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How to promote agricultural technologies that generate positive environmental effects? Evidence on tree planting in Indonesia

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Abstract

Agricultural technologies frequently have been introduced via subsidies to accelerate diffusion and spur adoption in the presence of market inefficiencies or missing information. Yet, for agricultural technologies that mainly generate positive environmental effects, it is not clear how to encourage adoption, maintenance, and additional investments most effectively. This study addresses this gap by introducing two policy interventions to foster tree planting in an oil palm hotspot in Indonesia. In the first treatment, oil palm farmers receive information about native tree planting and three different native tree seedlings for free (subsidy treatment). In the second treatment, oil palm farmers receive the same information and the opportunity to buy three different native tree seedlings through an auction (price treatment). Results from negative binomial regressions reveal that a full subsidy leads to higher tree planting at first, but the results from a double hurdle model show that conditional on being planted there is no significant difference in survival rates between the two treatments. Our results further show that conditional on tree planting farmers in the price treatment apply a higher number of maintenance practices than farmers in the subsidy treatment. Finally, the subsidy treatment has a significantly negative effect on additional planting efforts.

Keywords: Technology adoption, policy analysis, auction, subsidies, negative binomial estimation

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1. Introduction

In many developing nations, governments have recognized the adoption of productivity-increasing and hence, welfare-enhancing technologies as a relevant objective for development. In cases where markets do not work efficiently, for example, due to informational inefficiencies or low availability of the respective technology with relatively high prices, farmers often face difficulties to purchase the technology (Aker 2011; Jack 2013b). To overcome barriers such as market inefficiencies (Knowler and Bradshaw 2007; Jack2013b) or missing information (Aker 2011; Romero et al. 2019) subsidies have been used as one way to accelerate diffusion and spur adoption. This might also be helpful in the case of high uncertainties regarding the potential private benefits of the respective technology to allow the recipients to experiment with the good and get to know it. Yet, there has been a debate in the literature on whether technology promotion through subsidies is an effective means and sustainable in the long run. This becomes especially relevant when it comes to agricultural technologies that benefit society at large, with only delayed private benefits of income and production diversification for adopters. Many studies that look into promoting agricultural technologies that are socially desirable, such as native tree planting and similar technologies, focus on existing payment for ecosystem services (PES) programs that provide subsidies to individuals for adopting the specific practice (Cole 2010; Arriagada et al. 2015). Due to the delay of private benefits, this might be justified. However, scholars have raised concerns about subsidies in this context: A subsidy might reduce the use and/or maintenance of the technology (Dupas 2014), adopters with intrinsic motivations might be crowded out (Rode 2015) and future investments of adopters might be delayed (Kremer and Willis 2016) or negatively affected altogether due to price anchoring (Köszegi and Rabin 2006; Omotilewa et al. 2019). Market access, however, might lead to an increase in the adoption of such technologies although less than under a full subsidy scheme (Rist et al. 2010; Teuscher et al. 2015; Slingerland et al. 2019).

According to Aker (2011) and Romero et al. (2019), information provision can successfully promote the adoption of agricultural technologies in developing nations. However, respective studies mainly focus on technologies where the decision to adopt is motivated by productivity increases for the adopters, like the adoption of enhanced management practices (Van Campenhout 2019), improved seeds (Asfaw et al. 2012), and fertilizer applications (Duflo et al. 2010). Yet, for agricultural technologies that mainly aim to generate positive environmental effects, such as native tree planting, information provision alone may not be sufficient to motivate adoption. Related research on health products that benefit society at large shows that adoption rates tend to be low in the absence of subsidies, which is likely due to high price elasticities of demand (Cohen and Dupas 2010; Bensch and Peters 2017; Berry et al. 2020; Ashraf et al. 2010). Research on different policy options to promote native tree planting so far is

scarce; notable exceptions are Jack (2013a), Jack et al. (2015), and Rudolf et al. (2020), providing evidence that subsidies can increase the adoption of native tree planting.

Even if initial adoption is higher under subsidies, trees can only generate positive externalities if they survive in the medium to long term, which requires maintenance. In the case of easy-to-use technologies that do not require maintenance, previous literature has shown that subsidies are not associated with a decrease in use over time (Dupas 2014). The few studies that have looked at tree survival in this context, have compared different subsidy measures and found mixed results on survival (Jack 2013a; Jack et al. 2015; Rudolf et al. 2020). In some cases, (short-term) subsidies might even lead to a long-term boost in investments. This is more likely in the case of technologies such as cooking stoves and water filters because adopters have ample time to experience the positive benefits before they need to invest in the renewal of the technology (Dupas 2014). Yet, for technologies such as native tree planting, subsidies may not necessarily encourage further investments into tree planting, as the benefits are only experienced after many years, and thus may be associated with crowding effects (Köszegi and Rabin 2006; Greiner and Gregg 2011; Rode et al. 2015; Kremer and Willis 2016; Omotilewa et al. 2019).

This paper investigates the effects of two policy interventions on the adoption of native tree planting, as a maintenance-intense agricultural technology with positive environmental effects. To address our question, we implemented two treatments with small-scale oil palm farmers in Jambi, Sumatra, Indonesia. In one treatment oil palm farmers received information about native tree planting and were then given market access to native tree seedlings through an auction (price treatment). In a second treatment, oil palm farmers received the same information about native tree planting and three native tree seedlings for free (subsidy treatment). We analyze the two treatments concerning the number of native trees planted and the number of trees surviving after several months conditional on having been planted. We also test for crowding effects by looking at additional planting efforts and look at characteristics of adopters and non-adopters as well as the farmers' willingness to pay (WTP) for tree seedlings.

The rest of the paper is organized as follows: Section 2 describes the ongoing land use transformation in Jambi, Indonesia, and develops our conceptual framework. Section 3 introduces the research design, describes the treatments, and the econometric framework. Section 4 presents the results, which are further discussed in section 5. Section 5 also concludes.

2. Study context and conceptual framework

2.1 Study context

Our research was implemented in Jambi Province on the island of Sumatra, Indonesia. In the last two decades, Indonesia has experienced a rapid expansion of oil palm plantations, advancing to the largest exporter of palm oil worldwide (Rist et al. 2010; Gatto et al. 2015). Between 2000 and 2018, the oil palm area has increased from four million to twelve million hectares (BPS-Statistics Indonesia 2019), implying large-scale land-use transitions (Villamor et al. 2015). The Province of Jambi on the island of Sumatra is a hotspot for oil palm expansion: the area under oil palm cultivation increased from 150,000 hectares in 1996 to 770,000 hectares in 2018 (Gatto et al. 2015, BPS-Statistics Indonesia 2019). Most of the oil palm plantations in Jambi have been established on former forest land (Koh and Wilcove 2008; Schwarze et al. 2015) as well as on land previously used for rubber and food crops (Schwarze et al. 2015).

Besides large companies and the Indonesian government investing in oil palm estates, 75 percent of the oil palm area in Jambi Province is managed by small-scale farmers (BPS-Statistics Indonesia 2019). The Indonesian government has actively supported the spread of oil palm cultivation through a transmigration program that was set up in the 1980s as a concept for local socio-economic development. Under this program, families from Java were relocated to Sumatra and other islands (Rist et al. 2010; Gatto et al. 2015; Krishna et al. 2017) and received two to three hectares of land cultivated with oil palms. Since the phasing-out of the transmigration program, land conversion towards oil palm is mainly driven by independent smallholders (Gatto et al. 2015).

Previous literature has documented the positive economic effects (Rist et al. 2010; Austin et al. 2017) and the related improvements in rural livelihoods (Obidzinski et al. 2012) associated with the oil palm boom in Indonesia. On the other hand, the expansion of oil palm monocultures has raised social and environmental concerns (Koh and Wilcove 2008; Obidzinski et al. 2012; Lee et al. 2014). Sumatra is considered a biodiversity hotspot, where the rapid land-use transformation towards oil palm has led to a homogenization of the landscape, unprecedented forest loss, and decreases in biodiversity and water availability (Feintrenie and Levang 2009; Gibson et al. 2011; Merten et al. 2016; Austin et al. 2017; Dislich et al. 2017). Furthermore, oil palm expansion has been linked to decreases in soil carbon, and to increases in greenhouse gas emissions (Fargione et al. 2008; Van Straaten et al. 2015).

To restore important ecosystem functions in homogenized landscapes, native tree planting has been suggested as a promising management practice (Koh 2008; Potvin and Gotelli 2008; Lim et al. 2015; Gérard et al. 2017). Native tree planting increases habitat complexity and landscape heterogeneity (Atiqah et al. 2019) and thereby preserves plant and bird species (Feintrenie and Levang 2009; Cole et

al. 2010; Atiqah et al. 2019) and even some of the functions of a natural forest (Teuscher et al. 2016). If planted as clusters, trees can act as focal areas of recovery (Potvin and Gotelli, 2008). Cole et al. (2010) found that even small tree islands established in degraded tropical landscapes can increase bird activity and pollination through seed rains. Hence, farms could be used as biodiversity reservoirs (Acharya 2006).

Oil palm farmers in Jambi Province already experience negative consequences of widespread landscape homogenization, e.g. through income fluctuations (Slingerland et al. 2019), decreases in water availability (Merten et al. 2016), or polluting haze resulting from massive fires that are used to clear land for oil palm cultivation (Varkkey 2013). Planting native trees that provide fruit or timber could potentially allow farmers to diversify their income sources and reduce their exposure to income fluctuations (Slingerland et al. 2019). However, the profitability of oil palms is high, and accordingly, planting native trees on farmland is associated with high opportunity costs (Butler et al. 2009; Koh and Ghazoul 2010; Feintrenie et al. 2010a; Feintrenie et al. 2010b; Sayer et al. 2012). If native trees are integrated into oil palm plantations, this may entail negative economic effects due to competition for nutrients, light, and water between native trees and oil palms (Koh and Wilcove 2008). Despite these potential negative yield effects, there is evidence that oil palm farmers sometimes prefer mixed cropping systems, including trees in their oil palm plantations, for diversification and stabilization of income (Rist et al. 2010; Teuscher et al. 2015; Slingerland et al. 2019) suggesting some demand under a market scheme for tree seedlings.

Overall, there is not much information available on diversified systems regarding oil palms and native trees specifically. In addition, access to markets for native tree seedlings in rural areas of Jambi Province is very limited (Rudolf et al. 2020) which adds to the relevance of a better understanding of how to promote such technology with its positive environmental effects but very limited market access.

2.2 Conceptual framework

In this study, we test two policy interventions to promote the adoption of native tree planting in an oil-palm-dominated landscape. Adoption is defined as the actual planting of at least one of the distributed tree seedlings. The subsidy treatment provides farmers with information on native tree planting and three tree seedlings for free[2]. The price treatment which is a partial subsidy provides

[2] For the definition of the subsidy, we follow the paper of Dupas (2014): "Short-run subsidies and long-run adoption of new health products: Evidence from a field experiment", who defined subsidies for a good where the price varied between 100% and 40%.

farmers with the same information and an opportunity to acquire three tree seedlings by making a bid in an auction. Previous research found that generating market access for socially desirable technologies that require maintenance resulted in low adoption levels due to demand being highly price-elastic (Cohen and Dupas 2010; Bensch and Peters 2017). With regards to native trees, scholars have shown that there is some market demand for tree seedlings (Rist et al. 2010; Teuscher et al. 2015; Slingerland et al. 2019). On the other hand, Jack (2013a) and Rudolf et al. (2020) have shown that subsidies on trees are associated with significant increases in adoption rates. As markets for native tree seedlings are limited with rather high prices in the research area, we expect that farmers, in general, are more likely to offer a price (=WTP) for the native tree seedlings that is rather low leading to an overall low number of farmers being able to actually buy the tree seedlings. In the subsidy treatment, every farmer receives a bundle of native tree seedlings regardless of their WTP. Accordingly, we expect that in the subsidy treatment, farmers will plant most of the tree seedlings received for free. In contrast, in the price treatment, we expect that farmers' WTP is often too low to acquire the tree seedlings, resulting in lower adoption rates compared to the subsidy treatment.

For trees to survive and thus generate substantial environmental benefits, farmers need to invest in their maintenance. In this context, subsidies bear the risk that tree planting is adopted by farmers with lower utilities for native trees, who in the absence of immediate direct benefits, are not willing to invest in repeated maintenance activities after planting (Dupas 2014). In contrast, farmers making successful bids in the auction are likely to attach higher utilities to native trees and accordingly take care of the seedlings after planting. Hence, our first hypothesis is:

H1: Farmers in the price treatment apply more maintenance practices to their planted tree seedlings compared to farmers in the subsidy treatment.

Eventually, the environmental benefits generated depend on the total number of planted trees that survive, which is a combination of the initial rate of adoption and the tree survival rate. Thus, even if the subsidy motivates farmers to initially plant more trees compared to the price treatment, as argued above, low survival rates could potentially reverse the picture over time. If maintenance levels are indeed sufficiently low in the subsidy treatment, we expect that conditional on tree planting, tree survival rates will be lower in the subsidy treatment compared to the price treatment. Accordingly, we formulate the following second hypothesis:

H2: Six months after the intervention, the number of surviving trees conditional on having been planted is lower in the subsidy treatment compared to the price treatment.

From a policy perspective, besides the survival of the distributed trees, spurring more widespread adoption of tree planting is also critical to achieving significant environmental effects. Thus, for a policy

intervention to be effective, it is important that it does not discourage further investments into the technology. To raise interest in tree planting, we provided the same information about the benefits of native trees in both treatments as well as contact details of a nursery selling native tree seedlings. However, previous literature has shown that subsidies may negatively affect future investments due to crowding effects, e.g. price anchoring (Köszegi and Rabin 2006; Omotilewa et al. 2019). This means that farmers who receive tree seedlings for free might not be willing to pay a positive price at all for additional tree seedlings even though they decide to plant the free tree seedlings and take care of them. Accordingly, our third hypothesis is:

H3: The subsidy treatment has a negative effect on additional tree planting (beyond the three distributed trees) compared to the price treatment.

3. Empirical framework

3.1 Sampling and data collection

Our research was implemented in the lowland region of Jambi Province, where we conducted our survey in the three oil palm growing districts Muaro Jambi, Batanghari, and Sarolangun. These are the three districts in Jambi Province, where the oil palm area has expanded the most between 1995 and 2011 (Euler et al. 2016). We randomly selected 12 villages, including both local villages as well as villages established under the transmigration program. Subsequently, we randomly selected between 20 and 40 oil palm farmers per village, resulting in a total sample size of 408 farmers. Our sample includes independent oil palm farmers only. Contracts between small-scale oil palm farmers and companies that were set up during the time of the transmigration program are still common in Jambi Province today. Farmers with a contract typically have agreed to manage their oil palm plantation according to company regulations. Since this may limit their ability to make decisions regarding tree planting in their oil palm plantations, we decided to exclude them from our study. Our target to survey 40 farmers was achieved in 8 villages; in two villages we could only survey 24 farmers, and in two villages 20 farmers due to logistical problems.

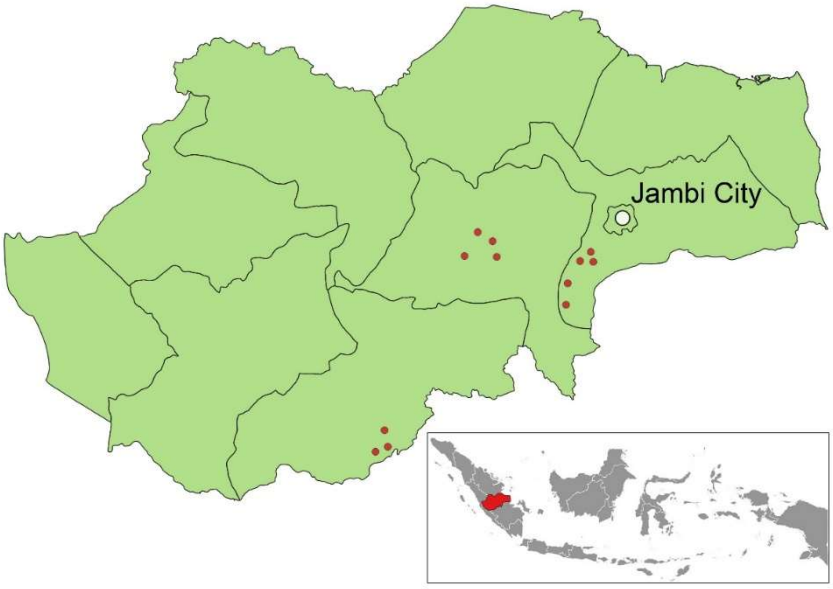

Figure 1: Research area: Jambi, Sumatra, Indonesia: The grey map in the right-hand corner shows Indonesia with Jambi Province highlighted in red. The green map shows the research area Jambi Province on Sumatra, Indonesia (The red dots mark the villages where the surveys were conducted and the white dot marks Jambi City, the capital of Jambi Province.).

Our total sample of 408 farmers was equally split between the two treatments. To reduce information spillovers, the randomization of the two treatments was done at the village level. Accordingly, six villages (204 farmers) were randomly assigned to the subsidy treatment and six villages (204 farmers) to the price treatment.

Data collection consisted of three steps. In April 2019, we conducted focus group meetings to identify native tree species preferred by farmers. During this field visit, we also pre-tested the questionnaire and the auction mechanism. From July to August 2019, we implemented the survey. Farmers were surveyed individually based on a structured questionnaire that incorporated the experiment with the respective treatment. Six months after the first survey, i.e., between January and February 2020, we visited each farmer again to conduct a follow-up survey. We asked the farmers detailed questions about what they did with the tree seedlings, where they planted them, and what type of maintenance they had given them[3]. This also included a visit to the place where each farmer stated to have planted the tree seedling(s). In the follow-up survey, we were able to reach 397 of the original 408 farmers, implying an attrition rate of 2.7 percent. Out of the 11 attritors, five are from the subsidy treatment and six from the price treatment. Attrition rates are not significantly different between the two treatments (p=0.76) and hence, attrition bias is unlikely to be an issue (Dumville et al. 2006)[4].

[3] Farmers might have adapted their behavior knowing that they take part in an experiment, which is known as the Hawthorne effect (Parsons, 1974). To perform well in the study or to meet experimenter expectations, they may plant more trees than they otherwise would have. To reduce such biases to the extent possible, we did not inform farmers during the first survey that we would return six months later.
[4] In order to understand if attrition is random or systematic and hence, if we have to include further measures, we run an attrition probit followed by a Wald test (Fitzgerald, Gottschalk and Moffitt 1998; Moffitt et al. 1999; Outes-Leon and Dercon 2008; Baulch and Quisumbing

3.2 Description of treatments

In both treatments, we offered each farmer one bundle of three native tree seedlings. Each bundle consisted of a variety of three different tree species because the overall goal of the intervention was to increase biodiversity. During the focus group meetings in April 2019, four native tree species were identified that are suitable to be planted with oil palm and highly valued by farmers. These include three fruit trees - Durian (*Durio zibethinus*), Duku (*Lansium domesticum*), and Mangosteen (*Garcinia mangostana*), and one timber tree - Meranti (*Shorea leprosula*). The four identified species were combined in four different tree bundles (Table 1) and then randomly assigned to the surveyed farmers. We varied the composition of the bundles to assess potential heterogeneity in preferences regarding tree species.

No.	Trees in the bundle	Full cost for each bundle in USD and (IDR)
1	Meranti, Duku, Mangosteen	6.09 (86,000)
2	Durian, Duku, Meranti	5.24 (74,000)
3	Meranti, Durian, Mangosteen	4.95 (70,000)
4	Durian, Duku, Mangosteen	6.09 (86,000)
Note: The full costs for each bundle consisted of the price that we had to pay for each tree seedling at the nursery in Jambi City plus an average amount per bundle of transport costs for the seedlings which consisted of fuel needed on average to reach the targeted villages, the costs for the trucks, the salary for the drivers plus per diem as well as the salary for the assistants and their per diem. The prices are shown in USD (conversion rate from June 2019) and Indonesian Rupiah (IDR).		

Table 1: Description of different tree bundles and their full costs

Both treatments consisted of two components: an information component and the distribution of seedlings. During the first component, each farmer received information about the benefits of planting native trees on their land including in oil palm plantations. We also gave each farmer an illustrated information booklet with more details on the economic and environmental benefits of native tree planting in oil palm landscapes as well as visualized instructions on how to plant and maintain the trees. During the second component, the tree bundles were offered to the farmer, with the distribution mechanism varying depending on the treatment. In the first treatment, the *subsidy treatment*, each farmer was given one randomly chosen tree bundle free of charge. In the second treatment, the *price treatment*, farmers had the opportunity to place a bid for one randomly chosen tree bundle in an

2011). If attrition is non-random our results of the ITT effects might be biased. The results show that we do not have significant predictors of attrition in our baseline variables (Wald test result: p=0.5640). Hence, no further measures are applied.

auction. We chose an auction as distribution mechanism to create market access, because in the research area access to markets for native tree seedlings is virtually absent, and hence no reliable market price of seedlings is available in the villages. As an upper bound for the auction price we, therefore, used the average full costs of providing the seedlings in the villages (see table 1). Jointly with the tree seedlings, in both treatments, we provided contact details of a forestry expert at the University of Jambi, whom the farmers could contact in case of questions, and also to order more seedlings.

The auction in the price treatment was implemented using the Becker-DeGroot-Marschak (BDM) method (Becker et al. 1964). The BDM method is a single-bid auction mechanism and preference revealing (Becker et al. 1964), and hence, allows us to measure farmers' WTP for the offered tree bundle. After offering the farmer a tree bundle, we explained that the auction price varies between 0.14 USD (2,000 IDR) and the maximum price of 4.95 USD (70,000 IDR), 5.24 USD (74,000 IDR), or 6.09 USD (86,000 IDR), depending on the bundle offered to the farmer (see table 1). Price chips were drawn from a bag and increased in steps of 2,000 IDR, to cover the full range of anticipated bids. Farmers were given time to inspect the tree seedlings and carefully consider their bid, before offering a price. Once the farmer had placed his or her bid, the auction price was randomly drawn from the bag and shown to the farmer. If the farmer's bid was equal to the auction price or higher, the farmer bought the tree bundle at the auction price. If the farmer's bid was lower than the auction price, the farmer could not buy the tree bundle.

Before auctioning the tree bundle, we explained to the farmer in detail how the process of the auction works. We then conducted practice rounds, where the farmer could offer a price for a pack of pencils to make sure the farmer understood the procedure, felt comfortable, and had enough time to ask questions. In the price treatment, we paid farmers a participation fee at the beginning of the survey of either 70,000 IDR, 74,000 IDR, or 86,000 IDR, depending on the tree bundle that was assigned to them. Although we are aware that such payment may influence farmers' behavior in the auction (Camerer and Ho, 2015), we decided to make this upfront payment to reduce ethical concerns of letting farmers pay out of their pocket (Alasuutari et al. 2008). We further aimed to minimize the importance of having cash during the survey (Jack et al. 2015) allowing farmers to deduct the price of the tree bundle from the participation fee. At the beginning of the survey, the payment was framed as compensation for participation in the survey and not linked to the purchase of tree bundles in any way. It was paid out in form of a voucher to be redeemed at the local store (if applicable, the auction price of the tree bundle was deducted from the voucher).

3.3 Econometric framework

We estimate the intent-to-treat (ITT) effect of the subsidy treatment on native tree planting and tree survival, in comparison to the price treatment. The model to be estimated is specified as follows:

$$Y_{hi} = ß_0 + ß_1 T1_i + ß_2 X_{hi} + \varepsilon_{hi} \quad (1)$$

where Y_{hi} is the outcome variable, i.e., either the binary adoption decision of tree planting, the number of trees planted, or the number of trees that survived for farmer h in village i. $T1_i$ is a dummy that equals 1 if the farmer was assigned to the subsidy treatment, and 0 if the farmer was assigned to the price treatment. X_{hi} is a vector of variables containing household characteristics. ε_{hi} is a random error term clustered at village level.

The binary adoption decision of planting trees is modeled using probit regressions (Long 1997). The number of trees planted represents count data and we have 52 percent zero-valued observations. For count data, if the variance exceeds the mean, there is overdispersion, which means that the traditional Poisson model does not produce correct standard errors for each parameter estimate (Greene 2012). Our outcome variable, the number of trees planted, indicates overdispersion. To formally test for overdispersion we applied a Likelihood-ratio (LR) test following Cameron and Trivedi (1986) and Hilbe (2011). The LR test with one degree of freedom is significant, indicating that the hypothesis of no overdispersion is rejected[5]. Hence, we apply negative binomial regressions for the number of trees planted. The negative binomial regression is a Poisson-Gamma mixture model (Long and Freese 2006; Hilbe 2011), which is also recommended in the case of large shares of zero-valued observations (Bellemare and Wichman 2019).

To analyze the number of trees that are still alive after six months we applied a two-part model. In this model, the adoption decision (planting the trees or not) is modelled in a first step and the intensity decision (number of trees alive) in a second step. The two-part model was originally developed by Cragg (1971) as an extension to the tobit model to account for the mass of zeros and highly skewed positive values (Deb et al. 2014). The tobit model treats the zeros as censored values of the positive outcome, whereas zeros in the two-part model are treated as true zeros/corner solutions to a constrained utility maximization problem (Dow & Norton 2003; Humphreys 2013; Belotti 2015)). In our dataset, the zeros are true zeros as they represent a choice made by the farmer (Humphreys 2013). Hence, from this perspective, the two-part model is preferred over the tobit model. Furthermore, in contrast to the tobit model, the two-part model assumes independence of the two choices made. This assumption is less restrictive and seems plausible, given that the decision to plant is likely influenced

[5] Number of trees planted: LR test of alpha=0: chibar2(01) = 18.11; Prob >= chibar2 = 0.0000

by different factors than the decision to take care of the planted tree seedlings and hence, the number of trees still alive. Results of a Vuong test (Shiferaw 2008) confirm that the two-part model fits our data better than the tobit model (p=0.00).

For the two-step model, we use a probit model (Humphreys 2013) to estimate the binary adoption decision. For the second part of the model, the intensity decision, we had to select between a generalized linear model (GLM) and an ordinary least squares (OLS) approach. In cases where one finds evidence of heteroscedasticity in the OLS residuals on the log-scale, OLS will be biased (Manning & Mullahy 2001) and GLM is preferred. Additionally, if the OLS log-scale residuals are heavier tailed than normal we would prefer OLS for ln(y) over GLM to reduce precision losses (Manning & Mullahy 2001). Results of a White test show that we cannot reject the null hypothesis of no heteroscedasticity (p=0.48). Moreover, the kurtosis value for the number of trees planted (log-scale residuals) shows a value of 1.85. Hence, OLS is preferred for the second-stage estimation.

4. Results

4.1 Descriptive results

Panel B of table 2 presents descriptive statistics of tree planting outcomes from the follow-up survey. From the 978[6] trees distributed in our treatments, a total of 385 trees (39.35 percent) had been planted at the time of the follow-up visit[7]. From these 385 trees planted, 177 tree seedlings were planted in oil palm and rubber plantations, and on fallow land, and 206 seedlings were planted in home gardens. All 204 farmers assigned to the subsidy treatment accepted the free tree seedlings given to them. In the price treatment, 131 out of 204 farmers (i.e., 64%) made a successful bid in the auction and received the bundle of tree seedlings. Furthermore, 110 farmers (54% of those who received trees) in the subsidy treatment and 79 farmers (60% of those who received trees) in the price treatment decided to plant at least one of the trees. Panel B of table 2 shows that based on the follow-up data, a significantly larger share of farmers in the subsidy treatment (55%) planted trees compared to the price treatment (40%). Furthermore, the comparison of the two treatments shows that significantly more trees were planted in the subsidy treatment.

[6] From the original 1.005 trees 27 trees had to be deducted for the analysis because these were received by the attritors.

[7] 21.06 per cent of the trees received were planted in home gardens, 14.31 per cent were planted in oil palm plantations, 2.86 per cent were planted in rubber plantations, 0.92 per cent was planted in fallow land and 0.20 per cent was planted in other places that the farmer did not specify and hence, could not be included in the analysis. 4.30 per cent of the tree seedlings were given away as present, stolen or the farmer could not remember what happened with the tree seedlings. 22.90 per cent of the trees received by the farmers have not been planted yet but are still alive. 33.44 per cent of the trees given died before being planted.

In the price treatment, farmers had the opportunity to make a price offer for a bundle of three tree seedlings and thus revealed their WTP for that specific tree bundle. The frequency distribution of farmers' WTP is shown in figure 2.

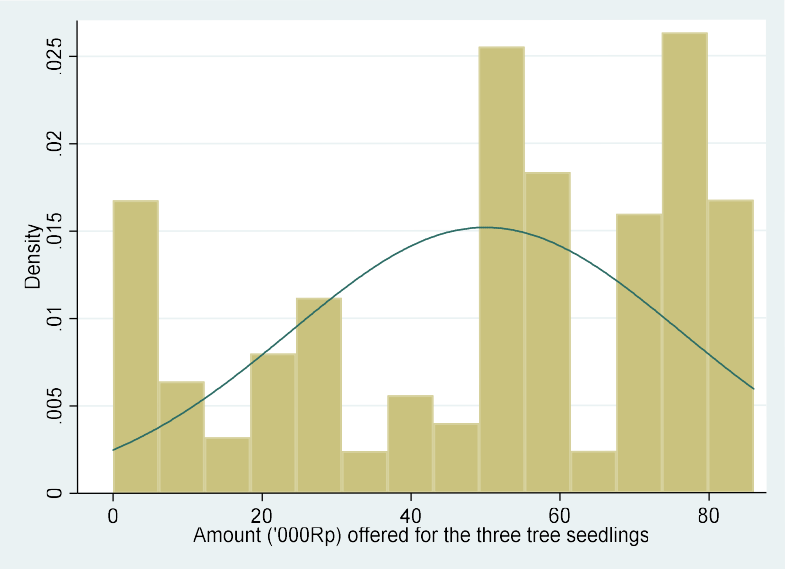

Figure 2: Histogram for the WTP of farmers in the price treatment

On average, farmers offered a price of 50.010 IDR (3,54 USD) for the bundle of three seedlings. Our data shows that the average market price of a tree seedling in the villages, as indicated by farmers in the price treatment, is 65.815 IDR (4,66 USD), which is substantially higher than the WTP for a bundle of three tree seedlings in the auction. Furthermore, around 79 percent of the farmers in the price treatment stated that it is difficult to get access to tree seedlings in their village. Although we observe substantial variation in the WTP for a bundle of tree seedlings, we did not find any significant farmer or tree bundle characteristics in our data explaining this variation.

Table 2, panel A, presents descriptive statistics of the baseline variables of our sample. We show mean estimates for the full sample (column (1)) and the two treatments (columns (2) and (3)) as well as 16 tests for mean differences (column (4)). Most mean differences tests are statistically insignificant, except for the dummy variable trees planted in oil palm in the last 12 months and the total size of the land owned, which is larger for farmers in the price treatment. Despite these significant differences in average land size, the average size of the oil palm area does not differ between the two treatments. Also, the number of trees in oil palm plantations and home gardens does not significantly differ between the treatments. Given that some imbalance can occur by chance, our randomization can be considered successful. In the econometric estimation, we include the imbalanced variables to reduce potential confounding effects.

	(1)	(2)	(3)	(4)
	Full sample	Subsidy treatment	Price treatment	Subsidy = Price
Panel A	Mean estimates			p-values
Household head characteristics				
Age of household head	50.54 (11.00)	50.54 (11.08)	50.53 (10.96)	0.995
Sex of household head (1=female)	0.06	0.07	0.05	0.32
Education of household head in years	9.53 (4.28)	9.61 (4.08)	9.45 (4.49)	0.80
Household characteristics				
Distance to Jambi City (in km)	93.57 (63.03)	89.54 (65.68)	97.60 (60.17)	0.83
Number of household members	3.80 (1.30)	3.83 (1.37)	3.76 (1.24)	0.69
Asset index[2]	1.83e-11 (0.62)	-0.04 (0.63)	0.04 (0.61)	0.39
Transmigration program (1/0) (farm level)	0.23	0.25	0.21	0.80
Savings account at a bank (1/0)	0.78	0.75	0.81	0.44
Land characteristics				
Land owned (in ha)	7.02 (7.90)	5.69 (4.93)	8.35 (9.86)	0.04**
Hectares of oil palms	4.37 (4.43)	4.05 (4.09)	4.69 (4.74)	0.44
Home garden (1/0)	0.93	0.95	0.91	0.47
Distance nearest oil palm plot to the house (in km)	3.39 (8.30)	2.49 (5.73)	4.29 (10.18)	0.32
Distance nearest oil palm plot to next market (in km)	7.46[1] (6.32)	7.11[1] (5.21)	7.81 (7.26)	0.67
Tree seedlings (baseline)				
Seedlings expensive (1/0)	0.77	0.79	0.75	0.81
Number of trees in oil palm plantations and home garden per ha	3.40 (7.45)	3.21 (8.79)	3.59 (5.82)	0.77
Trees planted in oil palm in the last 12 months (1/0)	0.29	0.25	0.33	0.02**
N (baseline)	408	204	204	
Panel B				
Tree planting outcomes				
Share of respondents that planted tree seedlings in home	0.48 (0.50)	0.55 (0.50)	0.40 (0.49)	0.00***

gardens, oil palm, rubber, and fallow land				
Number of tree seedlings planted in home gardens, oil palm, rubber, and fallow land	0.97 (1.16)	1.15 (1.18)	0.80 (1.12)	0.00***
Number of tree seedlings planted in oil palm, rubber and fallow land	0.45 (0.95)	0.57 (1.04)	0.32 (0.83)	0.08*
N (follow-up)	397	199	198	

Columns (1) to (3) show mean estimates with the respective standard deviations in parentheses. Column (4) shows p-values for mean difference tests that were conducted with linear regression models (negative binomial models in case of the tree planting outcome variables) with standard errors clustered at the village level.
** p < 0.1, ** p < 0.05, *** p < 0.01*
[1]: 3 missing observations
[2]: The asset index was constructed based on factor analysis (Sahn and Stifel (2003)). The following assets (dummy variables) are included: trailer cart, irrigation pipe, stereo system, computer, washing machine, fan, car or truck, and radio.

Table 2: Descriptive statistics

4.2 Adoption and tree survival

Table 3 shows the ITT effects on tree planting and tree survival outcomes. Columns (1) and (2) show the effects on the adoption decision with and without control variables. Columns (2) and (3) show the effects on the number of trees planted[8] with and without control variables. We find that being in the subsidy treatment increases the probability of planting trees by 17 percentage points, compared to farmers in the price treatment (column (2)). Overall, farmers in the subsidy treatment planted on average 0.46 trees more than farmers in the price treatment (column (4)). These results show that the subsidy treatment, as expected, has a positive effect on tree planting decisions.

Number of trees planted in home gardens, oil palm, rubber, and fallow land	Adoption decision to plant at least one tree seedling (0/1)	Adoption decision to plant at least one tree seedling (0/1)	Number of trees planted	Number of trees planted	Number of trees that survived	Number of trees that survived conditional on planting at least one tree seedling
	(1)	(2)	(3)	(4)	(5)	(6)
Subsidy treatment	0.15*** (0.05)	0.17*** (0.05)	0.36*** (0.12)	0.46*** (0.13)	0.38*** (0.12)	0.06 (0.11)
Control variables included	no	yes	no	yes	yes	yes
N	397	397	397	397	397	189

Column (1) shows average marginal effects (AME) for the adoption decision without control variables; column (2) shows AME for the adoption decision with control variables; column (3) reports AME for the number of trees planted without control variables; column (4) reports AME for the number of trees planted with control variables; column (5) reports AME for the unconditional number of trees alive with control variables; column (6) shows AME for the number of trees alive conditional on being planted with control variables; For columns (1) and (2) probit models have been applied, for columns (3), (4). And (5) negative binomial regressions, and for column (6) a two-step model. Control variables include age, education, whether the farmer was part of the transmigrant program, a dummy if the farmer has planted trees in his/her oil palm plantation in the last 12 months, the number of trees in oil palm plantation, and home garden per ha, land owned (in ha), the distance from the nearest oil palm plantation to the house of the farmer (in km), and three different tree bundles offered;

Standard errors clustered at village level in parentheses;

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

The full model for the results for tree seedlings that were planted in home gardens, oil palm, rubber, and fallow land can be found in the appendix (table A1).

The full model for the results for tree seedlings that were only planted in oil palm and rubber plantations as well as on fallow land and can be found in the appendix (table A2).

The full model for the number of tree seedlings that were planted and are alive can be found in the appendix (tables A3).

Table 3: ITT effects of trees planted and trees that are still alive for trees planted in home gardens, oil palm, rubber, and fallow land

Native tree planting practices can only contribute positive environmental effects if the trees survive in the long run. Testing our second hypothesis, we analyze ITT effects on the number of trees that survived. Results show that when considering the full sample we find a significant effect showing that in the subsidy treatment more trees survived on average, compared to the price treatment (table 3 column (5)). This is due to the fact that a much larger share of farmers in the subsidy treatment planted the tree seedlings. If we estimate the number of trees that survive conditional on the adoption of tree planting, we do not find significant differences between the two treatments (table 3 column (6)). Accordingly, our results do not support our second hypothesis (H2) that the subsidy treatment will result in lower tree survival. As a robustness check, we estimate the models again taking only tree planting in oil palm, rubber plantations, and on fallow land into account (excluding tree planting in home gardens). The results are in line with the results presented here (see appendix tables A2 and A4).

In absolute numbers though, more tree seedlings planted in the subsidy treatment have not survived compared to the price treatment as shown by the results presented before. Comparing maintenance practices in table 4 shows that farmers in the price treatment applied significantly more maintenance practices (watering, application of fertilizer, and pesticide application) right after planting as well as in the six months after planting until our second interview with the farmers which supports our first hypothesis. Hence, the farmers in the price treatment showed a higher utility for the tree seedlings after planting them compared to the farmers in the subsidy treatment.

Only for farmers that planted at least on tree seedling	**Full sample**	**Subsidy treatment (T1)**	**Price treatment (T2)**	**T1 = T2**
	(1)	(2)	(3)	(4)
Number of maintenance practices at planting (watering, fertilizer, pesticides)	1.59 (0.67)	1.54 (0.70)	1.67 (0.63)	0.075*
Number of maintenance practices until second survey after planting (watering, fertilizer, pesticides)	1.10 (0.79)	1.01 (0.81)	1.22 (0.76)	0.092*
N	189	110	79	189

Columns (1) to (3) show mean estimates with the respective standard deviations in parentheses. Column (4) shows p-values for mean difference tests that were conducted with linear regression models with standard errors clustered at the village level.
* p < 0.1, ** p < 0.05, *** p < 0.01

Table 4: Comparison of maintenance practices applied by the farmers after planting at least one tree seedling

4.3 Additional planting efforts

From a policy perspective, it is important to ensure that subsidies do not crowd out further investments into the promoted technology. We, therefore, look into additional planting efforts that took place during our first and second visit to the farmers. In our data, we observe that 25 farmers in the price treatment obtained a total of 674 tree seedlings on their own and planted them. In the subsidy treatment, 16 farmers obtained a total of 61 tree seedlings on their own and planted them. Table 5 presents results from probit and negative binomial regressions on the binary decision to obtain additional tree seedlings and the number of additional tree seedlings planted. The results show that the subsidy treatment is negatively related to additional tree planting, but the coefficients are not statistically significant. Farmers in the subsidy treatment tend to be five percentage points less likely to engage in additional tree planting efforts, and on average, plant 3.26 trees less than farmers in the price treatment. Although the effect size of 3.26 is relatively large, it is not significant. Overall, our data

do not provide strong support for our third hypothesis (H3) that the subsidy is associated with crowding out investments in tree planting.

Additional tree seedlings obtained and planted in home gardens, oil palm, rubber, and fallow land	Adoption decision to obtain more tree seedlings	Adoption decision to obtain more tree seedlings	Number of trees planted that were obtained by farmers	Number of trees planted that were obtained by farmers
	(1)	(2)	(3)	(4)
Subsidy treatment	-0.04 (0.03)	-0.03 (0.02)	-4.46 (3.10)	-3.26 (3.75)
Control variables included	no	yes	no	yes
N	397	397	397	397

Column (1) and shows AME for the adoption decision to obtain tree seedlings without control variables; column (2) shows AME for the adoption decision to obtain tree seedlings with control variables; column (3) reports the AME for the number of trees obtained and planted without control variables; column (4) also reports the AME for the number of tree seedlings obtained and planted with control variables. A negative binomial regression was applied.
Control variables include age, education, whether the farmer was part of the transmigrant program, a dummy if the farmer has planted trees in his/her oil palm plantation in the last 12 months, the number of trees in oil palm plantations per ha, land owned (in ha), the distance from the nearest oil palm plantation to the house of the farmer (in km), and three different tree bundles offered.
Standard errors clustered at village level in parentheses;
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
The full model can be found in the appendix (table A5).

Table 5: ITT effects of trees planted that were obtained by farmers themselves and planted in home gardens, oil palm, rubber, and fallow land

5. Discussion and conclusion

In this article, we look at the effects of two policy interventions on native tree planting, tree survival, and additional planting efforts. In the subsidy treatment, farmers are provided with information on native tree planting and a bundle of three native tree seedlings for free. The effects of the subsidy treatment are compared to the price treatment, in which farmers receive the same information as well as market access to tree seedlings and the opportunity to offer a price for a bundle of three tree seedlings under an auction mechanism. Native tree planting is a maintenance-intense agricultural technology that generates positive external effects for the environment. Due to the positive externalities market demand for tree seedlings might be lower compared to receiving tree seedlings for free, hence, a subsidy may be justified from a societal perspective, but may also raise concerns over crowding out further investments into tree planting. Our results reveal that tree planting intensity is higher in the subsidy treatment than in the price treatment which is what we expected based on the literature. For the survival rates, we do not find a significant difference between the two treatments. Yet, we find that in absolute numbers more tree seedlings did not survive in the subsidy treatment compared to the price treatment and we find a higher number of maintenance practices applied

among the farmers in the price treatment. Farmers in the subsidy treatment tend to engage less in additional planting activities compared to farmers in the price treatment, although the differences are not statistically significant.

Thus, our results underline the positive role that a subsidy can play in the promotion of a socially desirable good. The first hypothesis that farmers in the price treatment apply more maintenance practices to their planted tree seedlings compared to farmers in the subsidy treatment finds support in our data. Our second hypothesis that the full subsidy results in lower tree survival finds no support in our data. Even though a higher number of trees planted at first in the subsidy treatment, the number of trees surviving after six months is not significantly higher in the subsidy treatment compared to the price treatment which shows that in absolute terms more tree seedlings planted in the subsidy treatment did not survive. Our third hypothesis only finds some tentative support in our data: additional tree planting activities seem to be lower in the subsidy treatment than in the price treatment. Yet, overall, additional planting efforts were low in both treatments. Limited market access to seed material with high prices, in general, could have contributed to low additional planting efforts. For the farmers in the price treatment, this finds support in our data. The average WTP for the three tree seedlings in the price treatment was substantially below the average reported market price of tree seedlings faced by farmers. In addition, many farmers mentioned that access to seedlings in their villages was difficult.

Considering these results, we refrain from a policy recommendation favoring one approach over another. It rather seems that a policy mix consisting of the distribution of subsidized tree seedlings in combination with better market access is likely to be more effective and address multiple barriers to native tree planting. Through the distribution of free tree seedlings, we were able to reach a larger number of farmers and convince them to experiment with tree planting, than if they had to pay for the tree seedlings. For our sub-sample of farmers exposed to the price treatment, we could show that the average WTP for tree seedlings is below the average market price faced by farmers. Subsidies may thus be critical to overcome the gap between farmers' WTP for native tree seedlings and actual market prices. Also, in-kind subsidies offer the opportunity to influence which tree species farmers plant and accordingly the extent of biodiversity and associated environmental effects. Of course, farmers' preferences for different tree species (Van Noordwijk 2011), local knowledge on tree characteristics, the abundance and spatial distribution of species, and the variety of ecological and economic functions provided by different species need to be taken into account (Chazdon 2008).

It should also be noted that our results reflect short-term effects measured six months after the implementation of the treatments. This time span is likely relevant to capture planting of the distributed trees and initial evidence on tree survival. Yet, it may be too short to adequately reflect

further investments in tree planting, especially for those farmers who had no prior experience with native tree planting. Possibly farmers are experimenting with the technology and gathering experience to make more informed decisions later. In this context, the overall positive effect of both treatments on tree survival is encouraging, since it implies that farmers engage in maintenance, even though free seedlings are not necessarily targeted at those farmers with the highest WTP for tree seedlings.

Finally, market access to high-quality tree seedlings is essential in the villages. This could be achieved e.g. through the support of local nurseries for native tree species. Increasing local supply of high-quality seedlings may lead to lower market prices for native tree seedlings, thus reducing the gap between farmers' WTP and actual market prices faced by farmers in the villages. From the demand side, farmers' WTP for native tree seedlings may also increase as they gain more knowledge and experience the benefits of tree planting first-hand. This could be supported by information and training provided to farmers. That there is indeed demand for such knowledge is supported by our data, since 90 percent of the farmers in our sample stated that there is not enough information about native tree planting available in their villages.

After our first intervention, we interviewed the farmers again after six months. While this offers a good time span to capture some initial evidence on tree planting and tree survival, it is not enough time to fully reflect on further investments into tree seedlings by the farmers. This also takes time since there were many farmers that had no prior experience with tree planting at all. In addition, native tree planting can support income diversification as mentioned before. In order to measure such effects a longer time span is needed between the intervention and a second visit to measure and understand the income diversification strategies of the farmers. Revisiting the farmers again after several years after the initial intervention might allow to get a fuller picture. Finally, we did not assess any ecological effects that the trees planted by the farmers might have. Future research might therefore want to build on this work by planting different numbers of native trees in farm landscapes to better understand the ecological effects generated. In doing so, it can further be assessed whether the number of trees given to a farmer affects the farmers' decisions on where to plant trees and how many.

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Appendix

Number of trees planted (three tree seedlings) in home gardens, oil palm, rubber, and fallow land	Adoption decision	Adoption decision	Number of trees planted	Number of trees planted
	(1)	(2)	(3)	(4)
T1	0.15*** (0.05)	0.17*** (0.05)	0.36*** (0.12)	0.46*** (0.13)
Age		0.002 (0.003)		0.005 (0.005)
Education in years		0.0006 (0.005)		0.0007 (0.01)
Transmigrant program (1/0)		-0.10 (0.06)		-0.43*** (0.14)
Trees planted in oil palm in the last 12 months (1/0)		0.06 (0.06)		0.23* (0.14)
Number of trees in oil palm plantation and home garden per ha		0.003 (0.004)		0.003 (0.006)
Land owned (in ha)		0.0006 (0.004)		0.004 (0.009)
Distance nearest oil palm plantation to the house (in km)		0.003 (0.002)		0.009 (0.005)
Tree bundle 1 (Duku, Meranti, Mangosteen) (1/0)		0.18*** (0.04)		0.42*** (0.15)
Tree bundle 2 (Durian, Duku, Meranti) (1/0)		0.18*** (0.06)		0.38*** (0.14)
Tree bundle 4 (Durian, Meranti, Mangosteen) (1/0)		-0.05 (0.05)		-0.03 (0.16)
Control variables included	no	yes	no	yes
N	397	397	397	397

Column (1) shows AME for the adoption decision with control variables; column (2) shows AME for the adoption decision without control variables; column (3) reports AME for the number of trees planted with control variables; column (4) shows AME for the number of trees planted without control variables;
Control variables include age, education, whether the farmer was part of the transmigrant program, a dummy if the farmer has planted trees in his/her oil palm plantation in the last 12 months, the number of trees in oil palm plantations per ha, land owned (in ha), the distance from the nearest oil palm plantation to the house of the farmer (in km), and three different tree bundles offered;
Standard errors clustered at village level in parentheses;
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A1: ITT effects of planting trees in home gardens, oil palm, rubber, and fallow land

Number of trees planted (three tree seedlings) in oil palm and rubber, and fallow land	Adoption decision	Adoption decision	Number of trees planted	Number of trees planted
	(1)	(2)	(3)	(4)
T1	0.11* (0.06)	0.12*** (0.05)	0.26 (0.16)	0.32*** (0.12)
Age		0.001 (0.001)		0.0009 (0.003)
Education in years		0.005 (0.006)		0.01 (0.01)
Transmigrant program (1/0)		-0.15*** (0.05)		-0.55*** (0.19)
Trees planted in oil palm in the last 12 months (1/0)		0.06 (0.04)		0.25*** (0.08)
Number of trees in oil palm plantations per ha		0.02** (0.007)		0.01 (0.01)
Land owned (in ha)		-0.0004 (0.002)		-0.001 (0.004)
Distance nearest oil palm plantation to the house (in km)		0.0009 (0.002)		0.002 (0.005)
Tree bundle 1 (Duku, Meranti, Mangosteen) (1/0)		-0.08 (0.05)		-0.10 (0.17)
Tree bundle 2 (Durian, Duku, Meranti) (1/0)		0.05 (0.05)		0.22 (0.16)
Tree bundle 4 (Durian, Meranti, Mangosteen) (1/0)		-0.22*** (0.05)		-0.41*** (0.16)
Control variables included	no	yes	no	yes
N	397	397	397	397

Column (1) shows AME for the adoption decision with control variables; column (2) shows AME for the adoption decision without control variables; column (3) reports AME for the number of trees planted with control variables; column (4) shows AME for the number of trees planted without control variables;
Control variables include age, education, whether the farmer was part of the transmigrant program, a dummy if the farmer has planted trees in his/her oil palm plantation in the last 12 months, the number of trees in oil palm plantations per ha, land owned (in ha), the distance from the nearest oil palm plantation to the house of the farmer (in km), and three different tree bundles offered;
Standard errors clustered at village level in parentheses;
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A2: ITT effects of planting trees in oil palm and rubber plantations, and fallow land

Number of trees that survived (three tree seedlings) planted in home gardens, oil palm, rubber, and fallow land	Adoption decision Pr(Y>0|X)	Intensity decision E(Y|X, Y>0)	Overall E(Y|X)
	(1)	(2)	(3)
T1	0.17*** (0.05)	0.06 (0.11)	0.38*** (0.12)
Age	0.002 (0.003)	-0.003 (0.007)	0.002 (0.006)
Education in years	0.0006 (0.005)	0.003 (0.01)	-0.001 (0.02)
Transmigrant program (1/0)	-0.10 (0.06)	-0.11 (0.18)	-0.23 (0.16)
Trees planted in oil palm in the last 12 months (1/0)	0.06 (0.06)	0.05 (0.11)	0.16 (0.14)
Number of trees in oil palm plantation and home garden per ha	0.003 (0.004)	0.0008 (0.006)	0.01 (0.01)
Land owned (in ha)	0.0006 (0.004)	0.003 (0.02)	0.006 (0.01)
Distance nearest oil palm plantation to the house (in km)	0.003 (0.002)	0.005 (0.004)	0.01 (0.008)
Tree bundle 1 (Duku, Meranti, Mangosteen) (1/0)	0.18*** (0.04)	0.43*** (0.16)	0.62*** (0.16)
Tree bundle 2 (Durian, Duku, Meranti) (1/0)	0.18*** (0.06)	0.18 (0.15)	0.42** (0.17)
Tree bundle 4 (Durian, Meranti, Mangosteen) (1/0)	-0.05 (0.05)	0.50*** (0.18)	0.20 (0.19)
N	397	189	397

Column (1) shows AME for the adoption decision with control variables; column (2) shows AME for the number of trees alive conditional on being planted with control variables; column (3) reports AME for the unconditional number of trees alive with control variables;
Control variables include age, education, whether the farmer was part of the transmigrant program, a dummy if the farmer has planted trees in his/her oil palm plantation in the last 12 months, the number of trees in oil palm plantation and home garden per ha, land owned (in ha), the distance from the nearest oil palm plantation to the house of the farmer (in km), and three different tree bundles offered;
Standard errors clustered at village level in parentheses;
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

To understand the adoption and intensity decision of the number of trees that are still alive after six months we applied a two-part model. In this model, the adoption decision (planting the trees or not) is modeled in a first step and in a second step the intensity decision (number of trees alive).
The two-part model was originally developed by Cragg (1971) as an extension to the tobit model to account for the mass of zeros and highly skewed positive values (Deb et al. 2014).
The tobit model treats the zeros as censored values of the positive outcome whereas zeros in the two-part model are treated as true zeros/corner solutions to a constrained utility maximization problem (Dow & Norton 2003; Humphreys 2013; Belotti 2015) because we cannot observe a negative amount of trees planted (Dow & Norton 2003). In our dataset, the zeros are true zeros as they represent a choice made by each respondent in the survey (Humphreys 2013). Hence, from this perspective, the two-part model is preferred over the tobit model. Furthermore, the tobit model assumes that the two choices made by each respondent are not sequential. In comparison to that the two-part model assumes independence of the two choices made. The assumption that the two choices aren't independent of each other is quite restrictive. It is quite

reasonable to assume that the decision to plant or not to plant is different from the one that determines the decision on maintaining the planted tree seedlings and the number of trees still alive.
We conducted a Vuong Test to understand which of the two models fits our data better (Shiferaw 2008). A Vuong test is applied here because the two-part model is not nested in the tobit model. Results show that the two-part model fits our data better than the tobit model (p=0.00).
For the two-step model, we selected a probit model (Humphreys 2013) for modeling the binary adoption decision. For the second part of the model, the intensity decision, we had to select between a generalized linear model (GLM) and an ordinary least squares (OLS) approach. In cases where one finds evidence of heteroscedasticity in the OLS residuals on the log-scale, OLS will be biased (Manning & Mullahy 2001) and GLM is preferred. Additionally, if the OLS log-scale residuals are heavier tailed than normal we would prefer OLS for ln(y) over GLM to reduce precision losses (Manning & Mullahy 2001).
Our data shows that we prefer OLS over the GLM model as we firstly, don't have heteroscedasticity present (p=0.48) which was tested with a White test. Secondly, the kurtosis value for the number of trees planted (log-scale residuals) shows a value of 1.85. Hence, we use an OLS for ln(y).

Table A3: ITT effects for the number of trees alive (three tree seedlings) for trees planted in home gardens, oil palm, rubber, and fallow land

Number of trees that survived (three tree seedlings) planted in oil palm, rubber, and fallow land	Adoption decision Pr(Y>0|X)	Intensity decision E(Y|X, Y>0)	Overall E(Y|X)
	(1)	(2)	(3)
T1	0.12*** (0.05)	0.03 (0.23)	0.24*** (0.09)
Age	0.001 (0.001)	-0.001 (0.01)	0.001 (0.005)
Education in years	0.005 (0.006)	-0.003 (0.02)	0.007 (0.01)
Transmigrant program (1/0)	-0.15*** (0.05)	-0.51 (0.33)	-0.40*** (0.13)
Trees planted in oil palm in the last 12 months (1/0)	0.06 (0.04)	0.02 (0.22)	0.20* (0.11)
Number of trees in oil palm plantation and home garden per ha	0.02** (0.007)	-0.0005 (0.004)	0.01 (0.008)
Land owned (in ha)	-0.0004 (0.002)	0.04** (0.02)	0.007 (0.007)
Distance nearest oil palm plantation to the house (in km)	0.0009 (0.002)	-0.03 (0.04)	-0.002 (0.008)
Tree bundle 1 (Duku, Meranti, Mangosteen) (1/0)	-0.08 (0.05)	0.52** (0.22)	-0.02 (0.14)
Tree bundle 2 (Durian, Duku, Meranti) (1/0)	0.05 (0.05)	0.57* (0.29)	0.26** (0.12)
Tree bundle 4 (Durian, Meranti, Mangosteen) (1/0)	-0.22*** (0.05)	0.59 (0.49)	-0.19 (0.15)
N	397	84	397

Column (1) shows AME for the adoption decision with control variables; column (2) shows AME for the number of trees alive conditional on being planted with control variables; column (3) reports AME for the unconditional number of trees alive with control variables;
Control variables include age, education, whether the farmer was part of the transmigrant program, a dummy if the farmer has planted trees in his/her oil palm plantation in the last 12 months, the number of trees in oil palm plantation and home garden per ha, land owned (in ha), the distance from the nearest oil palm plantation to the house of the farmer (in km), and three different tree bundles offered;
Standard errors clustered at village level in parentheses;
* *p < 0.1,* ** *p < 0.05,* *** *p < 0.01*

Table A4: ITT effects for the number of trees alive (three tree seedlings) for trees planted in oil palm, rubber, and fallow land

Additional tree seedlings obtained and planted in home gardens, oil palm, rubber, and fallow land	Adoption decision	Adoption decision	Number of trees planted	Number of trees planted
	(1)	(2)	(3)	(4)
T1	-0.04 (0.03)	-0.03 (0.02)	-4.46 (3.10)	-3.26 (3.75)
Age		-0.003* (0.002)		-0.07 (0.10)
Education in years		0.008** (0.004)		0.34 (0.46)
Transmigrant program (1/0)		0.01 (0.03)		-0.19 (1.08)
Trees planted in oil palm in the last 12 months (1/0)		0.05 (0.03)		1.33 (1.94)
Number of trees in oil palm plantation and home garden per ha		-0.002 (0.003)		-0.07 (0.06)
Land owned (in ha)		0.002 (0.002)		0.12 (0.17)
Distance nearest oil palm plantation to the house (in km)		-0.004** (0.001)		0.10 (0.28)
Tree bundle 1 (Duku, Meranti, Mangosteen) (1/0)		-0.04 (0.04)		-3.07 (4.34)
Tree bundle 2 (Durian, Duku, Meranti) (1/0)		-0.06 (0.04)		0.02 (1.24)
Tree bundle 4 (Durian, Meranti, Mangosteen) (1/0)		-0.02 (0.04)		0.07 (1.45)
Control variables included	no	yes	no	yes
N	397	397	397	397

Column (1) reports the AME for the adoption decision to obtain tree seedlings without control variables; column (2) also reports AME for the adoption decision to obtain tree seedlings but with control variables; column (3) shows AME for the number of additional tree seedlings planted without control variables; column (4) reports the AME for the number of additional tree seedlings planted with control variables included. A negative binomial regression was applied.
Control variables include age, education, whether the farmer was part of the transmigrant program, a dummy if the farmer has planted trees in his/her oil palm plantation in the last 12 months, the number of trees in oil palm plantations per ha, land owned (in ha), the distance from the nearest oil palm plantation to the house of the farmer (in km), and three different tree bundles offered;
Standard errors clustered at village level in parentheses;
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A5: ITT effects for additionally obtained tree seedlings planted in home gardens, oil palm, rubber, and fallow land