oil palm

[6] The video and the manual can be found at https://www.uni-goettingen.de/en/412111.html.

Table 1
Descriptives and baseline balance tests.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Total	Control	T1	T2	C = T1	C = T2	T1 = T2
Household head characteristics	Mean estimates, standard deviation in parentheses				P-values		
Age of HH head (in years)	49.52	49.14	49.62	49.79	0.686	0.645	0.902
	(10.42)	(10.19)	(10.97)	(10.11)			
Years of education HH head	7.53	7.67	7.42	7.49	0.480	0.598	0.835
	(3.61)	(3.65)	(3.62)	(3.58)			
Access to env. extension (1 = Yes/0 = No)	0.08	0.05	0.08	0.09	0.339	0.349	0.870
Gender of HH head (1 = female/0 = male)	0.02	0.03	0.01	0.01	0.108	0.184	0.738
Household characteristics							
Household size (No. of persons)	3.96	3.93	3.83	4.13	0.474	0.110	0.009***
	(1.50)	(1.57)	(1.38)	(1.53)			
Value of assets (in 1000 IDR)	49,745.24	32,778.05	84,134.21	32,011.06	0.262	0.949	0.253
	(492,402.0)	(56,654.4)	(846,562.7)	(55,756.9)			
Other crops cultivated (1 = Yes/0 = No)	0.28	0.29	0.26	0.29	0.655	0.994	0.715
Total land owned (in ha)	5.69	5.68	5.81	5.58	0.845	0.830	0.720
	(6.85)	(5.20)	(9.38)	(5.07)			
Home garden (1 = Yes/0 = No)	0.91	0.83	0.91	0.96	0.273	0.094*	0.216
Farm characteristics							
Total ha oil palm managed	4.45	4.42	4.63	4.29	0.752	0.701	0.603
	(6.16)	(4.15)	(8.95)	(4.06)			
Share of plots with systematic land titles	0.68	0.70	0.66	0.70	0.452	0.942	0.586
	(0.43)	(0.43)	(0.43)	(0.42)			
Share of plots flooded in last 12 months	0.13	0.10	0.16	0.15	0.186	0.293	0.759
	(0.32)	(0.28)	(0.35)	(0.33)			
Plot age (in years)	14.83	15.52	14.40	14.59	0.222	0.503	0.842
	(6.57)	(6.13)	(6.26)	(7.25)			
Number of existing trees per ha in OP	3.43	5.07	2.62	2.63	0.336	0.340	0.948
	(26.76)	(43.24)	(12.28)	(11.96)			
Farmer planted trees on his/her own (1 = Yes/0 = No)	0.17	0.15	0.18	0.16	0.428	0.829	0.626
Number of trees planted in OP in the past per ha	1.84	2.46	1.43	1.64	0.584	0.670	0.793
	(18.56)	(30.53)	(6.88)	(7.99)			
Trees cut in OP in last 12 months (1 = Yes/0 = No)	0.03	0.03	0.06	0.01	0.160	0.122	0.004***
Price received for oil fruits per kg (in 1000 IDR)	1.02	1.03	0.99	1.05	0.414	0.593	0.232
	(0.17)	(0.17)	(0.02)	(0.19)			
Seed access constraints (1 = Yes/0 = No)	0.57	0.63	0.51	0.58	0.002***	0.259	0.106
Information constraints (1 = Yes/0 = No)	0.63	0.67	0.61	0.61	0.337	0.259	0.920
N	817	270	274	273			

Columns (1) to (4) show mean estimates and corresponding standard deviations for continuous variables in parentheses. Columns (5) to (7) report p-values for mean difference tests based on a linear regression model with village-level clustered standard errors and stratification variables included. Stars refer to * 0.10 ** 0.05 and *** 0.01 significance level.

yield effects resulting from competition for nutrients and sunlight between trees and oil palms, but also pointed out that fruit and timber trees can generate additional income. The six species distributed in the experiment were mentioned as examples of native species that could be planted in oil palm and that generate economic returns. The planting process and the maintenance activities necessary to support tree survival were presented in detail. Farmers were instructed that native trees could be planted in between existing oil palms or around the border of the plantation. Rather than cutting productive oil palms, we suggested to remove old and dead oil palms and plant native trees in the resulting gaps. The movie did not provide a recommendation on the precise number of trees to be planted. 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 role model farmers described their experience with tree planting and also mentioned the species that they chose to plant in their oil palm plantations. The movie was complemented by an illustrative manual designed by a local artist. The manual provided the same information on potential environmental and economic outcomes of native tree planting as well as instructions on how to plant and maintain trees. It was distributed to the farmers during the movie screenings to be taken home as a later reference.

Since focus group discussions that we conducted in our research area prior to data collection 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[7] 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*

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

'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 handed out after the end of the video screening. Measured in local prices in Jambi city, the six seedlings are worth approximately 37,500 Indonesian Rupiah (IDR).[8] In total, 1,458 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 screenings took place in the village offices. 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, 71.1% of all farmers assigned to the two treatment arms attended the video screening. For the informational intervention (T1) this share was 67.9%, for the combined (information plus seedlings) intervention (T2) it was 74.4%. The difference between both groups is not statistically significant (p-value: 0.164).[9] Farmers who did not attend the video screening were visited at their houses at a later time 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. In T1, 26.3% of farmers 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.[10] 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 approximately 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.[11]

In order to reduce possible experimental effects such as the Hawthorne effect 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. 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.[12]

2.4. 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.[13] We estimate the following model:

$$Y_{ij} = \beta_o + \beta_1 T_{1j} + \beta_2 T_{2j} + \beta_3 S_j + \beta_4 X_{ij} + \beta_5 Y_{ij}^{PRE} + e_{ij} \quad (1)$$

where Y_{ij} is the outcome variable of interest, i.e., the per hectare number of trees planted in oil palm by farmer i in village j. 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 farmers' baseline characteristics. Following McKenzie (2012) we employ an ANCOVA estimator by including the baseline dependent variable Y_{ij}^{PRE} to reduce the variance of the treatment estimator. ANCOVA is preferred over difference-in-difference estimation in case of low autocorrelation between the pre-treatment and current outcome variable (McKenzie, 2012), as is the case in our data.[14] e_{ij} is an individual-specific error term that is clustered at the village level. Two model specifications are tested. The first one in addition to the treatment dummies controls for the stratification variables and the baseline dependent variable. In the second specification, we additionally include the baseline characteristics that are imbalanced between groups and the control variables in Table 1 to increase the precision of our estimates.[15]

8 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.

9 Test for significance was done in a linear regression framework with the sample of treatment villages only and village-level clustered standard errors. Attendance to movie was regressed on a dummy for T2.

10 Farmers who did not receive any of the interventions were not in the village at the moment when the video screening and the mid-term survey were conducted.

11 Mostly farmers get seedlings for free from their neighbors. Controlling for the external interventions does not change the results presented in section 3.

12 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 spill-over effects threaten the internal validity of our results.

13 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.

14 The autocorrelation coefficient is 0.09 in our case.

15 Strong collinear variables were not included in the model. This choice is supported by the joint insignificance of the variables in the unconditional predictive margins estimation of the double hurdle model (p-value of 0.373).

We analyze the planting decision of the farmers using a double-hurdle (DH) model (Cragg, 1971), where adoption is modelled as a two stage process. In a first step, farmers decide about whether to plant trees in their oil palm plantation or not. In the second step, 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.[16]

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 (Cragg, 1971). The DH-model is especially appealing in cases where imperfect markets hinder adoption, e.g. due to restricted access to information or seed markets (Shiferaw et al., 2015). As shown in the focus group discussions, these aspects appear to be relevant in our context. To further support the use of the DH-model, a Vuong test is conducted (Shiferaw et al., 2015). The test results suggest that the DH-model is closer to the true data generating process than the Tobit model (p-value < 0.001).

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 by adopting farmers (Figure A.1 in the Appendix) we use a more flexible Generalized Linear Model (GLM) approach with log-link and gamma distribution of the dependent variable to estimate the effects of the treatments on the conditional intensity decision (Manning and Mullahy, 2001). We cannot reject the use of the log-link and of the gamma distribution.[17]

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 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 perceived benefits and costs of tree planting. In a first step, the farmer decides whether to plant or not. The decision to adopt depends on the expected utility of adoption. In case the expected utility is positive, we will observe adoption in a perfect market environment. However, in reality, farmers often face constraints which need to be overcome before adoption can occur. In particular, we assume that farmers need to have reached a specific level of knowledge about tree planting before they will adopt the technology. In addition, farmers need to have access to seedlings in order to observe a positive adoption decision. Therefore, we will observe adoption if three conditions are simultaneously fulfilled: A farmer has reached a sufficient level of knowledge, transaction costs of accessing seedling markets are not too high, and a farmer desires a positive quantity of trees in his or her oil palm plantation. Conditional on a positive decision to plant, the farmer will then decide in a next step about the utility maximizing number of trees. Following Belotti et al. (2015), the adoption decision can be described as:

$$\Pr(y > 0|x) = F(x\delta) \tag{2}$$

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 distribution function of the error term.

The conditional intensity decision is expressed as:

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

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:

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

$$E(y|x) = \Pr(y > 0|x) * E(y|y > 0, x) \tag{5}$$

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

[16] Test for independence done with help of a Heckman selection model. Test results and more information are provided in Table A.V in the Appendix.

[17] We cannot reject the use of log-link based on the results of a Pregibon-test (p-value 0.331) and the use of the gamma distribution with help of a modified Park-test (p-value: 0.801). 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). The AIC and the BIC are also lower when the log-link instead of the identity-link is used.

Table 2
Descriptives of outcome variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Total	Control	T1	T2	T1 = C	T2 = C	T1 = T2
Share of farmers who planted in oil palm plots	0.20	0.05	0.10	0.43	0.082*	<0.001***	<0.001***
N	737	239	245[a]	253			
Number of trees planted per hectare	1.07	0.13	1.13	1.90	0.049**	0.013**	0.358
	(5.561)	(0.826)	(6.581)	(6.801)			
N	736	239	244[a]	253			
Number of trees planted per hectare by adopters	5.47	2.90	11.48	4.40	0.060*	0.351	0.128
	(11.608)	(2.718)	(18.268)	(9.839)			
N	144	11	24	109			

Columns (1) to (4) show mean values and, for continuous variables, standard deviations in parentheses. Test for mean difference conducted with a linear regression of the outcome variables on the treatment dummies with clustered standard errors and stratification variables included. P-values indicated in columns (5) to (7). Stars refer to * 0.10 ** 0.05 and *** 0.01 significance level.

[a] Different sample size due to the fact that one farmer could not remember how many trees he planted in his oil palm plantation.

3. Results

During the one-year period between baseline and follow-up survey, 145 farmers (19.7%) planted a total number of 2909 trees in oil palm plantations.[18] Descriptives of our outcome variables are reported in Table 2.

3.1. Adoption decision

The intention-to-treat (ITT) estimates are reported in Table 3. Given the discrete character of the treatment dummies, we report average marginal effects (AME) of the interventions on the unconditional expected number of trees planted per hectare (eqn. (5)), which are shown in the first two columns. Columns (3) and (4) show AME of the interventions on the farmers' decision to plant trees (eqn. (2)). Columns (5) and (6) report conditional AME on the intensity decision for the subsample of the tree-planting individuals only (eqn. (3)). Besides standard p-values, we also report 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] Full model results, i.e., the coefficients and AME of all covariates for the adoption decision, the conditional and unconditional expected number of trees, are reported in Tables A.I-A.III in the Appendix.[20]

Both treatments significantly increase the unconditional expected number of trees planted per hectare (columns (1) and (2)). On the average, farmers in T1 plant 1.0 tree 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.[21] 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 approximately 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 approximately 39 percentage points on average. 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). However, if we assume that negative interaction effects between information and tree seedling provisions are unlikely, the 33 percentage point difference in effect size between T1 and T2 could be interpreted as an upper bound for the effect size of pure seedling provision. These results suggest that input provision is important to motivate tree planting in oil palm plantations for a large share of the farmers.

[18] 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.

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

[20] With regard to the covariates that are significantly different between treatment arms (balance checks in Table 1), we only find that the possession of a home garden, which is however only marginally significantly different between T2 and the control group, significantly influences the adoption decisions. Imbalances between groups therefore do not appear to threaten the internal validity of the results.

[21] 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 3
Intention-to-treat estimation.

	Unconditional expected values		Adoption decision		Conditional expected values	
	(1)	(2)	(3)	(4)	(5)	(6)
	E(Y|X)	E(Y|X)	Pr(Y > 0|X)	Pr(Y > 0|X)	E(Y|X, Y > 0)	E(Y|X, Y > 0)
T1	0.995**/a	0.984**/a	0.057*/c	0.061**/b	8.127***/a	7.938**/b
	(0.422)	(0.452)	(0.033)	(0.029)	(2.673)	(3.578)
T2	1.583***/a	1.721***/a	0.381***/a	0.398***/a	0.762	1.026
	(0.347)	(0.412)	(0.028)	(0.028)	(1.012)	(1.683)
N	736	736	737	737	144	144
Control group[a]	0.172**	0.150*	0.047***	0.042 ***	3.578***	3.582***
	(0.078)	(0.089)	(0.018)	(0.015)	(0.778)	(1.1249)
P-values of *t*-test for T1 = T2	0.296	0.208	<0.001***	<0.001***	0.011**	0.047**
Controls[b]	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 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 and the pre-treatment (baseline) dependent variable are included in all model specifications.
*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.
[a] Predicted mean for control group displayed. Significance level reported for test E(Y) = 0.
[b] Baseline controls include the number of household members, whether a farmer cut trees in OP in 2015, education, whether he or she had a home garden, the total area of oil palm managed, the mean oil palm price received, whether he or she received environmental extension, the share of plots that were flooded and whether farmers experienced information and/or seed access constraints.

At the intensive margin, columns (5) and (6) show that the average 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 on average only few trees each, whereas in T1 few farmers adopt, but each of them plants a relatively large number of trees. 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.

3.1.1. Attrition

From the original 817 farmers interviewed in 2015, 737 could be re-interviewed in the follow-up implying an attrition rate of 10%. To test whether attrition is random, we compare attrition rates between treatment and control groups. This shows that assignment to T2 reduces the probability of attrition by four percentage points at the 5% significance level (p-value: 0.03). To further test for differential attrition, we run mean comparison tests[22] for attritors' characteristics in the different treatment groups (Duflo et al., 2006). The results show that attritors do not differ systematically between groups except that farmers dropping out in T2 are statistically more often women (p-value: 0.080) and older than the farmers remaining in the sample (0.026). Robustness checks for our results are conducted based on inverse probability weights and bounds and confirm that our results are not sensitive to attrition (Tables A.VI-A.VIII in the Appendix).

3.1.2. Outlier analysis

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.

The results (Table 4) indicate that overall the significance levels of the estimated AME are not affected by outliers. Although the sizes of the estimated coefficients decrease, both treatments still have significantly positive effects on the unconditional number of trees, and T1 has a significantly positive effect on the conditional number of trees planted per hectare. However, for the unconditional expected values, the difference in effect size between T1 and T2 is now statistically significant – at least when including baseline controls. Hence, our finding that both interventions are similarly effective in terms of increasing the unconditional number of trees planted per hectare is dependent on the 1% of farmers who plant the most.

[22] Mean comparison tests (here and in subsequent analyses) are based on linear regression models with village-level clustered standard errors.

Table 4
Intention-to-treat estimates with distribution winsorized at 99 percentile.

	Unconditional expected values		Adoption decision[b]		Conditional expected values	
	(1)	(2)	(3)	(4)	(5)	(6)
	E(Y|X)	E(Y|X)	Pr(Y > 0|X)	Pr(Y > 0|X)	E(Y|X, Y > 0)	E(Y|X, Y > 0)
T1	0.716**	0.723**	0.057*	0.061**	5.442***	5.226**
	(0.299)	(0.333)	(0.033)	(0.029)	(1.708)	(2.582)
T2	1.366***	1.467***	0.381***	0.398***	0.400	0.376
	(0.262)	(0.318)	(0.028)	(0.028)	(0.816)	(1.564)
	736	736	737	737	144	144
P-values of *t*-test for T1 = T2	0.111	0.089*	<0.001***	<0.001***	0.008***	0.053*
Controls[a]	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 and pre-treatment (baseline) dependent variable included in all model specifications. Before estimation, distribution was winsorized at the 99 percentile.
*p < 0.1, **p < 0.05, ***p < 0.01.
[a] Baseline controls include the number of household members, whether a farmer cut trees in OP in 2015, education, whether he or she had a home garden, the total area of oil palm managed, the mean oil palm price received, whether he or she received environmental extension, the share of plots that were flooded and whether farmers experienced information and/or seed access constraints.
[b] For completeness, the results of the participation decision are also shown even though they are not affected by winsorizing the distribution.

3.2. *Subgroup-specific treatment effects by seed access constraint*

In the previous section, we found that the combined intervention (T2) significantly increases the likelihood of adoption compared to the pure information intervention (T1). Our conceptual model suggests that adoption of tree planting will only occur if individuals, besides having a positive intention to plant trees, are also able to overcome potential knowledge and seedling access barriers (section 2.3). This would imply that information provision alone (T1) can only have a positive effect on the tree planting decision of farmers who are not seed access constrained. In contrast, seedling in combination with information provision (T2) can potentially induce adoption even under seed access constraints. In order to test whether T1 and T2 have differential effects on adoption under seed access, farmers are divided into two subgroups: The first comprising farmers who stated in the baseline that access to seeds was limited in their village, and the second consisting of farmers who indicated that seed material was easily available in the village.[23] To test whether the treatments have a significant effect on the adoption decision in the respective subgroup, we create dummies for the combinations of treatment status (T1 and T2, respectively) and the two subgroups defined above (Glennerster and Takavarasha, 2013). Results of a linear probability model are presented in Table 5 [24]

The results show that the effect of T1 on adoption is only significant in the absence of seed access constraints, as expected. In contrast, the combined intervention (T2) significantly increases adoption rates in both subgroups. Accordingly, our results support the need of a comprehensive approach, like the combined intervention in T2, to induce adoption in the presence of multiple constraints.

3.3. *Does free seedling delivery discourage tree planting beyond what is given for free?*

Previously, we have found that the effect of T2 on the conditional expected number of trees planted per hectare is significantly smaller than that of T1 (Table 3). We consider two potential interpretations for the lower average conditional planting intensity in T2. First, we observe that a large share of adopters in T2 (77%) plant only six or less trees. It is possible that the free provision of seedlings motivates adoption among farmers who derive relatively low utility from tree planting. For these farmers, free 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 (Lazear et al., 2012). Second, a common concern regarding the provision of free inputs is that it might undermine further acquisitions of the good (Omotilewa et al., 2019). Accordingly, the provision of free seedlings in T2 may discourage additional planting efforts beyond what is given for free. This could be due to motivational crowding (Gneezy et al., 2011) or due to an anchoring effect. The latter could either be a price anchoring that sets the benchmark price for trees at zero, or a quantity anchoring if farmers in T2 interpreted the number of seedlings provided as being optimal. To assess whether the lower conditional planting intensity of

[23] Farmers were asked to rate on a 5-point Likert scale whether they agree that native tree seedlings are easily available in the village, where (strongly) disagree indicates a perceived constraint. Accordingly, farmers were asked to assess the general situation in their village, and not whether they personally had tried to access seedlings. Descriptive statistics for the two categories are reported in Table 1.
[24] We use a linear probability model because we are interested in probabilities. The sign of the interactions might differ when logarithmized odds ratios, as used in the logistic regression, instead of probabilities are compared between different groups (Ganzach et al., 2000).

Table 5
Heterogeneous treatment effects.

	(1)	(2)
	Planting in OP	Planting in OP
T1, seed access constraints = 1	0.014	0.024
	(0.034)	(0.032)
T1, no seed access constraints = 1	0.105**	0.114**
	(0.050)	(0.049)
T2, seed access constraints = 1	0.385***	0.392***
	(0.050)	(0.049)
T2, no seed access constraints = 1	0.376***	0.392***
	(0.042)	(0.044)
Seed access constraints = 1	0.016	0.021
	(0.027)	(0.030)
Constant	0.080**	0.138
	(0.039)	(0.122)
N	737	737
Controls[a]	No	Yes

Village-level clustered standard errors in parentheses. Coefficients from a linear probability model reported. Stratification variables and the pre-treatment (baseline) dependent variable included in both model specifications.
*p < 0.1, **p < 0.05, ***p < 0.01.
[a] Baseline controls include the number of household members, whether a farmer cut trees in OP in 2015, education, whether he or she had a home garden, the total area of oil palm managed, the mean oil palm price received, whether he or she received environmental extension and the share of plots that were flooded.

adopters in T2 reflects a lower willingness of these farmers to procure additional seedlings, we re-estimate our models considering only the number of self-procured seedlings planted in oil palm (i.e., not provided for free through our intervention) (Table 6).

Results show that both interventions have very similar effects on the number of self-procured seedlings. Effect sizes of T1 and T2 on the adoption decision, the unconditional, and conditional number of trees planted, do not significantly differ from each other. Thus, in both groups we observe similar (albeit small) shares of farmers motivated to incur additional planting efforts beyond what is provided for free by the intervention and displaying similarly high levels of conditional planting intensity on the average. Thus, there is no indication that the free provision of seedlings in T2 crowds out own tree planting efforts; it rather seems to encourage tree planting also among farmers deriving lower utility from tree planting.

3.4. *Cost effectiveness considerations*

To be able to draw more informed policy recommendations, tree-planting outcomes induced by the two interventions should be assessed in relation to the costs incurred. So far we have considered the number of trees planted per hectare as relevant outcome indicator to assess the effectiveness of the interventions. Tree planting is certainly a necessary first step towards more biodiversity-friendly plantation management, however, ultimately environmental effects are only generated if trees survive. When assessing cost effectiveness, we therefore consider not only the total number of trees planted due to the intervention, but also the total number of trees that survived after one year. The first year is a crucial time period for tree survival, as trees are especially vulnerable during this early stage and require more care (Jack et al., 2015). The numbers reported in Table 7 indicate that in total T2 has resulted in around 41% more trees planted and 84% more trees survived compared to T1. Yet, the total costs incurred by T2 are also higher: when considering the sunk costs of designing the information campaign (video and manual), the total costs are around 53% higher, without sunk costs they are around 81% higher in T2 compared to T1.

Based on these numbers, we calculate cost effectiveness measures for the two policy interventions (Table 8). Since we are interested in the incremental effect of the interventions (compared to no intervention), we subtract the number of trees planted/survived in the control group. Cost effectiveness measures are reported with and without the sunk costs of designing the information material. A comparison of the measures reported in Table 8 reveals that the two interventions perform very similarly in terms of aggregate cost effectiveness – none of the measures differ significantly between the two interventions. Accordingly, while costs of T2 are substantially higher than those of T1, the better aggregate tree outcomes generated by T2 compensate for the higher program costs.

Table 6
Intention-to-treat estimates for planting of self-procured tree seedlings.

	Unconditional expected values		Adoption decision		Conditional expected values	
	(1)	(2)	(3)	(4)	(5)	(6)
T1	1.072**	1.267**	0.057*	0.061**	8.837***	10.479***
	(0.433)	(0.536)	(0.033)	(0.028)	(2.532)	(3.661)
T2	1.001**	1.615**	0.063**	0.070***	6.924**	11.678**
	(0.407)	(0.779)	(0.027)	(0.023)	(3.107)	(5.737)
	736	736	737	737	63	63
P-values of *t*-test for T1 = T2	0.902	0.679	0.850	0.752	0.624	0.853
Controls[a]	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 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 and the pre-treatment (baseline) dependent variable are included in all model specifications.
*p < 0.1, **p < 0.05, ***p < 0.01.
[a] Baseline controls include the number of household members, whether a farmer cut trees in OP in 2015, education, whether he or she had a home garden, the total area of oil palm managed, the mean oil palm price received, whether he or she received environmental extension, the share of plots that were flooded and whether farmers experienced information and/or seed access constraints.

Table 7
Total costs and outcomes of interventions.

	Total number of trees		Total program costs	
	Trees planted in oil palm plantations	Surviving trees in oil palm plantations	With sunk costs (USD)	Without sunk costs (USD)
T1	1140	666	4591	3001
T2	1606	1226	7025	5435
C	163	135	0	0

Sunk costs include the salaries for the local movie-maker and the artist who designed the manual. Running costs include assistants' salary and per diem, car rental, printing of the manual and costs for the tree seedlings. Costs due to video or manual design were equally accounted for in T1 and T2. For conversion of local currency in USD, the official 2016 exchange rate was used.

Table 8
Cost effectiveness measures.

	With sunk costs		Without sunk costs		
	Trees planted in oil palm plantations per USD spent	Surviving trees in oil palm plantations per USD spent	Trees planted in oil palm plantations per USD spent	Surviving trees in oil palm plantations per USD spent	N
T1	0.22	0.11	0.33	0.18	245
	(1.55)	(1.07)	(2.37)	(1.63)	
T2	0.21	0.15	0.27	0.19	253
	(0.90)	(0.77)	(1.16)	(1.00)	
P-values of T1 = T2	0.881	0.718	0.688	0.897	

Cost effectiveness measures present the number of planted or survived trees per farmer divided by the per capita costs of the interventions. We subtract the average number of trees planted per household in the control group from the number of trees planted per household in the treatment groups to express the incremental effect of our interventions. Test for difference in cost effectiveness between T1 and T2 done in a linear regression with village-level clustered standard errors and stratification variables.

3.5. *Tree survival*

An important leverage point for improving the cost effectiveness of the interventions is raising the tree survival rate. At the aggregate level, only around 58% and 76% of the planted trees in T1 and T2, respectively, survived (Table 7). Since tree planting and maintenance activities are implemented at the farm level, any measures to enhance tree survival would best be targeted at farmers. Table 9 presents average tree survival rates at the farm level by treatment group. Since tree planting is a pre-condition for tree survival, only adopters are considered in the analyses in this subsection. The average survival rates

Table 9
Descriptives of farm-level survival rates (adopters only).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Overall	Control	T1	T2	T1 = C	T2 = C	T1 = T2
	0.660	0.923	0.854	0.590	0.462	<0.001***	0.022**
	(0.399)	(0.140)	(0.320)	(0.408)			
N	144	11	24	109			

In columns (1) to (4), standard deviations are reported in parentheses. Columns (5) to (7) show p-values of mean difference test with clustered standard errors.

reported in Table 9 differ from the aggregate measures reported in the previous subsection, since many farmers in T2 plant only small numbers of trees in comparison to farmers in T1 and the control group – therefore in the latter groups it is more likely that even a small reduction in the survival rate can imply a large loss in the number of trees.[25] The descriptive comparison reveals that adopters in T2 perform significantly lower with respect to tree survival rates than adopters in T1 and in the control group (Table 9). There is no significant difference in survival rates achieved by farmers in T1 and the control group. These results are supported by estimates from a fractional probit regression regressing farm-level tree survival rates on treatment assignment (Table 10, column (1)).[26]

We identify four different categories of factors that are likely to be associated with farmers' performance regarding tree survival in our context. If these factors are unbalanced between the treatment groups, they can help explain the differential survival rates between the treatment groups. First, the planting pattern might determine tree survival. Many trees planted together in clusters are more resilient and hence likely to show higher survival rates (Goldman et al., 2007). We control for both the number of trees planted by the farmer and the share planted in clusters. Second, farmers' characteristics such as experience and skills and the related maintenance given to trees might positively influence tree survival.[27] Farmers who received seedlings for free may also 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, we expect that the plot conditions, including exposure to flooding and drought, the oil palm plantation age, the number of oil palms planted per hectare and whether a river borders the plot, 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.

We test for these potential correlations conditional on tree planting adoption, and thus are leaving the randomized framework of our experiment. We regress tree survival rates on a range of farm and household factors belonging to the different categories using a fractional probit model. Columns (1) and (2) in Table 11 report those variables that turn out to be significant predictors of tree survival rates (full model results are reported in Table A.IX in the Appendix).

We find ample support for the relevance of the second category of factors identified above. Prior experience with tree planting in oil palm and maintenance given to the trees[28] are significantly and positively associated with the probability of tree survival at the farm level. Regarding the third category of factors, only the share of plots that border a river is positively and significantly correlated with the tree survival rate in both 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 share of the species distributed in the experiment in overall species planted is significantly and negatively correlated with the tree survival rate. To further explore the relevance of the significant predictors in explaining the lower tree survival rates exhibited by farmers in T2 compared to T1 and the control group, we report mean difference tests in Table 12.[29]

From the variables that exhibit a significant correlation with the tree survival rate, only the share of the distributed tree species in total trees planted is significantly different between the treatment groups (Table 12). Thus, our species choice might be one relevant reason why we observe a lower tree survival rate among farmers in T2. In fact, a rather low survival rate of

[25] The lower aggregate number of surviving trees in T1 is driven by two farmers. These farmers planted together 300 trees, but none of the planted trees survived.

[26] 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.

[27] We proxy skills with education and wealth. Variable choice is discussed in Table A.XI in the Appendix.

[28] We acknowledge that reverse causality between the survival rate and maintenance might be present in case theseedlings 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.

[29] 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 A.X in the Appendix, for which we do not find any systematical differences between treatment groups either.

Table 10
Difference in tree survival rate between different treatment groups.

	(1)	(2)
	Tree survival rate	Tree survival rate
T1	−0.366	−0.366
	(0.437)	(0.437)
T2	−1.196***	
	(0.297)	
T2 − no planting beyond intention		−1.022***
		(0.354)
T2 − planting in excess of intention		−1.394***
		(0.282)
Constant	1.424***	1.424***
	(0.241)	(0.241)
N	144	138

Coefficients from a fractional probit estimation are reported. Village-level clustered standard errors in parentheses. In column (2), farmers in T2 who did not plant the distributed tree species were excluded from the analysis. P-values of test for T1 = T2 in column (1): 0.014, for test T1 = T2-no planting beyond intention: 0.143, for test T1 = T2-planting in excess of intention: 0.009; for test T2-no planting beyond intention = T2-planting in excess of intention: 0.099 in column (2).

Table 11
Potential determinants of tree survival.

	(1)	(2)	(3)
	Tree survival rate	Tree survival rate	Survival rate of distributed species (only T2 adopters)
Share of provided species in total trees planted	−0.275***	−0.199**	
	(0.081)	(0.093)	
Share of plots with a river bordering	0.144***	0.171***	0.096
	(0.055)	(0.057)	(0.059)
Experience with tree planting in OP (1 = Yes)	0.206***	0.233***	0.234***
	(0.059)	(0.056)	(0.049)
Maintenance done to trees (1 = Yes)	0.181***	0.200***	0.209***
	(0.055)	(0.051)	(0.053)
Distance from Jambi to village (in km)		−0.002*	
		(0.001)	
Number of free seedlings planted in excess of intention			−0.029***
			(0.010)
N	141	141	101

AME from fractional probit estimations shown. Village-level clustered standard errors estimated with help of Delta method and displayed in parentheses. Columns (1) and (2) include the whole sample of adopters and all species planted. In column (3), the analysis is restricted to the species distributed in T2, and accordingly only includes the adopting farmers in T2 who plant the provided tree species in their oil palm plantation.
*p < 0.1, **p < 0.05, ***p < 0.01.

Table 12
Mean comparison test of significant predictors for tree survival.

	(1)	(2)	(3)	(4)
Variable	Overall	Control + T1	T2	Control + T1 = T2
Maintenance[a] (Yes = 1)	0.333	0.314	0.339	0.810
Experience with tree planting (Yes = 1)	0.230	0.286	0.211	0.539
Share of plots which border a river[b]	0.204	0.118	0.231	0.156
	(0.400)	(0.327)	(0.418)	
Share of tree species provided in total trees planted	0.700	0.278	0.832	<0.001***
	(0.439)	(0.441)	(0.346)	
N	144	35	109	

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

three of the species, Meranti, Durian and Jelutung, is also found in an ecological experiment in the study area (Zemp et al., 2019b). While native to Jambi, these tree species may not perform well when planted in immediate proximity to oil palm.

In addition, it could be that the tree species distributed in the experiment do not correspond to farmers' preferences, or that farmers' in T2 were given more seedlings of selected species for free than they actually intended to plant. To explore this further, we calculate the number of "preferred" seedlings received by farmers in T2 – this is the number of seedlings out of the six tree species distributed for free, for which the farmer had previously indicated a positive planting intention.[30] The number of "preferred" seedlings was then subtracted from the number of the freely distributed seedlings that were *actually* planted in order to obtain the number of free seedlings that were planted in excess of the farmer's originally stated intention. In Table 11 column (3) we restrict our analysis to adopters in T2 in order to explore whether the *number of free seedlings planted in excess of intention* explains survival rates of the distributed species. Indeed, we find a significantly negative effect indicating that farmers who planted more than they intended – possibly because they received the seedlings for free – exhibit lower tree survival rates among the distributed species. This may at least to some extent explain the lower overall tree survival rates observed among farmers in T2 (Table 10). In Table 10 column (2) we split T2 farmers into two subgroups – those who planted free seedlings in excess of intentions and those who did not – and compare average tree survival rates between these two subgroups, T1, and the control group. The results show that survival rates in the subgroup of T2 farmers planting in excess of intentions are significantly lower compared to all other groups (p-values reported below Table 10). Thus, non-correspondence between our species choice and farmers' preferences seems to represent an important factor influencing the effectiveness of the interventions, even if it does not fully explain the lower survival rates in T2 since the survival rate achieved by T2 farmers *not* planting beyond their intentions is still significantly lower than that of the control group.

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 reasons for the low survival rate of the distributed species and hence for the lower tree survival rate observed among farmers in T2. In particular, 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 latter is provided by the significant and negative correlation between the distance from Jambi to the respective village and the tree survival rate that is however small in size (column (2) in Table 11).

4. Conclusion

Results from a randomized controlled trial implemented in Jambi Province, Indonesia, suggest that information (T1) and information in combination with seedling provision (T2) 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 combined intervention (T2) leads to a higher planting probability but lower conditional planting intensity than sole information provision (T1). Our results suggest that the lower average conditional number of trees planted per hectare in T2 is driven by a large share of farmers planting only the seedlings provided for free. Nonetheless, the free provision of seedlings in T2 does not seem to discourage additional planting efforts – which are carried out by similar shares of farmers with similar planting intensities in both treatment groups. From a policy perspective, comparing the cost effectiveness of the two interventions is critical. Although the combined intervention incurs higher program costs due to seedling purchase and delivery, it is also more effective in terms of the total number of trees planted and survived. As a result, we find no significant difference in cost effectiveness between the two interventions.

In order to generate broader biodiversity effects and allow for ecological scaling effects from the local to the regional level, diversified plantations likely need to be spread over a large area. This could enable species movements between diversified plantations and could act as corridors to link remaining forest patches (Koh et al., 2009). While both interventions in our experiment motivate a small share of farmers to make substantial planting efforts, the combined intervention (T2) additionally induces low-intensity planting (up to six trees per hectare) among a large share of farmers. This more likely generates a landscape design where diversified plantations are spread over a large area. Here, a potential advantage of the combined intervention is that it also motivates adoption of tree planting among farmers who had initially stated that seedlings were not easily available in their village. Thus, in particular in remote areas of developing countries, where seed markets may be missing or characterized by high transaction costs, combining information with seedling provision may be the more viable approach to achieving considerable uptake of tree planting.

An important leverage point to increasing cost effectiveness of the interventions is increasing tree survival rates, in particular in the context of free seedling provision, where we found farm-level survival rates to be significantly lower. Our results suggest that here species choice is critical and should be based on recent evidence from ecological experiments (Zemp et al., 2019b) and in particular reflect farmers' preferences. 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

[30] Farmers in T2 were asked after the information campaign but before the seedlings were handed out how many trees of each of the six species they would plant in their oil palm plantation if provided for free.

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 the number of trees planted. This will generate important insights regarding the feasibility of up-scaling tree planting intensities among larger numbers of farmers, which will be important for the generation of broader biodiversity effects.

A limitation of our study is that we did not measure biodiversity outcomes, e.g. in terms of arthropod or bird diversity, and therefore cannot establish the relationship between the number of native trees planted or survived and actual biodiversity outcomes. Several recent studies comparing monoculture and polyculture practices in oil palm smallholdings have found significant positive effects of the latter on arthropod, bird and bat communities (Ashraf et al., 2018; Ghazali et al., 2016; Syafiq et al., 2016; Yahya et al., 2017). However, polycultural farming here refers to complex agricultural systems combining oil palm with other crops such as banana, coconut, tapioca, corn, and sugar cane, as well as fruit trees such as jackfruit, mango and cacao. Accordingly, the studies have not been designed to derive the relationship between (native) tree planting intensity and biodiversity outcomes. Only Teuscher et al. (2015) explicitly analyze the effects of the number of trees in oil palm on bird abundance and species diversity. In their sample of 120 smallholder oil palm farmers, predicted bird diversity conditional on the number of trees ranges from 2.58 species (when there are zero trees) to 5.15 species (in case of 125 trees). Over the same range of trees, bird abundance ranges from 3.66 individuals to 8.05 individuals. The response of tree diversity and abundance to tree planting is non-linear, indicating a strong decrease in the marginal effect of additional trees on bird diversity and abundance with increasing number of trees. The results presented by Teuscher et al. (2015) suggest that if six trees are planted in a 1-ha monoculture oil palm plantation (with no native trees to start with), as done by a large share of the farmers receiving free seedlings in our study, the predicted increase in bird diversity ranges around 0.6 species and in bird abundance around one individual. However, it needs to be taken into account that ecological effects measured at the plot level depend also on other factors such a ground vegetation cover and chemical inputs (Yahya et al., 2017; Azhar et al., 2014). Further, feedback effects between landscape- and plot-level characteristics exist such that plot-level effects cannot be easily extrapolated to the landscape level (Tscharntke et al., 2012).

The expansion of oil palm plantations in South East Asia is a key driver of global biodiversity loss (Diaz et al., 2019). Ecological research has suggested that the introduction of more structural complexity, e.g. in form of diversified oil palm systems, can sustain increased biodiversity outcomes compared to monoculture landscapes (Koh et al., 2009; Yahya et al., 2017; Syafiq et al., 2016). Our research suggests that in particular the combination of information with free seedlings robustly motivates smallholder farmers to increase the number of trees planted in their oil palm plantations, thereby promoting the uptake of more diversified plantations. With regard to the external validity of our results, two aspects deserve mentioning. Many smallholders in Jambi, Indonesia, were previously part of an outgrower scheme or have received extension services from large-scale plantations, propagating homogeneous plantation structures. This has resulted in some skepticism among smallholder farmers about planting trees together with oil palms as shown in focus group discussions held prior to data collection. Hence, if in other contexts prior concerns are less pronounced, farmers may be more inclined to experiment with tree planting in oil palm (Slingerland et al., 2019). 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, similar studies in other oil palm producing areas would be useful to explore the extent to which our results can be generalized to other contexts.

Financial disclosure statement

We certify that no party having a direct interest in the results of the research supporting this article has or will confer a benefit on us or on any organization with which we are associated, and we certify that all financial and material support for this research and work are clearly identified in the title page of the manuscript.

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Declaration of competing interest

The authors of this manuscript certify that they have no affiliations with or involvement in any organization or entity with any financial interest, or non-financial interest in the subject matter or materials discussed in this manuscript.

Appendix

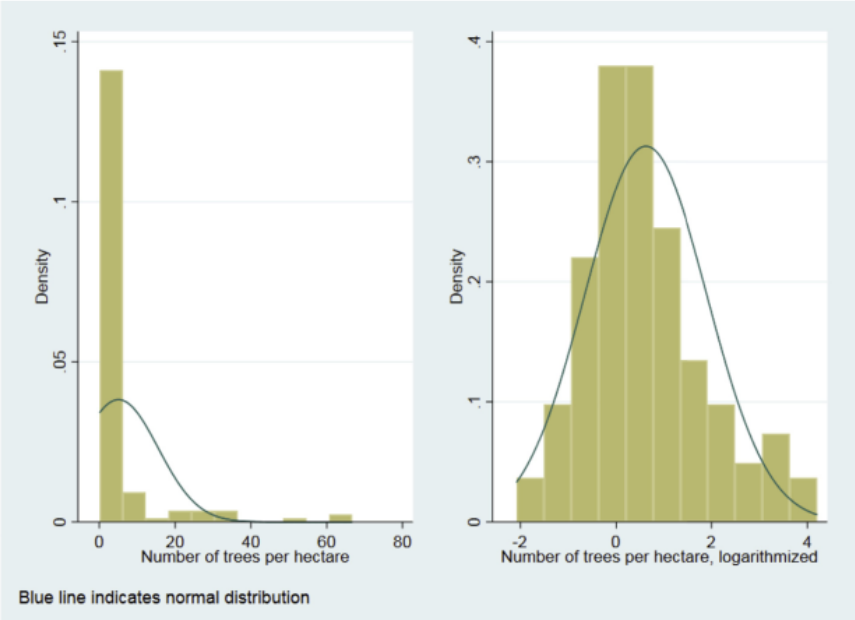

Fig. A.1. Distribution of strictly positive tree planting quantities.

Table A.I
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	0.872*/c	0.994**/b	0.057**/c	0.061**/b
	(0.510)	(0.472)	(0.033)	(0.029)
T2	2.772***/a	3.051***/a	0.381***/a	0.398*** /a
	(0.419)	(0.392)	(0.028)	(0.028)
Access to seeds	−0.199	−0.231	−0.025	−0.028
	(0.221)	(0.231)	(0.027)	(0.028)
Local village	−0.279	−0.431	−0.035	−0.052
	(0.285)	(0.338)	(0.035)	(0.040)
Oil palm share > 73.5%	−0.277	−0.316*	−0.035	−0.039*
	(0.195)	(0.178)	(0.024)	(0.021)
Total number of trees planted per ha in OP	0.030**	0.032**	0.004**	0.004**
	(0.012)	(0.013)	(0.002)	(0.002)
Number HH members		0.032		0.004
		(0.062)		(0.007)
Trees cut in OP		−0.205		−0.025
		(0.831)		(0.101)
Years of education		0.071**		0.009**
		(0.030)		(0.004)
Home garden		−1.275***		−0.155***
		(0.384)		(0.048)

(continued on next page)

Table A.I (*continued*)

	Estimated Coefficients		Marginal Effects	
	(1)	(2)	(3)	(4)
	Planting in OP	Planting in OP	Planting in OP	Planting in OP
Total hectare OP managed		−0.018		−0.002
		(0.022)		(0.003)
Price for oil fruits per kg		−0.224		−0.027
		(0.705)		(0.085)
Environmental extension received		0.925**		0.113***
		(0.367)		(0.043)
Share of plots flooded		0.178		0.022
		(0.303)		(0.037)
Information constraints		0.336		0.041
		(0.226)		(0.028)
Seed access constraints		−0.240		−0.029
		(0.270)		(0.033)
Constant	−2.746***	−2.252**		
	(0.393)	(0.940)		
Observations	737	737	737	737
McFadden pseudo R^2	0.198	0.226		

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. Due to computational complexity, bootstrapped confidence intervals were only computed for the treatment variables.

Table A.II
Intention-to-treat estimates for intensity decision.

	Estimated Coefficients		Marginal Effects	
	(1)	(2)	(3)	(4)
	Trees planted per ha	Trees planted per ha	Trees planted per ha	Trees planted per ha
T1	1.185***/a	1.168***/a	8.127***/a	7.938**/b
	(0.267)	(0.415)	(2.673)	(3.578)
T2	0.193	0.252	0.762	1.026
	(0.262)	(0.432)	(1.012)	(1.683)
Access to seeds	−0.327	0.006	−1.753	0.036
	(0.320)	(0.306)	(1.759)	(1.711)
Local village	0.418	0.552	2.241	3.088
	(0.389)	(0.511)	(2.183)	(3.214)
Oil palm share > 73.5%	−0.888***	−0.882***	−4.762***	−4.93***
	(0.312)	(0.301)	(1.798)	(1.754)
Total number of trees planted per ha in OP	0.012	0.016	0.062	0.089
	(0.015)	(0.020)	(0.079)	(0.123)
Number HH members		−0.032		−0.179
		(0.095)		(0.529)
Trees cut in OP		−0.029		−0.162
		(0.668)		(3.728)
Years of education		0.013		0.071
		(0.024)		(0.137)
Home garden		−0.420		−2.349
		(0.431)		(2.475)
Total hectare OP managed		−0.159***		−0.892***
		(0.018)		(0.212)
Price for oil fruits per kg		0.030		0.167
		(0.962)		(5.394)
Environmental extension received		0.418		2.336
		(0.322)		(1.934)
Share of plots flooded		0.400		2.238
		(0.338)		(1.722)
Information constraints		−0.004		−0.023
		(0.261)		(1.459)
Seed access constraints				

Table A.II (*continued*)

	Estimated Coefficients		Marginal Effects	
	(1)	(2)	(3)	(4)
	Trees planted per ha	Trees planted per ha	Trees planted per ha	Trees planted per ha
		0.098		0.548
		(0.243)		(1.396)
Constant	1.559***	1.980		
	(0.519)	(1.568)		
Observations	144	144	144	144
BIC	725.6	737.5	.	.

Results presented from a GLM model with log-link and gamma distribution of error terms for the subsample of adopters only. Columns (1) and (2) present estimated coefficients. Columns (3) and (4) 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 the bootstrap-t procedure. 1000 replications used for estimating confidence intervals. For the bootstrapped model, the dummy for cutting trees in oil palm in the last 12 months was 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 A.III
Intention-to-treat effects on the unconditional predicted number of trees planted per hectare.

	(1)	(2)
	Trees planted per ha	Trees planted per ha
T1	0.995**/a	0.984**/a
	(0.422)	(0.452)
T2	1.583***/a	1.721***/a
	(0.347)	(0.412)
Access to seeds	−0.459	−0.115
	(0.387)	(0.363)
Local village	0.217	0.278
	(0.477)	(0.657)
Oil palm share > 73.5%	−1.131***	−1.173***
	(0.405)	(0.406)
Total number of trees planted per ha in OP	0.033*	0.039
	(0.018)	(0.026)
Number HH members		−0.013
		(0.112)
Trees cut in OP		−0.158
		(0.921)
Years of education		0.067*
		(0.037)
Home garden		−1.326**
		(0.579)
Total hectare OP managed		−0.190***
		(0.049)
Price for oil fruits per kg		−0.080
		(1.146)
Environmental extension received		1.088**
		(0.484)
Share of plots flooded		0.585
		(0.401)
Information constraints		0.238
		(0.334)
Seed access constraints		−0.042
		(0.323)
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 shown.
*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. Due to computational complexity, bootstrapped confidence intervals were only computed for the treatment variables.

Table A.IV
Bootstrap-t confidence intervals for treatment groups.

	(1)		(2)	
	T1	T2	T1	T2
AME unconditional expected value	99%-CI [0.273; 3.303]	99%-CI [0.384; 3.709]	99%-CI [0.195; 3.594]	99%-CI [0.725; 3.830]
Coefficients adoption decision	90%-CI [0.104; 1.568]	99%-CI [1.824; 4.086]	95%-CI [0.165; 1.692]	99%-CI [2.147; 3.950]
AME adoption decision	90%-CI [0.008; 0.102]	99%-CI [0.297; 0.465]	95%-CI [0.004; 0.113]	99%-CI [0.291; 0.448]
Coefficients intensity decision	95%-CI [0.664; 1.778]	90%-CI [-0.151; 0.884]	95%-CI [0.082; 2.123]	90%-CI [-0.683; 1.243]
AME intensity decision	99%-CI [1.147; 29.485]	90%-CI [-0.710; 3.029]	95%-CI [3.106; 17.365]	90%-CI [-2.051; 3.695]

1000 replications are used for bootstrapping. The table shows the confidence interval for the highest significance level. In case coefficients or AME are 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 A.I- A.III.

Table A.V
Heckman selection model.

	(1)	(2)
	Trees planted per ha (log.)	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**	−0.066
	(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)
Home garden		−0.657***
		(0.217)
Observations	737	737

Estimated coefficients from a Heckman selection model. Standard errors clustered at the village level and reported in parentheses.
Wald test of independent equations. (rho = 0): chi2(1) = 0.83, p-value: 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 the possession of a 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 A.II. 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 A.VI
Weighted Intention-to-treat effects of interventions.

	Unconditional expected values		Adoption decision		Conditional expected values	
	(1)	(2)	(3)	(4)	(5)	(6)
	E(Y|X)	E(Y|X)	Pr(Y > 0|X)	Pr(Y > 0|X)	E(Y|X, Y > 0)	E(Y|X, Y > 0)
T1	0.982**	0.964**	0.055*	0.059**	8.173***	7.908**
	(0.414)	(0.438)	(0.033)	(0.029)	(2.617)	(3.559)
T2	1.583***	1.715***	0.381***	0.398***	0.721	0.953
	(0.348)	(0.414)	(0.028)	(0.028)	(1.005)	(1.712)
	736	736	736	736	144	144
P-values of t-test for T1 = T2	0.281	0.190	0.000***	0.000***	0.009***	0.044**
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 and past number of trees planted per hectare in oil palm included in all model specification. Inverse probability weights applied.
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 A.VII.
*p < 0.1, **p < 0.05, ***p < 0.01.
[1]Baseline controls include the number of household members, whether a farmer cut trees in OP in 2015, education, whether he or she had a home garden, the total area of oil palm managed, the mean oil palm price received, whether he or she received environmental extension, the share of plots that were flooded and whether farmers experienced information and/or seed access constraints.

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

	(1)	(2)
	selection	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 palmmanaged	−0.011	−0.011
	(0.008)	(0.008)
Environmentalextension 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]		

(continued on next page)

Table A.VII (*continued*)

	(1)	(2)
	selection	selection
		-0.329
		(0.261)
Constant	0.801***	24.74
	(0.215)	(18.63)
N	817	817
McFadden pseudo R^2	0.017	0.057

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 predictions based on (1) and (2).
*p < 0.1, **p < 0.05, ***p < 0.01.
[1] Out of eleven dummy variables for the assistants collecting the baseline data, only two are statistically significant at the 10% level.

Table A.VIII
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	1.002	−0.061	0.156	0.050	0.057
	[3.630]	[0.164; 0.840]	[-0.116;−006]	[0.103; 0.209]	[-0.020; 0.121]	[0.010; 0.104]
T2	0.632	1.845	0.247	0.432	0.360	0.403
	[0.115; 1.150]	[0.960; 2.730]	[0.174; 0.320]	[0.367; 0.496]	[0.284; 0.436]	[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 A.IX
Fractional probit estimation for tree survival.

	Estimated Coefficients			Marginal Effects		
	(1)	(2)	(3)	(4)	(5)	(6)
	Tree survival rate	Tree survival rate	Survival rate of distributed species	Tree survival rate	Tree survival rate	Survival rate of distributed species
Share of trees planted in islands	0.071	−0.027	−0.119	0.022	−0.008	−0.039
	(0.405)	(0.418)	(0.430)	(0.124)	(0.124)	(0.141)
Share of provided species in total trees planted	−0.898***	−0.670**		−0.275***	−0.199**	
	(0.267)	(0.306)		(0.081)	(0.093)	
Total number of trees planted	0.000	−0.000	0.001	0.000	−0.000	0.000
	(0.001)	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)
Mean plot age	0.013	0.012	0.011	0.004	0.004	0.004
	(0.019)	(0.017)	(0.019)	(0.006)	(0.005)	(0.006)
Mean number of oil palms	−0.002	−0.005	−0.000	−0.001	−0.001	−0.000
	(0.005)	(0.005)	(0.006)	(0.002)	(0.001)	(0.002)
Share of plots with a river bordering	0.470**	0.574***	0.293	0.144***	0.171***	0.096
	(0.184)	(0.200)	(0.181)	(0.055)	(0.057)	(0.059)
Share of flood prone plots	−0.135	−0.353	−0.533	−0.041	−0.105	−0.175
	(0.536)	(0.507)	(0.581)	(0.164)	(0.150)	(0.187)
Share of drought prone plots						

Table A.IX (*continued*)

	Estimated Coefficients			Marginal Effects		
	(1)	(2)	(3)	(4)	(5)	(6)
	Tree survival rate	Tree survival rate	Survival rate of distributed species	Tree survival rate	Tree survival rate	Survival rate of distributed species
	−0.275	−0.226	−0.405	−0.084	−0.067	−0.133
	(0.232)	(0.240)	(0.307)	(0.071)	(0.070)	(0.098)
Years of education	0.029	0.023	0.034	0.009	0.007	0.011
	(0.028)	(0.026)	(0.030)	(0.009)	(0.008)	(0.010)
Experience with tree planting in OP	0.674***	0.784***	0.713***	0.206***	0.233***	0.234***
	(0.193)	(0.192)	(0.149)	(0.059)	(0.056)	(0.049)
Value of assets in 1000 IDR	0.004	0.004	0.000	0.001	0.001	0.000
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
Maintenance done to trees	0.591***	0.671***	0.637***	0.181***	0.200***	0.209***
	(0.193)	(0.187)	(0.174)	(0.055)	(0.051)	(0.053)
Distance to asphalt road (in km)		0.014			0.004	
		(0.017)			(0.005)	
Distance to Jambi city (in km)		−0.006*			−0.002*	
		(0.003)			(0.001)	
Species planted in excess of intent			−0.087**			−0.029***
			(0.034)			(0.010)
Constant	0.634	1.393	−0.208			
	(0.969)	(0.956)	(1.050)			
Observations	141	141	101	141	141	101

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 A.XI. In columns (3) and (6) only farmers in T2 who planted the distributed species are included.
*p < 0.1, **p < 0.05, ***p < 0.01.

Table A.X
Descriptives of other explanatory variables.

Variable	(1)	(2)	(3)	(4)
	Overall	Control + T1	T2	Control + T1 = T2
Share of trees planted in islands	0.06	0.086	0.060	0.622
	(0.247)	(0.284)	(0.234)	
Total number of trees planted	24.944	37.229	21	0.358
	(91.812)	(71.062)	(97.502)	
Mean plantation age	13.552	13.043	13.716	0.763
	(7.606)	(7.413)	(7.693)	
Mean number of oil palms per ha	141.091	139.749	141.509	0.621
	(15.936)	(17.072)	(15.624)	
Share of plots which are flood prone	0.105	0.147	0.092	0.584
	(0.307)	(0.359)	(0.290)	
Share of plots which are drought prone	0.608	0.451	0.657	0.056*
	(0.485)	(0.498)	(0 .472)	
Education	8.188	8.6	8.055	0.457
	(3.861)	(4.146)	(3.776)	
Asset index (in 1000 IDR)	33.835	44.157	30.521	0.310
	(58.814)	(55.326)	(59.757)	
N	144	35	109	

In columns (1) to (3), standard deviation reported in parentheses. 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.
*p < 0.1, *p < 0.05, ***p < 0.01.

Table A.XI
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, where both information and tree seedlings were provided = 0 otherwise
Access to seeds*	= 1 if the farmers in the village have access to tree seedlings = 0 otherwise
Local village*	= 1 if mostly local Melayu farmers live in the village = 0 mostly transmigrant farmers live in the village
Oil palm share >73.5%*	= 1 if more than 73.5% of the farmers in one village are engaged in oil palm cultivation = 0 otherwise
Number HH members*	Number of persons in a household
Trees cut in OP*	= 1 if a farmer has cut trees in his or her oil palm plantation in the last 12 months = otherwise
Years of education*	Years of education of household head
Home garden*	= 1 if a farmer has a home garden = 0 otherwise
Number of trees planted per ha in OP in the past *	Number of trees per hectare a farmer has planted 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.
Price received for oil fruits 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.
Environmental extension received*	= 1 if the farmer has received any environmental extension in the last 12 months = 0 otherwise
Share of plots flooded*	Number of plots flooded in 2015 divided by total number of plots
Seed access constraint*	Farmers were asked on a five point Likert scale ranging from strongly disagree (=1) to strongly agree (=5) whether seedlings are easily available in the village. Farmers who (strongly) disagreed were classified as seed access constrained = 1 and = 0 otherwise.
Information constraint*	Farmers were asked on a five point Likert scale ranging from strongly disagree (=1) to strongly agree (=5) whether there is enough information about tree planting available in the village. Farmers who (strongly) disagreed were classified as information constrained = 1 and = 0 otherwise.
Tree survival equation	
Variable Name	Explanation
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 1000 IDR. Assets considered for the compilation are television, motorbike, car, fridge, washing machine and cell-phone.
Experience with tree planting in OP*	= 1 if a farmer has trees in his or her oil palm plantation which he or she planted on his or her own. = 0 otherwise
Share of plots with river bordering	Share of plots a farmer planted trees which border a river.
Share of plots which are flood prone	Share of plots a farmer planted trees on which were flooded 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°.
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
Number of free seedlings planted in excess of intention	Farmers were asked after the intervention how many of the six species distributed they would like to plant per ha if provided for free. Based on this, we estimated the number of species a farmer would like to plant. This number was subtracted from the number of species a farmer actually planted to derive the number of species a farmer planted beyond his or her intent.

Variables indicated with a * refer to baseline levels.

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