Promoting sustainable land use choices in Indonesia
-
experimental evidence on the role of changing mindsets and structural barriers

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EFForTS discussion paper series Nr. 25

Romero, Miriam; Wollni, Meike; Rudolf, Katrin; Asnawi, Rosyani; Irawan, Bambang: Promoting sustainable land use choices in Indonesia :experimental evidence on the role of changing mindsets and structural barriers
Göttingen : GOEDOC, Dokumenten- und Publikationsserver der Georg-August-Universität, 2019
(EFForTS discussion paper series 25)

Bibliographische Information der Deutschen Nationalbibliothek

Die Deutsche Nationalbibliothek verzeichnet diese Publikation in der Deutschen Nationalbibliographie; detaillierte bibliographische Daten sind im Internet über <http://dnb.dnb.de> abrufbar.

Erschienen in der Reihe
EFForTS discussion paper series

ISSN: 2197-6244

Herausgeber der Reihe
SFB 990 EFForTS, Ecological and Socioeconomic Functions of Tropical Lowland Rainforest Transformation Systems (Sumatra, Indonesien) - Ökologische und sozioökonomische Funktionen tropischer Tieflandregenwald-Transformationssysteme (Sumatra, Indonesien)

Georg-August-Universität Göttingen
Johann-Friedrich-Blumenbach Institut für Zoologie und Anthropologie, Fakultät für Biologie und Psychologie

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March 2019

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This publication was funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) – project number 192626868 – in the framework of the collaborative German-Indonesian research project CRC 990 (SFB): "EFForTS, Ecological and Socioeconomic Functions of Tropical Lowland Rainforest Transformation Systems (Sumatra, Indonesia)"

https://www.uni-goettingen.de/de/about+us/413417.html

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ISSN: 2197-6244

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Promoting sustainable land use choices in Indonesia: experimental evidence on the role of changing mindsets and structural barriers

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Abstract

This study evaluates the effects of two environmental policy instruments on the adoption of native tree planting in oil palm plantations. The first instrument is an information campaign on tree planting in oil palm. The second instrument combines the information campaign with a structural intervention that provides native tree seedlings for free. We implemented a randomized controlled trial in oil palm growing villages in Jambi, Indonesia. Our study addresses the underlying mechanisms of behavioral change, by investigating how the policy instruments shape farmers' perceptions, intentions and actual adoption decisions. The results show that information campaigns and structural interventions can motivate tree planting among smallholder oil palm farmers in Indonesia. While both treatments have a positive and significant effect, the intervention combining information with seedling provision leads to significantly higher adoption rates, indicating that overcoming structural barriers is critical. While changes in perceptions and intentions fully mediate the effect of the information campaign on adoption, they can only partially explain the effect of the combined intervention. Thus, to promote a transition towards more sustainable development pathways, facilitating easy access to critical inputs may be key to motivate adoption among large numbers of potential users.

Keywords: tree-planting; oil palm; intentions; mediation; Asia

1 Introduction

In many tropical regions land conversion from tropical rainforest and other diverse and complex land-use systems into monoculture plantations is progressing rapidly. In Southeast Asia for example, oil palm cultivation is expanding at the cost of tropical lowland rainforest and traditional land use systems, like rubber agroforest, leading to the homogenization of landscapes (Carter *et al.*, 2007; Burgess *et al.*, 2012; Corley and Tinker, 2016). In Indonesia, the area cultivated with oil palm increased 106 fold to about 9 million hectares between 1961 and 2016 (FAOSTAT, 2018) and current investment plans of the government foresee further expansion (Coordinating Ministry of Economic Affairs, 2011). Land conversion towards oil palm is increasingly driven by independent smallholder farmers, to whom oil palm has brought increases in welfare and food security (Euler *et al.*, 2015). However, the conversion of land towards homogenous structures leads to the degradation of important ecosystem functions and an unprecedented loss of tropical biodiversity (Foley *et al.*, 2005; Fitzherbert *et al.*, 2008).

Identifying more biodiversity-friendly oil palm management options is therefore considered critical to reconcile economic and ecological functions in tropical lowland regions. Recent research has shown that biodiversity enrichment can restore important ecosystem functions in monoculture systems (Klasen *et al.*, 2016; Teuscher *et al.*, 2016).[1] Biodiversity enrichment refers to the integration of native tree species in existing oil palm plantations and has been shown to increase abundance and diversity of birds and invertebrate communities at the plantation scale (Teuscher et al. 2016; Teuscher et al. 2015). While these positive externalities accrue to society at large, potential costs of lower oil palm yields or revenues are borne by the farmer. On the other hand, lower oil palm yields may be compensated for by benefits derived from the trees, including timber and fruits (Teuscher *et al.*, 2015).

Only few studies have examined which policy instruments effectively change behavior towards tree planting among landholders in developing countries. Given the positive externalities generated by trees, most of the experimental studies focus on the effects of Payments for Ecosystem Services on tree planting (Leimona, Joshi and van Noordwijk, 2009; Cole, Holl and Zahawi, 2010; Jack *et al.*, 2013). These studies thus only shed light on the role of financial rewards, whereas evidence on other policy instruments is scarce. However, as experimental studies on agricultural technology adoption have shown, alternative instruments like information and input provision can be important especially during early stages of technology diffusion (Carter, Laajaj and Yang, 2013; Duflo, Kremer and Robinson, 2011).

Furthermore, there is a lack of research on the underlying mechanisms driving observed changes in behavior. Previous research has provided descriptive evidence for the link between attitudes, beliefs and tree planting behavior. Meijer et al. (2015) find that positive attitudes and intentions are associated with a higher probability of actual tree planting among Malawian farmers. Zubair & Garforth (2006) and Ndayambaje et al. (2012) provide evidence that tree planting decisions in Pakistan and Rwanda are driven by expected economic gains, rather than by perceived environmental benefits. These studies are however based on cross-

[1] Earlier research on biodiversity conservation in oil palm plantations also shows that the management of ground vegetation, conservation of forest fragments inside the plantation or having forest at the edge of the plantation have positive effects on species richness (Fitzherbert *et al.*, 2008; Koh and Wilcove, 2008; Edwards *et al.*, 2010; Azhar *et al.*, 2015).

sectional data and thus cannot derive conclusions about the drivers of attitudinal change and the association between attitudinal and behavioral change.

The current study aims to fill these research gaps by evaluating the impact of two policy interventions on perceptions towards tree planting, intention to plant trees and actual tree planting behavior. The first intervention consists of an information campaign that aims at filling knowledge gaps and changing mindsets of farmers. The second intervention combines the information campaign with the provision of native tree seedlings to farmers, thereby addressing structural barriers of missing seed markets. With our study we contribute to the scarce experimental literature field-testing the effects of non-monetary policy instruments on actual behavior. Our main contribution is that we address the underlying mechanisms of behavioral change by investigating how the policy instruments shape farmers' perceptions, intentions and actual adoption decisions. To evaluate these policy instruments, we implemented a randomized controlled trial in oil palm growing villages in Jambi province, Indonesia. Jambi is a biodiversity hotspot and characterized by rapid expansion of intensively managed oil palm plantations, which is to a large extent driven by independent smallholder farmers (Gatto *et al.*, 2017).

2 Conceptual framework

Conversion to oil palm monoculture plantations is mainly driven by profitability considerations (Clough *et al.*, 2016). Thus, to promote more biodiversity-friendly land use systems, it seems straightforward to provide economic incentives that shift relative profitability (Table 1). This can be achieved, e.g., through payments for ecosystem services or subsidies for certain land-use types. The challenge is, however, that the profitability of tropical cash crops is high, thus requiring substantial funds in order to achieve a tangible impact (Butler, Koh and Ghazoul, 2009). In addition, palm oil prices are subject to fluctuations in world markets – which makes setting adequate incentives for conservation difficult. Due to the high priority given to profitability considerations, financial incentives and compensation will most likely be an important component in a toolbox of incentive mechanisms to achieve more sustainable land use. Nonetheless, given the challenges, it is critical to consider the role of other mechanisms as well.

Table 1 Policy instruments to change behavior

Mechanism	**Instruments**	**Examples**
Shifting relative profitability	Provide financial rewards and compensation	PES, subsidies for diverse land-use types, certification and price premiums
Changing mindsets	Raise awareness, provide how-to and principles knowledge, create social consensus	Information campaigns, tv and radio, extension
Overcoming structural barriers	Facilitate access to resources	Provision of seed material, technical assistance, credit for conservation activities

Studies investigating pro-environmental behavior have shown that it is determined by intrinsic factors (e.g. motivations, moral values, attitudes) and by the external environment in which the behavior is performed (Steg *et al.*, 2014). Thus, changing mindsets and overcoming structural barriers can be critical components of a strategy to induce more environmentally friendly behavior (Table 1). According to socio-psychological theory, the adoption decision is a cognitive process shaped by knowledge, information exposure and contextual factors (Ajzen, 1991; Steg *et al.*, 2014). Social-psychology theories suggest that the antecedent knowledge an individual has about the benefits, use, and cost of a technology shape perceptions and intentions and eventually drive adoption (Rogers, 1983; Sood *et al.*, 2004; Hansson, Ferguson and Olofsson, 2012; Ndayambaje, Heijman and Mohren, 2012; Klöckner, 2013; Meijer *et al.*, 2015; Campos *et al.*, 2017). Thus, informing people about the consequences of their actions, providing them with alternatives, and creating social consensus are important measures that can alter mindsets. These measures can induce more sustainable land use through changing people's perceptions and intentions, which are then translated into actions. However, in some environments access to resources that are necessary to implement biodiversity-friendly land use systems may be limited or lacking completely. In this context, individuals may be constrained by the costs and structural barriers associated with adoption (Bamberg, 2003; Steg and Vlek, 2009). Thus, measures that aim to overcome structural barriers should influence action directly by removing the existing constraints.

Figure 1 illustrates these relationships. According to Steg & Vlek (2009) and Meijer et al. (2014) the characteristics of the decision-maker, the environment and the technology to be implemented create knowledge, new experiences and perceptions that in turn will shape intentions and eventually actual behavior. We hypothesize that information provision can induce a positive and significant change in perceptions, intentions, and actual behavior. We further expect the effect of information provision on actual adoption behavior to be fully mediated by changes in farmers' perceptions and intentions. The effect of information provision on actual behavior will be limited in the presence of structural constraints. A structural intervention can help to overcome such barriers – we therefore expect it to have a stronger and direct effect on actual adoption, which is not mediated by changes in perceptions and intentions.

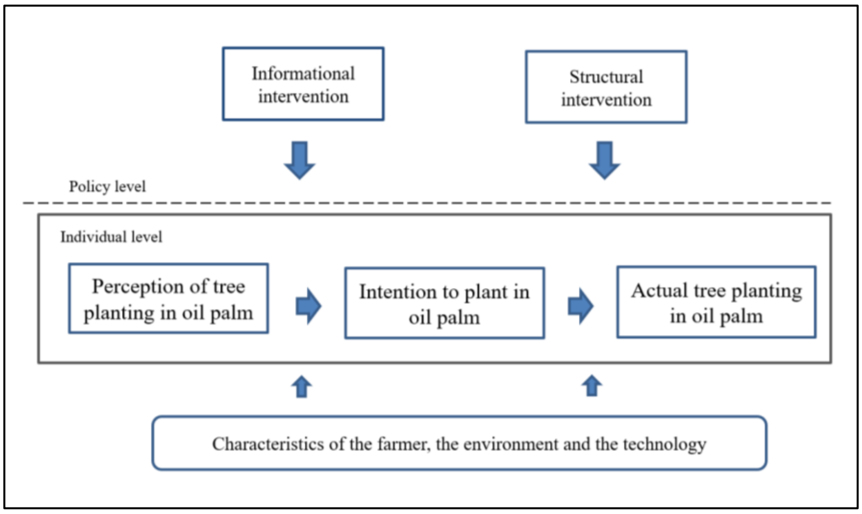

Figure 1 Conceptual framework
Note: Adapted from Meijer et al. (2014) and Steg & Vlek (2009)

3 Experimental design and data

We implemented a cluster-randomized controlled trial in Jambi Province, Indonesia (see Figure 2, panel a). Jambi Province is characterized by rapid monoculture expansion and associated losses in biodiversity (Drescher *et al.*, 2016). While initially driven by large-scale plantations with contract-based out-grower schemes, oil palm expansion is increasingly driven by independent smallholder farmers (Euler *et al.*, 2016; Gatto *et al.*, 2017). The study was conducted in 36 oil-palm growing villages in five districts (Muaro Jambi, Tebo, Sarolangun, Batanghari and Bungo) (see Figure 2, panel b). Villages were randomly assigned to two treatment arms and one control group, each group containing 12 villages.[2]

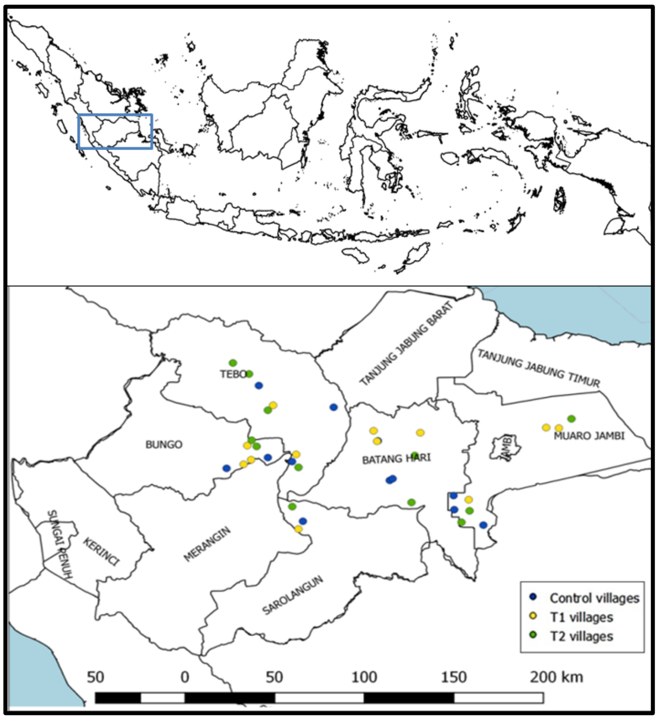

Figure 2 a) Location of Jambi on the Island of Sumatra and b) sample villages in Jambi Province

[2] Random assignment was based on stratification. As stratification variables, we used the share of oil palm farmers in the village (cut-off 73.5%), access to tree seed markets at the village level (1 = yes) and type of village (1 = local village; 0 = village was established by transmigration program).

3.1 Treatments

In order to narrow down potential policy instruments suitable to promote the adoption of biodiversity enrichment in oil palm, we conducted qualitative focus group discussions in the research area. The discussions revealed that farmers are skeptical about tree planting in oil palm due to nutrient competition and the potential negative impacts on palm oil yields. But also, farmers mentioned that trees can be beneficial for the environment and for the provision of wood and fruits. Overall, the qualitative insights suggest that lack of knowledge on the management of trees as well as missing markets for seed material inhibit adoption. Based on these qualitative results, we designed two policy interventions to be tested in our study.

Treatment 1 (T1) is an environmental information campaign designed to close knowledge gaps on the benefits and management of tree enrichment in oil palm plantations. The campaign was implemented as a video-based intervention. We filmed an short video, in which a professor from the University of Jambi explained in detail the establishment and management of tree enrichment in oil palm plantations, the ecological benefits and economic risks. Based on a role model approach, the video features three testimonies from local farmers that have planted trees in their oil palm plantations and share their experiences. In addition, participants of the video session were provided with an illustrative manual for them to take home for future reference. This manual was designed by a local artist and describes through story-telling how Jambi Province has undergone a land use transformation and how tree enrichment in oil palm could help to restore critical ecosystem functions and biodiversity in an oil palm dominated landscape.

Treatment 2 (T2) combines the information campaign (exactly as in T1) with the provision of native tree seedlings. In addition to the information campaign, farmers received a package of six seedlings (six different species) to facilitate seed access. All six tree species are native to Jambi and well-known and valued by local people (Teuscher *et al.*, 2016; Gérard *et al.*, 2017). We delivered three fruit trees ("Jengkol" (*Archidendron pauciflorum)*, "Durian" (*Durio zibethinus)* and "Petai" (*Parkia speciosa)*), one natural latex ("Jelutung" (*Dyera costulata*)), and two timber trees ("Sungkai" (*Peronema canescens*) and "Meranti" (*Shorea leprosula*)).[3] In addition to the market goods produced by these trees (e.g. fruits, timber, natural latex), Petai and Jengkol are also nitrogen fixing and provide nutrients to the soil that can benefit the oil palms (PROSEA, 2016).

The interventions were implemented in February 2016, i.e., before the end of the rainy season. The video screenings took place in the administrative office of the village. A list of the randomly selected oil palm farmers from the respective village was provided to the village head three days prior to the video session. These farmers received official invitation letters to attend the sessions. Attendance was voluntary and open to all village members. However, to increase compliance of the farmers assigned to our treatment, we sent them a text message reminder one day before the session. Five assistants with a university degree, who had been extensively trained on their tasks, helped to carry out the sessions. When farmers arrived to the session, they entered their name in an attendance sheet. After the screening of the video, farmers had the possibility to ask questions about the contents of the video. In the case of T2, each farmer received six tree seedlings after the meeting was concluded. Farmers who were assigned to treatment but did not attend the video session were visited in their home afterwards and were provided with the illustrative manual, and in the case of T2, with six native tree seedlings.

[3] Scientific name in italics and local name in quotation marks.

3.2 Compliance

In our study, non-compliance or partial compliance may have occurred at the individual level, when individual farmers do not comply with their treatment status (Duflo et al. 2008). Full compliance is fulfilled in T1, if the assigned farmers attend the video screening and receive the manual. In T2, the assigned farmers additionally need to receive the package of six native tree seedlings. Given that we distributed manuals and seedlings (in T2) also to those farmers who did not show up for the video screening, we were able to ensure that almost all assigned farmers received these components. Therefore, non-compliance occurs in particular with respect to the attendance of the video screening. Here, the compliance rate is 68 percent in T1, and 74 percent in T2 (see Table 2). The difference between treatments is not statistically significant.

Table 2 Compliance with the random assignment

	(1)	(2)	(3)	(4)	(4a)	(4b)
	Farmers assigned to treatment	Farmers who received manual	Farmers who received seedlings	Farmers attending the video session	Compliance rate	T2-T1 p-value
T1	274	258	-	186	67%	0.384
T2	273	262	262	203	74%	

Note: Column 4b reports p-values for a test of mean difference based on a linear regression model.

3.3 Survey data

We conducted a baseline survey from October to December 2015. Our sample includes independent[4] smallholder oil palm farmers selected through a multi-stage random sampling procedure. We randomly selected 22 to 24 farmers per village. If a farmer was not available, he or she was substituted with the next farmer on the sampling list. In total, we interviewed 817 households. We collected detailed information on oil palm management, tree planting activities, environmental perceptions, subjective expectations and socio-economic data. The questionnaire was pre-tested with the help of a local translator in four villages not included in the sample. After pre-testing, an intensive classroom and practical training was given to a group of twelve students from the Universities of Jambi, who assisted with the household survey data collection. In addition to the household data, a short form was filled out with the village head to gather information about extension services and access to seedlings in the village.

[4] We excluded farmers with contractual ties to oil palm companies, because they cannot make independet planting decisions on their oil palm plots.

Directly after the completion of the interventions, a short follow-up survey was conducted to capture immediate effects on perceptions and intentions. A total of 745 farmers were interviewed, covering both treatment as well as control villages. Finally, an endline survey was carried out from October to December 2016. A team of twelve enumerators administered the same questionnaire as in the baseline, with only minor adjustments. We were able to reach a total of 738 farmers in the endline.

3.4 Balance

To test for balance at baseline between treatment and control groups, we conduct 45 tests of mean differences and Kolmogorov–Smirnov tests (see Table 5 in the Appendix). The variables “household size” and “cutting trees in oil palm” are significantly different between treatment groups at the five percent and one percent levels, respectively. To further explore balance, we provide Kolmogorov–Smirnov tests that assume under the null hypothesis that the sample is drawn from the same distribution. The results of this test show that only “household size” is statistically significant between treatment groups at the five percent level. Given the random chance of errors, these test results support that our randomization has generated comparison groups that are balanced at baseline (Bloom, 2006; Duflo, Glennerster and Kremer, 2008; Morgan and Rubin, 2012).

3.5 Attrition

We encounter attrition at two points in time (see Table 3): during the follow-up and during the endline survey. In the follow-up survey about 9 percent of the farmers and in the endline survey about 10 percent of the farmers interviewed in the baseline were not found. These attrition rates are similar to the rates observed in other RCT studies (Pamuk, Bulte and Adekunle, 2014). Comparison of attrition rates across treatment and control groups reveals statistically significant differences between treatments and control in the follow-up, and between T2 and control in the endline. Data from all three survey rounds is available for 679 farmers, out of the 817 farmers initially interviewed in the baseline. Since for nine farmers information was incomplete, our final data set used in the analysis consists of 670 observations. In the econometric analysis we control for potential attrition bias resulting from non-random attrition across treatment and control groups (see next section).

Table 3 Attrition rates

	Farmers interviewed at baseline	Attrition % Follow-up	Attrition % Endline
Treatment group			
Control	270	17	11
Treatment 1	274	6	10
Treatment 2	273	4	7
Full sample	817	9	10
C-T1[1]		0.003	0.827
C-T2[1]		0.000	0.047
T1-T2[1]		0.144	0.225

Note: 59 farmers interviewed in the follow-up were not interviewed in the endline. While, 65 farmers interviewed in the endline were not interviewed in the follow-up. 14 farmers interviewed in the baseline were not interviewed in any of the sub-sequent surveys.

[1]p-values for a test of mean difference based on a linear regression.

4 Econometric approach

4.1 Intent-to-treat effects

We estimate Intent-to-treat (ITT) effects of the interventions on perceptions, intention and actual adoption. The model is specified as follows:

$$Y_{iv} = \beta_1 + \beta_2 T1_v + \beta_3 T2_v + \beta_4 X_{i,v} + u_{i,v} \qquad (1)$$

Y_{iv} represents a vector of outcome variables, i.e. perceptions, intention and actual adoption decision of farmer i in village v. $T1$ = 1 if village v was assigned to receive the environmental information campaign only and $T2$ = 1 if village v was assigned to receive seedlings for free in addition to the information campaign. To increase the precision of our estimates, vector $X_{i,v}$ contains household characteristics and stratification variables . u_{iv} is a random error term. The parameters are estimated using OLS in the case of perceptions and intentions, and using logit regression in the case of the binary adoption decision.

To control for possible biases in our estimates due to differential attrition across treatment groups at endline, we employ inverse probability weights (Fitzgerald, Gottschalk and Moffitt, 1997). First, we estimate probabilities of selection on observables into the endline based on a set of auxiliary variables that are associated with attrition. Second, we re-estimate the probabilities excluding those auxiliary variables that explain attrition. We construct weights by the ratio of the predicted probabilities. The auxiliary variables include household head and household characteristics, as well as a set of enumerator proxies to control for interview quality.

4.2 Mediation analysis

Using a structural equation model, we explore causal mediation analysis in order to identify the underlying mechanisms that help to explain observed treatment effects (Acharya, Blackwell and Sen, 2016; Imai *et al.*, 2016). Following our conceptual framework, we test to what extent the effect of the interventions on actual adoption is mediated by perceptions and intention. Frequently, mediation analysis draws on Baron & Kenny's (1986) work, however, it is often highlighted that this framework does not fulfill the identification assumption (sequential ignorability and conventional exogeneity). Given the randomization of treatments in our study, the assumption is fulfilled here (Imai, Keele and Yamamoto, 2010; de Brauw *et al.*, 2015). The mediation analysis basically examines a conceptualized mechanism through which an independent variable might affect a dependent variable through an intervening process (Lacobucci, 2008).

We estimate the following two-mediator model:

$$Y = i_1 + cX + e_1, \quad (2.1)$$

$$Y = i_2 + c'X + b_1M_1 + b_2M_2 + e_2, \quad (2.2)$$

$$M_1 = i_3 + a_1X + e_3, \quad (2.3)$$

$$M_2 = i_4 + a_2X + e_4, \quad (2.4)$$

where i_i are the intercepts and e_i the model fit errors. We are interested in $a, b, and\ c'$ which are the regression coefficients that capture the relation between the variables of interest (Lacobucci, 2008). Y is the outcome variable, X refers to the independent variables, M_1 and M_2 represent the two mediators. a_1 and a_2 measure the relations between the independent variable and the two mediators, respectively (Hayes, 2018). With two mediators in the model, we have a total of three mediated effects for X; that is, the effect of X on Y through M_1, the effect of X on Y through M_2, and the total mediated effect of X on Y through M_1 and M_2 (MacKinnon, Cheong and Pirlott, 2012). It is assumed that M_1 and M_2 are causally located between the interventions and the outcomes. This means that X would have an effect on the mediators, and in turn will have an effect on Y (Hayes, 2018). M_1 and M_2 cannot transmit $X's$ effect on Y, if they are not causally located between X and Y (Hayes, 2018).

To identify a mediating effect it is necessary that:

1. a_i in eq 2.3 and eq 2.4 is significant. There is a linear relationship between X and M_i
2. c in eq 2.1 is significant. There is a linear relationship between X and Y
3. b_i in eq 2.2 is significant. M_i helps to predict the outcome variable Y
4. Finally, c' in eq 2.2 is significantly smaller in size compared to c in eq 2.1.

We can then conclude that if a or b are not significant, there is no mediation, and assume that the variance of Y is attributable to the direct effect of X. If all four conditions hold, we conclude that there is full or partial mediation. This means that, the variance of Y attributable to X is explained partly by an indirect effect mediated by M_i . If c' is no longer significant, we assume that all the effect runs through M_i . M_i has only a partial effect when c' is smaller than c, but still significant (Lacobucci, 2008).

Figure 3 shows the mediation analysis explored in this article. We model the direct effect and three mediating effects for each treatment. These are obtained as follows: the causal effect of T1 on adoption can be mediated through perceptions ($a_{T11}b_1$), mediated by intention ($a_{T12}b_2$), and mediated through perceptions and intention ($a_{T11}*d_{pi}*b_2$). The sum of these mediating effects gives the total indirect effect of T1 on actual adoption. The direct effect of T1, without the mediators, on actual adoption is observed in c'_{T1}. The sum of the direct and indirect effects equals the total effect c_{T1}. Similarly, we obtain the mediating effects for T2. The causal effect of T2 on actual adoption can be mediated by perceptions ($a_{T21}b_1$), by intention ($a_{T22}b_2$), and by perceptions and intentions together ($a_{T21}*d_{pi}*b_2$). The direct effect of T2 on actual adoption is provided by c'_{T2}.

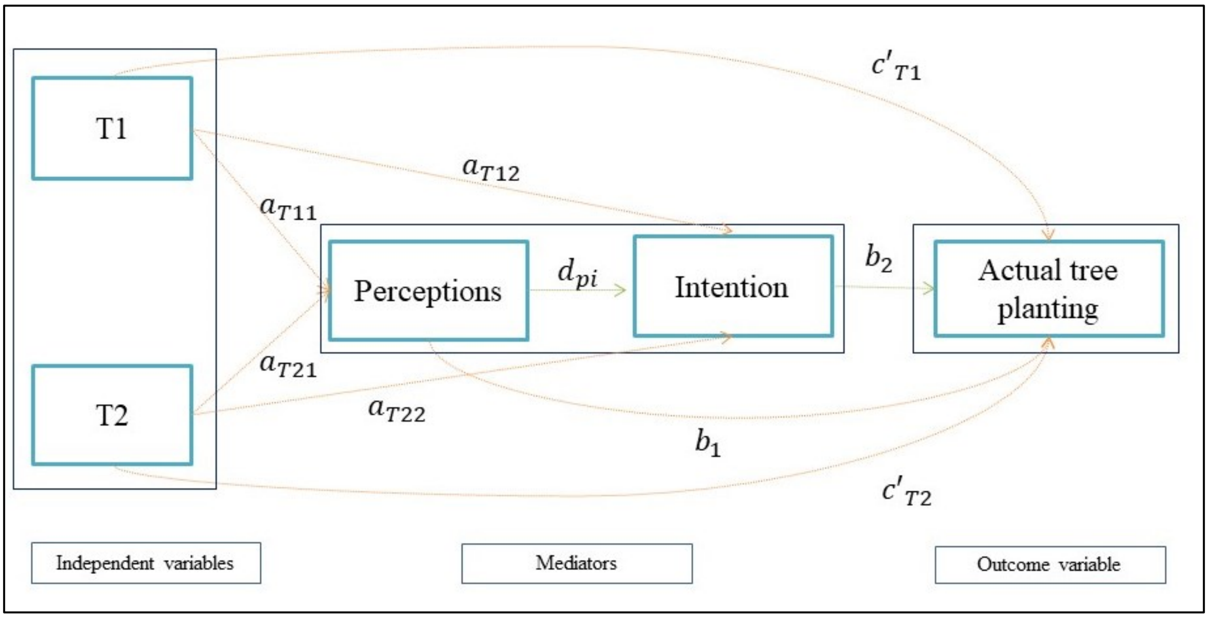

Figure 3 Schematic representation of mediation analysis
Note: Adapted from Hayes (2018).

4.3 Measurement of key outcome variables

We measure three outcomes in this study. First, we are interested in farmers' perceptions of the provision of ecosystem functions by trees in oil palm. The measure was designed according to similar studies on tree planting (Meijer *et al.*, 2015) including 17 items assessed on a Likert scale. Using exploratory factor analysis, we constructed a total score to reflect perceptions. Second, the intention to plant was elicited by the subjective belief that the farmer will plant trees in his or her oil palm plantation. To obtain this information, farmers were asked to assess the probability that they will decide to plant, using elicitation methods recommended by Delavande et al. (2011). Third, actual adoption was measured as self-reported tree planting in oil palm plantations. Chandon et al. (2005) suggest capturing changes in perceptions and intentions before observing actual adoption. Therefore, we elicited perceptions and intentions in the follow-up survey in February 2016, shortly after the intervention was completed[5]. Data on actual adoption stems from the endline survey, which was implemented in October 2016.

4.3.1 Perceptions of the provision of ecosystem functions by trees in oil palm

The scale that we use to assess farmers' perceptions captures regulation, habitat, information, and provisioning functions (Groot et al. 2002) (see Table 6 in the Appendix). Regulating functions include those that maintain and regulate ecosystems through bio-geochemical and biospheric processes. Habitat functions provide refuge and reproduction of wild plants and animals allowing succession of biological and genetic diversity. Provisioning functions provide ecosystem goods for human consumption (e.g. food and raw materials). Information functions support cultural services such as spiritual enrichment, reflection, recreation and aesthetic experience. Items are measured on a 5-point-Likert scale, where 5 represents strongly agree. Looking at the mean values, we see that farmers perceive that trees in oil palm provide regulation and provisioning functions. Similarly, on average farmers agree that trees in oil palm provide habitat for bird and insect diversity, while farmers are indifferent to the role that trees have in terms of aesthetic services in oil palm.

We use exploratory factor analysis to summarize all the statements in one latent factor. Since the statements were measured on a 5-point Likert scale, we use the Polychoric correlation. Due to the large number of statements we define the loading with a Varimax rotation and retain factors with an Eigen value greater than one (Yong and Pearce, 2013). Six statements did not load significantly on the factor. Internal validity was checked with help of the Kaiser-Meyer-Olkin indicator, which measures sampling adequacy (KMO=0.85), and Cronbach's alpha (α=0.8205). Values above 0.7 are acceptable for both indicators. Generally, perceptions of ecosystem functions provided by native trees in oil palm are positive (see total factor score in Table 6 in the Appendix). Comparing the distribution across treatment groups, we can observe that on the average farmers assigned to the treatments have more positive perceptions than those in the control group.[6]

4.3.2 Intention to plant trees

The intention to plant trees is elicited by subjective expectations. A subjective expectation is the belief of a person regarding the probability that an event will occur in the future (Manski,

[5] Perceptions and intentions can be subject to social desirability that could lead to over/under reporting (Clayton 2012; Gifford & Nilsson 2014). It has been found that social desirability is only weakly correlated with environmental attitudes and not related to pro-environmental behavior (Milfont 2009). To minimize potential bias in our results, we carefully phrased and tested the scales prior to data collection. In addition, we explained to the respondents the importance of their honest answer, as it was done in other studies (Meijer et al. 2015).

[6] Mean differences for each statement between control and treatment groups can be observed in Table 6 in the Appendix.

1990). Conventionally, subjective probabilities have been assessed on Likert scales, with open-ended or binary questions. However, these approaches generate less information than assessing probabilities, which can be done with the help of visual aids, such as beans (Delavande et al. 2011; Manski 1990). We gave farmers 20 beans to illustrate their subjective expectations. At first, we explained to them that the amount of beans they choose represents the likelihood that a future event will happen. Training questions were used to ensure that farmers understood the concept of probabilities (Delavande, Giné and McKenzie, 2011). Then, we asked farmers to assess how likely they consider it to be that in the next 12 months they will plant native trees within their oil palm plantation.[7] The number of beans chosen by the farmer was multiplied by 0.05 to obtain probabilities. Figure 4 shows the distribution of farmers' subjective expectations that they will plant trees in their oil palm plantations for the full sample and for the different groups. We observe that, on the average, farmers assigned to the treatments stated a higher intention to plant than farmers assigned to the control group.

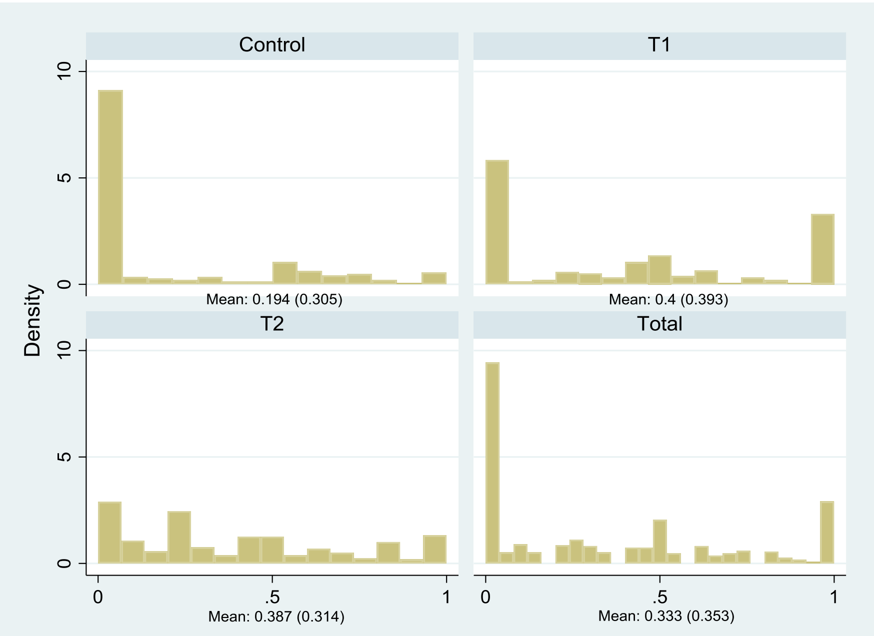

Figure 4 Intention to plant trees in oil palm

Note: Distribution of the subjective belief that farmer will plant trees in oil palm. Below each quadrant is the corresponding mean and standard deviation in parenthesis. Sample size: 670

[7] The question asked to farmers was: "How likely do you think it is that in the next 12 months you will plant native trees within your oil palm plantation?"

5 Econometric results

5.1.1 Effects of policy interventions

Table 4 reports the intent-to-treat estimates. We observe that assignment to the information campaign only (T1) on average increases the perception factor by 0.34 points, and assignment to the information campaign plus seedling provision (T2) by 0.27 points in comparison to the control group. Although the difference between T1 and T2 is statistically significant, it is small in absolute terms. Intent-to-treat estimates further reveal that farmers' subjective probability that they will plant trees is 20 percentage points higher in both, T1 and T2, compared to the control group. Our findings are in line with earlier, non-experimental, studies emphasizing that informational interventions succeed in increasing the knowledge of an individual and creating awareness about a specific topic (Zelenski, Dopko and Capaldi, 2015; De Martino *et al.*, 2016).

Column 3 of Table 4 shows marginal effects of the interventions on actual tree planting adoption. We observe that farmers assigned to the information campaign only (T1) are on average 7 percentage points more likely to plant trees in their oil palm plantations in comparison to the control group. Farmers assigned to the information campaign plus seedling provision (T2) are 42 percentage points more likely to plant trees in their oil palm plantations compared to the control group. While both interventions have a significant and positive effect, t-test results show that the effect of T2 is significantly larger than that of T1, suggesting that the structural intervention is crucial to induce behavioral change more widely.

Table 4 Intent-to-treat effects

	(1) Perceptions	(2) Intention to plant	(3) Actual tree planting
T1	0.34*** (0.028)	0.20*** (0.046)	0.07*** (0.024)
T2	0.27*** (0.028)	0.20*** (0.040)	0.42*** (0.030)
Control variables[1]	Y	Y	Y
P-values of t-test for T1=T2	0.003	0.932	0.000
Observations	670	670	670
R^2	0.362	0.117	
Pseudo R^2			0.236

Note: Each column is a separated weighted regression. Columns 1 and 2 show the estimated coefficient of an OLS regression. Column 3 shows marginal effects from a logit regression. Standard errors are cluster-corrected at village level, shown in parenthesis. Results for the full regressions are provided in Table 7 in the Appendix).

[1]Control variables include household characteristics and stratification variables.

5.2 Are the treatment effects mediated by changes in perceptions and intentions?

As postulated in the conceptual framework, we hypothesize that the effect of the information campaign on actual adoption is mediated through changes in perceptions and intentions. Accordingly, the information campaign, which was delivered in both treatments, will have positive effects on farmers' perceptions and intentions, which in turn will increase the likelihood of actual adoption among the treated farmers. Results of the mediation analysis are depicted in Figure 5.[8] The causal effect of the assignment to the information campaign only (T1) is mediated through perceptions and intentions: The indirect effect of T1 on adoption, which runs through perceptions and intentions, is 0.045 and statistically significant at the one percent level. Once controlling for the mediated effect, the direct effect of T1 on adoption turns insignificant ($c'_{T2} = 0.135$). This indicates that the effect of the information campaign on adoption is fully explained by increases in perceptions and intentions. We further find that the causal effect of the information campaign plus seedling provision (T2) is also mediated by perceptions and intentions: The indirect effect of T2 on adoption, mediated by perceptions and intentions, is 0.038 and statistically significant. However, even when controlling for the mediating effect of perceptions and intentions, the direct effect of T2 on actual adoption is still positive and significant. Thus, in the combined intervention (information campaign plus seedling provision) a significant portion of the causal effect on adoption remains unexplained. Beyond the pathway of changing mindsets, there seem to be other mechanisms through which T2 leverages adoption, most likely related to the free and easy access to seedlings, which may facilitate adoption and experimentation even among farmers who are not fully convinced by the information campaign.

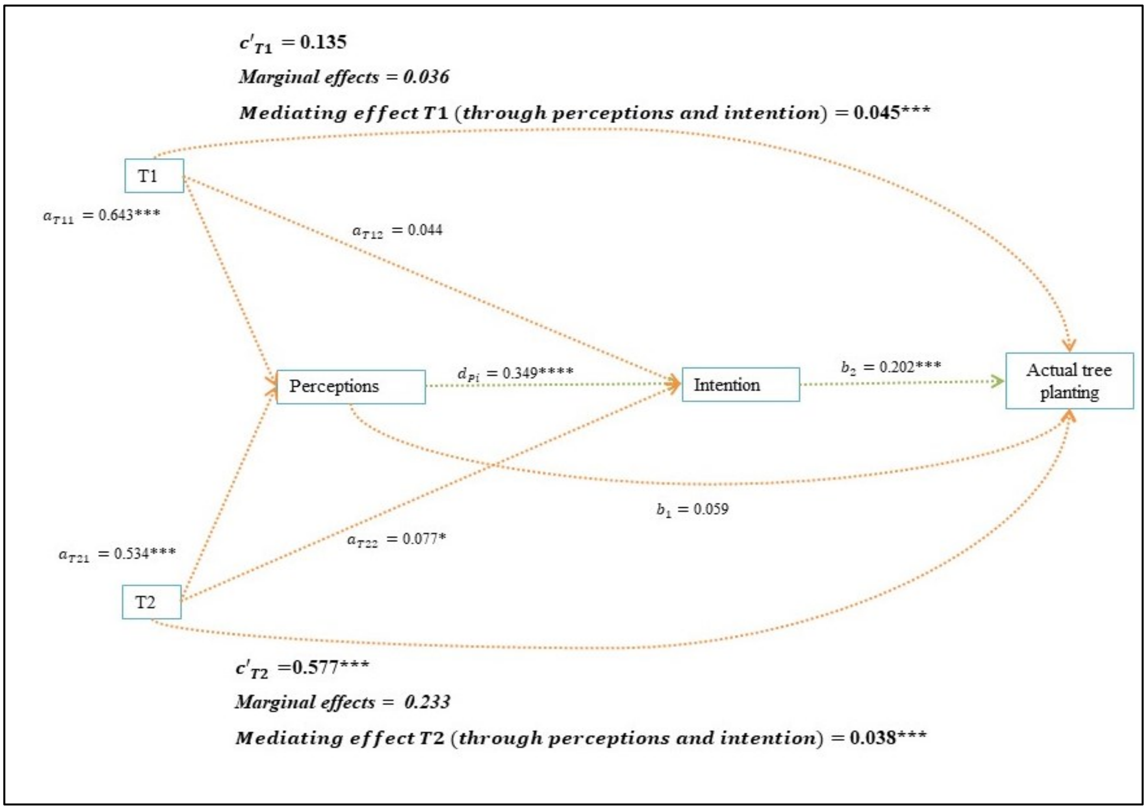

Figure 5 Results of the mediation analysis

[8] Full model results are shown in Table 8 in the Appendix

Note: N=670. Estimates for each path are given in standardized form. Full estimations are provided in Table 8 in the Appendix. We control for additional baseline covariates as a robustness check. The regression coefficients are next to their respective path. Effects of T1 are shown in the upper part of the diagram, while effects of T2 are shown in the lower part. The model was performed with a Maximum Likelihood Robust (MLR) estimator in Mplus. Since the mediators are continuous variables those regressions can be interpreted as in an OLS regression. The regression coefficient for actual behavior can be interpreted as in a Logit regression. Model fit: Log-likelihood user model (H0): -320.477, Akaike (AIC): 688.955, Bayesian (BIC): 797.130, Sample-size adjusted Bayesian: 720.928

6 Conclusion

Rapid loss of biodiversity caused by oil palm expansion is likely to continue in Indonesia. This trend urges for policies that influence behavioral change towards the adoption of more biodiversity-friendly oil palm management. This article evaluates the effects of two policy instruments on attitudes, intentions and tree planting behavior among smallholder oil palm farmers in Sumatra, Indonesia. Using a randomized controlled trial, we test the effects of an information campaign only and an information campaign combined with seedling provision on attitudes , intentions, and adoption of native tree planting in smallholder oil palm plantations. Both interventions have positive and significant effects on attitudes towards tree planting and on the intention to plant trees in oil palm. Furthermore, both interventions have a positive and significant effect on actual tree planting, increasing the probability of adoption by 7 and 42 percentage points respectively. This result suggests that despite profitability considerations that favor tropical cash crops, non-financial instruments and mechanisms can be effective in steering behavior towards more biodiversity-friendly land use choices. It is encouraging that we do find these positive effects even though our intervention was relatively short and low cost (one video-screening per village, distribution of a manual, provision of a small number of seedlings) and despite the fact that farmers were initially quite skeptical about biodiversity enrichment in their oil palm plantations.

What are the underlying mechanisms then through which farmers are motivated to change their behavior and plant trees in oil palm? Using a path model, we tested to what extent the effects of our interventions can be explained by changes in farmers' mindsets, measured here in terms of their perceptions and intentions. Results show that the effect of the information campaign (T1) on actual tree planting is fully mediated by changes in mindsets. Assignment to T1 has a significantly positive effect on perceptions and intentions, which then translates into actual adoption. In contrast, changes in mindsets are only partial mediators for the combined intervention (T2). There is a significant portion of T2's effect on actual tree planting that cannot be explained by the observed changes in perceptions and intentions triggered by the information campaign. Providing free and easy access to seed material may thus have motivated even some of the farmers that were not fully convinced of the advantages of tree planting to experiment with a few trees on their oil palm plots. We thus conclude that an information campaign is important to change mindsets, but if the goal is to spread the technology widely to induce experimentation, facilitating easy access to critical inputs may be key to motivate adoption among large numbers of potential users.

References

Acharya, A., Blackwell, M. and Sen, M. (2016) 'Explaining Causal Findings Without Bias : Detecting and Assessing', *American Political Science Review*, 110(3), pp. 512–529. doi: 10.1017/S0003055416000216.

Ajzen, I. (1991) 'The Theory of Planned Behavior', *Organizational Behavior and Human Decision Processes*, 50(2), pp. 179–211. doi: 10.1016/0749-5978(91)90020-T.

Azhar, B. *et al.* (2015) 'Promoting landscape heterogeneity to improve the biodiversity benefits of certified palm oil production: Evidence from Peninsular Malaysia', *Global Ecology and Conservation*, 3, pp. 553–561. doi: 10.1016/j.gecco.2015.02.009.

Bamberg, S. (2003) 'How does environmental concern influence specific environmentally related behaviors? A new answer to an old question', *Journal of Environmental Psychology*, 23(1), pp. 21–32. doi: 10.1016/S0272-4944(02)00078-6.

Baron, R. M. and Kenny, D. a. (1986) 'The Moderator-Mediator Variable Distinction in Social Psychological Research: Conceptual, Strategic, and Statistical Considerations', *Journal of Personality and Social Psychology*, 51(6), pp. 1173–1182. doi: 10.1037/0022-3514.51.6.1173.

Bloom, H. S. (2006) 'The core analytics of randomized experiments for social research', *MDRC Working Papers on Research Methodology*, (August), pp. 1–41. doi: 10.4135/9781446212165.

de Brauw, A. *et al.* (2015) 'Biofortification, Crop Adoption, and Health Information: Impact Pathways in Mozambique and Uganda. IFPRI HarvestPlus Working Paper N. 21', (November). Available at: www.ifpri.org/cdmref/p15738coll2/id/129795/filename/130006.pdf.

Burgess, R. *et al.* (2012) 'The Political Economy of Deforestation in the Tropics', *The Quarterly Journal of Economics*, 127(4), pp. 1707–1754. doi: 10.1093/qje/qjs034.Advance.

Butler, R. A., Koh, L. P. and Ghazoul, J. (2009) 'REDD in the red: palm oil could undermine carbon payment schemes', *Conservation Letters*, 2(2), pp. 67–73. doi: 10.1111/j.1755-263X.2009.00047.x.

Campos, F. *et al.* (2017) 'Teaching personal initiative beats traditional training in boosting small business in West Africa', *Science*, 357(6357), pp. 1287–1290. doi: 10.1126/science.aan5329.

Carter, C. *et al.* (2007) 'Palm oil markets and future supply', *European Journal of Lipid Science and Technology*, 109(4), pp. 307–314. doi: 10.1002/ejlt.200600256.

Carter, M. R.; Laajaj, R.; Yang, D. (2013): The Impact of Voucher Coupons on the Uptake of Fertilizer and Improved Seeds. Evidence from a Randomized Trial in Mozambique. In *American Journal of Agricultural Economics* 95 (5), pp. 1345–1351.

Chandon, P., Morwitz, V. G. and Reinartz, W. J. (2005) 'Do Intentions Really Predict Behavior? Self-Generated Validity Effects in Survey Research', *Journal of Marketing*, 69(April), pp. 1–14. doi: 10.1509/jmkg.69.2.1.60755.

Clough, Y. *et al.* (2016) 'Land-use choices follow profitability at the expense of ecological functions in Indonesian smallholder landscapes', *Nature Communications*, 7. doi: 10.1038/ncomms13137.

Cole, R. J. ., Holl, K. . D. . and Zahawi, R. . (2010) 'Seed rain under tree islands planted to restore degraded lands in a tropical agricultural landscape.', *Ecological Society of America*, 20(5), pp. 1255–69. Available at: https://doi.org/10.1890/09-0714.1%0A.

Coordinating Ministry of Economic Affairs (2011) *Masterplan: Acceleration and Expansion of Indonesia Economic Development 2011–2025*. Jakarta. Available at: https://www.dezshira.com/library/treaties/master-plan-acceleration-and-expansion-of-indonesia-economic-development-2011-2025-2764.html (Accessed: 15 May 2017).

Corley, R. H. V. . and Tinker, P. B. (2016) *The Oil Palm*. Fifth Edit. Chichester, England: Wiley Blackwell.

Delavande, A., Giné, X. and Mckenzie, D. (2010) *Eliciting probabilistic expectations with visual aids in developing countries: How sensitive are answers to variations in elicitation design?. The World Ban*. doi: 10.1002/jae.1233.

Delavande, A., Giné, X. and McKenzie, D. (2011) 'Measuring subjective expectations in developing countries: A critical review and new evidence', *Journal of Development Economics*. Elsevier B.V., 94(2), pp. 151–163. doi: 10.1016/j.jdeveco.2010.01.008.

Drescher, J. *et al.* (2016) 'Ecological and socio-economic functions across tropical land use systems after rainforest conversion', *Philosophical transactions of the Royal Society of London. Series B, Biological sciences*, 231(20150275), pp. 1–7. doi: 10.1098/rstb.2015.0275.

Duflo, E., Glennerster, R. and Kremer, M. (2008) 'Using Randomization in Development Economics: A Toolkit', *Handbook of Development Economics*, 53, p. 68. doi: 10.1016/S1573-4471(07)04061-2.

Duflo, E.; Kremer, M.; Robinson, J. (2011): Nudging Farmers to Use Fertilizer. Theory and Experimental Evidence from Kenya. In American Economic Review 101 (6), pp. 2350–2390.

Edwards, D. P. . *et al.* (2010) 'Wildlife-friendly oil palm plantations fail to protect biodiversity effectively', *Conservation Letters*, 3(4), pp. 236–242. doi: 10.1111/j.1755-263X.2010.00107.x.

Euler, M. *et al.* (2015) 'Oil palm adoption, household welfare and nutrition among smallholder farmers in Indonesia', *World Development*. Elsevier Ltd. doi: 2197-6244.

Euler, M. *et al.* (2016) 'Oil Palm Expansion among Smallholder Farmers in Sumatra, Indonesia', *Journal of Agricultural Economics*, 67(3), pp. 658–676. doi: 10.1111/1477-9552.12163.

FAOSTAT (2018) *Statistics division. Food and Agricultural Organization, Rome.* Available at: http://faostat.fao.org (Accessed: 12 January 2018).

Fitzgerald, J., Gottschalk, P. and Moffitt, R. (1997) 'An analysis of sample attrition in panel data: The Michigan panel study of income dynamics'. Available at: www.nber.org/papers/t0220.pdf.

Fitzherbert, E. B. . *et al.* (2008) ‘How will oil palm expansion affect biodiversity?’, *Trends in Ecology and Evolution*, pp. 538–545. doi: 10.1016/j.tree.2008.06.012.

Foley, J. A. *et al.* (2005) ‘Global consequences of land use’, *Science*, 309(5734), pp. 570–574. doi: 10.1126/science.1111772.

Gatto, M. *et al.* (2017) ‘Oil Palm Boom, Contract Farming, and Rural Economic Development: Village-Level Evidence from Indonesia’, *World Development*. Elsevier Ltd, 95, pp. 127–140. doi: 10.1016/j.worlddev.2017.02.013.

Gérard, A. *et al.* (2017) ‘Oil palm yields in diversified plantations: initial results from a biodiversity enrichment experiment in Sumatra, Indonesia’, *Agriculture, Ecosystems and Environment*, 240, pp. 253–260. doi: 10.1016/j.agee.2017.02.026.

Hansson, H., Ferguson, R. and Olofsson, C. (2012) ‘Psychological Constructs Underlying Farmers’ Decisions to Diversify or Specialise their Businesses - An Application of Theory of Planned Behaviour’, *Journal of Agricultural Economics*, 63(2), pp. 465–482. doi: 10.1111/j.1477-9552.2012.00344.x.

Hayes, A. F. (2018) *Introduction to Mediation, Moderation, and Conditional Process Analysis. A regression-Based Approach*. 2nd Ed. New York: Guilford Publications.

Imai, K. *et al.* (2016) ‘Unpacking the Black Box of Causality : Learning about Causal Mechanisms from Experimental and Observational Studies’, *The American Political Science Review*, 105(4), pp. 765–789. Available at: http://www.jstor.org/stable/23275352.

Imai, K., Keele, L. and Yamamoto, T. (2010) ‘Identification, Inference and Sensitivity Analysis for Causal Mediation Effects’, *Statistical Science*, 25(1), pp. 51–71. doi: 10.1214/10-STS321.

Jack, B. K. *et al.* (2013) ‘Private Information and the Allocation of Land Use Subsidies in Malawi’, *American Economic Journal: Applied Economics*, 5(3), pp. 113–135. doi: 10.1257/app.5.3.113.

Klasen, S. *et al.* (2016) ‘Economic and ecological trade-offs of agricultural specialization at different spatial scales’, *Ecological Economics*. The Authors, 122, pp. 111–120. doi: 10.1016/j.ecolecon.2016.01.001.

Klöckner, C. A. (2013) ‘A comprehensive model of the psychology of environmental behaviour-A meta-analysis’, *Global Environmental Change*, 23(5), pp. 1028–1038. doi: 10.1016/j.gloenvcha.2013.05.014.

Koh, L. P. and Wilcove, D. S. (2008) ‘Is oil palm agriculture really destroying tropical biodiversity?’, *Conservation Letters*, 1(2), pp. 60–64. doi: 10.1111/j.1755-263X.2008.00011.x.

Lacobucci, D. (2008) *Mediation Analysis: Quantitative Applications in the Social Sciences*. 156th edn. California: SAGE.

Leimona, B., Joshi, J. and van Noordwijk, M. (2009) ‘Can rewards for environmental services benefit the poor ? Lessons from Asia’, *International Journal of the Commons*, 3(1), pp. 82–107. Available at: http://doi.org/10.18352/ijc.121.

MacKinnon, D., Cheong, J. and Pirlott, A. G. (2012) *An Introduction to Statistical Mediation Analysis*, *Handbook of Research Methods in Psychology*.

Manski, C. F. (1990) 'The Use Of Intentions Data To Predict Behaviour : A Best- Case Analysis', *Journal of the American Statistical Association*, 85(412), pp. 934–940. doi: 10.1093/restud/rdu044.

De Martino, S. *et al.* (2016) *Do They Do As They Say? Stated versus revealed preferences and take up in an incentives for conservation prgram*, *Environmental and Natural Resources*. Available at: https://openknowledge.worldbank.org/handle/10986/25177.

Meijer, S. S. . *et al.* (2014) 'The role of knowledge, attitudes and perceptions in the uptake of agricultural and agroforestry innovations among smallholder farmers in sub-Saharan Africa', *International Journal of Agricultural Sustainability*. Taylor & Francis, 13(1), pp. 40–54. doi: 10.1080/14735903.2014.912493.

Meijer, S. S. . *et al.* (2015) 'Tree planting by smallholder farmers in Malawi: Using the theory of planned behaviour to examine the relationship between attitudes and behaviour', *Journal of Environmental Psychology*. Elsevier Ltd, 43, pp. 1–12. doi: 10.1016/j.jenvp.2015.05.008.

Morgan, K. L. and Rubin, D. B. (2012) 'Rerandomization to improve covariate balance in experiments', *The Annals of Statistics*, 40(2), pp. 1263–1282. doi: 10.1214/12-AOS1008.

Ndayambaje, J. D. ., Heijman, W. J. M. and Mohren, G. M. J. (2012) 'Household Determinants of Tree Planting on Farms in Rural Rwanda', *Small-scale Forestry*, 11(4), pp. 477–508. doi: 10.1007/s11842-012-9196-0.

Pamuk, H., Bulte, E. and Adekunle, A. A. (2014) 'Do decentralized innovation systems promote agricultural technology adoption ? Experimental evidence from Africa', *Food Policy*. Elsevier Ltd, 44, pp. 227–236. doi: 10.1016/j.foodpol.2013.09.015.

PROSEA (2016) *Plant resources of South-East Asia*. Available at: http://www.proseanet.org (Accessed: 1 September 2016).

Ray, B. and Bhattacharya, R. (2004) *Stakeholder Attitudes and Conservation of Natural Resources: Exploring Alternative Approaches*, *Development and Sustainability*. doi: 10.1007/978-81-322-1124-2.

Rogers, E. M. (1983) *Diffusion of Innovations*. doi: 82-70998.

Sood, K. K. *et al.* (2004) 'Do Socio-psychological Factors Matter in Agroforestry Planning? Lessons from Smallholder Traditional Agroforestry Systems', *Small-scale Forest Economics, Management and Policy*, 3(2), pp. 239–255. doi: 10.1007/s11842-004-0017-y.

Steg, L. *et al.* (2014) 'An Integrated Framework for Encouraging Pro-environmental Behaviour: The role of values, situational factors and goals', *Journal of Environmental Psychology*, 38, pp. 104–115. doi: 10.1016/j.jenvp.2014.01.002.

Steg, L. and Vlek, C. (2009) 'Encouraging pro-environmental behaviour: An integrative review and research agenda', *Journal of Environmental Psychology*. Elsevier Ltd, 29(3), pp. 309–317. doi: 10.1016/j.jenvp.2008.10.004.

Teuscher, M. *et al.* (2015) ‘Trade-offs between bird diversity and abundance, yields and revenue in smallholder oil palm plantations in Sumatra, Indonesia’, *Biological Conservation*. Elsevier Ltd, 186, pp. 306–318. doi: 10.1016/j.biocon.2015.03.022.

Teuscher, M. *et al.* (2016) ‘Experimental Biodiversity Enrichment in Oil-Palm-Dominated Landscapes in Indonesia’, *Frontiers in Plant Science*, 07(October), pp. 1–15. doi: 10.3389/fpls.2016.01538.

Yong, A. G. and Pearce, S. (2013) ‘A Beginner’s Guide to Factor Analysis: Focusing on Exploratory Factor Analysis’, *Tutorials in Quantitative Methods for Psychology*, 9(2), pp. 79–94. doi: 10.20982/tqmp.09.2.p079.

Zelenski, J. M., Dopko, R. L. and Capaldi, C. a. (2015) ‘Cooperation is in our nature: Nature exposure may promote cooperative and environmentally sustainable behavior’, *Journal of Environmental Psychology*. Elsevier Ltd, 42, pp. 24–31. doi: 10.1016/j.jenvp.2015.01.005.

Zubair, M. and Garforth, C. (2006) ‘Farm Level Tree Planting in Pakistan: The Role of Farmers’ Perceptions and Attitudes’, *Agroforestry Systems*, 66(3), pp. 217–229. doi: 10.1007/s10457-005-8846-z.

Appendix

Table 5 Baseline characteristics and mean difference between treatment and control groups

	(1) Total	(2) Control	(3) T1	(4) T2	(5) C=T1	(6) C=T2	(7) T1=T2	(8) C=T1	(9) C=T2	(10) T1=T2
Household head characteristics										
Age of HH head	49. 52 (0.59)	49.14 (1.02)	49.62 (0.77)	49.79 (1.23)	0.708	0.687	0.909	0.946	0.838	0.677
Years of education HH Head	7.53 (0.16)	7.67 (0.21)	7.42 (0.32)	7.49 (0.26)	0.510	0.604	0.850	0.802	0.211	0.897
=1 if access to environmental education past 12m	0.076 (0.02)	0.052 (0.02)	0.084 (0.02)	0.092 (0.04)	0.325	0.380	0.870	0.999	0.983	1.000
=1 if female	0.02 (0.004)	0.03 (0.010)	0.01 (0.008)	0.01 (0.006)	0.141	0.203	0.706	1.000	1.000	1.000
Perception of trees in OP	2.15 (0.044)	2.03 (0.044)	2.28 (0.068)	2.13 (0.09)	0.004***	0.335	0.175	0.013**	0.235	0.215
Household charactersitics										
Household size (nr of persons)	3.96 (0.06)	3.93 (0.11)	3.83 (0.09)	4.13 (0.11)	0.502	0.209	0.047**	0.937	0.591	0.086**
Value of assets (in 1,000 IDR)	49,745.24	32,778.05	84,134.21	32,011.06	0.295	0.880	0.288	0.875	0.987	0.927
	(16749.47)	(3473.89)	(48120.35)	(3661.573						
=1 if other crops are cultivated	0.28 (0.04)	0.29 (0.07)	0.26(0.07)	0.29 (0.08)	0.732	0.997	0.754	0.998	1.000	0.998
Total land owned (ha)	5.69 (0.29)	5.68 (0.38)	5.81 (0.62)	5.58 (0.48)	0.863	0.865	0.771	0.253	0.184	0.504
=1 if homegarden	0.91 (0.03)	0.833 (0.08)	0.91 (0.03)	0.96 (0.01)	0.324	0.113	0.139	0.262	0.016**	0.919
Farms' oil palm characteristics										
Total hectare oil palm managed	4.47 (0.24)	4.42 (0.23)	4.63 (0.62)	4.29 (0.27)	0.750	0.714	0.616	0.404	0.169	0.319
Share of plots with systematic certificate	0.684 (0.05)	0.695 (0.09)	0.661 (0.06)	0.698 (0.09)	0.752	0.983	0.741	0.841	1.000	0.622

Plot age	14.83 (0.74)	15.52 (1.16)	14.40 (6.26)	14.59 (1.48)	0.501	0.626	0.920	0.014**	0.020**	0.649
Mean number of trees per hectare in OP	3.43 (0.95)	5.07 (2.57)	2.62 (0.60)	2.63 (0.90)	0.360	0.377	0.992	1.000	0.924	0.756
=1 Trees planted in OP	0.01 (0.00)	0.003 (0.003)	0.007 (0.005)	0.01 (0.006)	0.554	0.279	0.619	1.000	1.000	1.000
=1 Trees cut in OP	0.034 (0.01)	0.033 (0.01)	0.06 (0.01)	0.01 (0.01)	0.169	0.127	0.004***	1.000	1.000	0.918
Actual tree planting Endline										
=1 Trees planted in OP (Endline)	0.20 (0.032)	0.04 (0.016)	0.10 (0.027)	0.43 (0.031)	0.072*	0.000***	0.000***	0.770	0.000***	0.000***
N	817	270	274	273						

Columns (1) to (4) show mean estimates and corresponding standard errors. Columns (5) to (7) report p-values for a test of mean difference based on a linear regression model.

Columns (8) to (10) report p-values for Kolmogorov–Smirnov test (K–S test).

Stars refer to * 0.10 ** 0.05 and *** 0.01 significance level.

Standard errors are cluster-corrected at village level, shown in parenthesis.

Table 6 Perceptions of the provision of ecosystem functions from tree planting in oil palm in the follow-up1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	Item used for the Factor Baseline	Item used for the Factor Follow-up
Planting native multi-purpose trees on and along my oil palm plantation …	N 744	Total	Control (n= 240)	Information ($T1$) (n=245)	Structural ($T2$) (n= 253)	T1-C	T2-C	T2-T1		
Regulation										
1. …increases soil fertility	744	3.56 (0.09)	2.89 (0.140)	3.78 (0.12)	3.91 (0.05)	0.00***	0.00***	0.339	Y	Y
2. …decreases soil erosion	744	4.17 (0.06)	3.99 (0.15)	4.37 (0.10)	4.12 (0.09)	0.018**	0.380	0.086*		Y
3... increase temperature in the plantation.	744	4.38 (0.05)	4.17 (0.04)	4.71 (0.05)	4.23 (0.04)	0.00***	0.369	0.00***		Y
4. …decreases water availability	744	2.11 (0.11)	2.93 (0.15)	1.55 (0.10)	1.94 (0.11)	0.00***	0.00***	0.02**	Y	Y
5. …increases water quality	744	4.15 (0.06)	3.98 (0.07)	4.50 (0.06)	3.97 (0.11)	0.00***	0.92	0.00***		Y
Habitat										
6. …increases bird diversity	742	4.30 (0.05)	4.36 (0.06)	4.50 (0.06)	4.05 (0.06)	0.143	0.00***	0.00***		
7. …increases insect diversity	743	4.02 (0.06)	4.04 (0.06)	4.32 (0.06)	3.70 (0.09)	0.00***	0.00***	0.00***		
8. …decreases the likelihood of pests and diseases in oil palm	742	3.46 (0.07)	3.05 (0.06)	3.63 (0.10)	3.66 (0.09)	0.00***	0.00***	0.00***	Y	Y
9. …leads to nutrient competition between trees and oil palms	744	3.86 (0.08)	4.27 (0.08)	4.07 (0.07)	3.31 (0.07)	0.09*	0.00***	0.00***	Y	
10. …takes too much space	744	3.49 (0.08)	3.95 (0.03)	3.64 (0.05)	2.96 (0.12)	0.00***	0.00***	0.00***	Y	
Information										
11. …makes my plantation more beautiful	743	3.52 (0.13)	2.50 (0.18)	3.96 (0.10)	3.96 (0.12)	0.00***	0.00***	0.95	Y	Y
Provisioning										
12. …increases the availability of nutritious food for my family	743	3.96 (0.08)	3.29 (0.13)	4.38 (0.04)	4.13 (0.06)	0.00***	0.00***	0.04**		Y
13. …is an important source of timber	744	4.09 (0.10)	3.29 (0.15)	4.57 (0.06)	4.30 (0.06)	0.00***	0.00***	0.00***		Y
14. …increases my income	743	3.60 (0.12)	2.60 (0.10)	4.18 (0.04)	3.88 (0.09)	0.00***	0.00***	0.00***	Y	Y

15. …decreases the stability of my income	744	3.23 (0.08)	2.82 (0.08)	3.77 (0.09)	3.06 (0.08)	0.00***	0.04**	0.00***		
16. …increases the well-being of my family	744	3.64 (0.12)	2.66 (0.11)	4.22 (0.06)	3.92 (0.09)	0.00***	0.00***	0.01**	Y	y
17… increase the time that I can spend on doing other things	744	3.36 (0.06)	2.98 (0.10)	3.64 (0.07)	3.43 (0.06)	0.00***	0.00***	0.05*		
Total factor	740	4.46 (1.21)	3.40 (0.13)	5.08 (0.05)	4.76 (0.08)	0.00***	0.00***	0.00***		
KMO									0.733	0.857
Cronbach's alpha									0.6763	0.820

Note: Columns (2) to (5) show mean estimates and corresponding standard errors. Columns (6) to (8) report p-values for a test of mean difference based on a linear regression model. Standard errors are cluster-corrected at village level, shown in parenthesis. 5-point Likert scale employed, where 5= strongly agree, 4= Slightly agree, 3=indifferent, 2=slightly disagree, 1=strongly disagree. Statements were adapted from Meijer et al. (2015) to the context of oil palm. The classification of ecosystem functions was based on Dislich et al. (2016). Standard deviation in parenthesis Min-Max value for the total factor: (1.170 – 6.065) *p < 0.1 **p < 0.05, *** p < 0.01

Table 7 Intent-to-treat effects (full model)

	(1) Actual tree planting	(2) Perceptions	(3) Intention to plant
T1	1.332^{***} (0.485)	0.333^{***} (0.028)	0.203^{***}(0.046)
T2	3.466^{***} (0.458)	0.275^{***} (0.028)	0.200^{***} (0.040)
Access to seedlings	-0.222 (0.240)	0.050^{**} (0.019)	0.002 (0.046)
Autochtonous	-0.293 (0.318)	0.026 (0.022)	0.085^{*}(0.045)
Share of oil palm	-0.421^{***}(0.152)	0.039 (0.024)	0.086^{**}(0.033)
Age	-0.038 (0.074)	0.0006 (0.007)	0.017^{**} (0.008)
Age (sqr)	0.0002 (0.000)	-6.13e-08 (0.000)	-0.0001^{**} (0.000)
Years of education	0.059^{*} (0.035)	0.002 (0.002)	0.008^{**}(0.003)
Number of hh members at home past 12m	0.055 (0.067)	0.005 (0.005)	0.002 (0.007)
=1 if farmer has a homegarden	-1.511^{***}(0.450)	-0.009 (0.0197)	-0.059 (0.055)
=1 if farmers has trees in oil palm plantation	0.167 (0.294)	0.041^{**}(0.020)	0.102^{***}(0.027)
=1 if farmer has cut trees in the past 12 months	-0.110 (0.932)	-0.0110 (0.038)	-0.015 (0.071)
Perceptions on tree benefits-baseline	0.083 (0.116)	0.018^{**}(0.008)	0.025^{*} (0.014)
Constant	-1.382 (1.990)	0.282 (0.197)	-0.415^{**}(0.196)
Observations	670	670	670
R^2		0.362	0.117
Pseudo R^2	0.236		

Note: Each column is a separated weighted regression. Columns 1 and 2 show the estimated coefficient of an OLS regression. Column 3 shows marginal effects from a logit regression.

Standard errors are cluster-corrected at village level, shown in parenthesis.

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

Table 8 Path analysis to test perceptions and intention as mediators

		Unstandardized		Standardized		
		(1)	(2)	(3)	(4)	(5)
Perceptions			p-values		p-values	Odds ratio
	T1	0.341 (0.020)	0.000	0.643 (0.037)	0.000	
	T2	0.276 (0.021)	0.000	0.534 (0.041)	0.000	
	Access to seedlings	0.050 (0.019)	0.008	0.087 (0.033)	0.008	
	Autochtonous	0.027(0.023)	0.239	0.047 (0.040)	0.239	
	Share of oil palm	0.040 (0.019)	0.040	0.080 (0.039)	0.040	
	Age	0.001 (0.001)	0.410	0.029 (0.035)	0.410	
	Years of education	0.003 (0.002)	0.251	0.040 (0.035)	0.251	
	Household members	0.005 (0.006)	0.351	0.031 (0.034)	0.351	
	Homegarden	-0.010 (0.028)	0.728	-0.011(0.031)	0.728	
	If trees in oil palm	0.042 (0.018)	0.021	0.076 (0.033)	0.021	
	Perceptions-baseline	0.018 (0.008)	0.025	0.076 (0.034)	0.025	
	=1 if cut trees last 12 m	-0.012 (0.042)	0.776	-0.009 0.032)	0.776	
R-square		0.364		0.364		
Intention						
	Perceptions	0.499 (0.056)	0.000	0.349 (0.040)	0.000	
	T1	0.033 (0.039)	0.406	0.044 (0.053)	0.406	
	T2	0.057 (0.034)	0.092	0.077 (0.046)	0.092	

R-square		0.147		0.147		
Actual adoption						
	Intention	1.307 (0.335)	0.000	0.202 (0.049)	0.000	3.694
	Perceptions	0.548 (0.603)	0.363	0.059 (0.065)	0.363	1.730
	T1	0.651 (0.471)	0.167	0.135 (0.095)	0.154	1.918
	T2	2.761 (0.431)	0.000	0.577 (0.073)	0.000	15.815
R-square		0.360		0.372		
Intercepts						
	Intention	-0.036 (0.029)	0.221	-0.101 (0.083)	0.221	
	Perceptions	0.280 (0.067)	0.000	1.133 (0.278)	0.000	
Thresholds						
OP$1		3.952 (0.507)	0.000	1.726 (0.170)	0.000	
Residual Variance						
	Intention	0.107 (0.005)	0.000	0.853 (0.023)	0.000	
	Perceptions	0.039 (0.002)	0.000	0.636 (0.035)	0.000	
Direct effect T1		0.651 (0.471)	0.167	0.135 (0.095)	0.154	
Indirect effect T1 (through only perceptions)		0.183 (0.202)	0.364	0.038 (0.042)	0.362	
Indirect effect T1 (through only intention)		0.043 (0.053)	0.419	0.009 (0.011)	0.418	
Indirect effect T1 (through perceptions and intention)		0.218 (0.063)	0.001	0.045 (0.013)	0.000	
Total indirect effect T1		0.444 (0.204)	0.030	0.092 (0.011	0.027	
Total effect T1		1.095 (0.450)	0.015	0.092 (0.042)	0.027	

Direct effect T2	2.761 (0.431)	0.000	0.577 (0.073)	0.000
Indirect effect T2 (through only perceptions)	0.151 (0.167)	0.366	0.032 (0.035)	0.364
Indirect effect T2 (through only intention)	0.074 (0.048)	0.124	0.015 (0.010)	0.120
Indirect effect T2 (through perceptions and intention)	0.180 (0.052)	0.000	0.038 (0.010)	0.000
Total indirect effect T2	0.405 (0.171)	0.018	0.085 (0.035)	0.015
Total effect T2	3.166 (0.419)	0.000	0.661 (0.063)	0.000
Direct effect perceptions	0.548 (0.603)	0.363	0.059 (0.065)	0.912
Indirect effect perceptions (through intention)	0.652 (0.183)	0.000	0.070 (0.019)	0.000
Total indirect effect perceptions	0.652 (0.183)	0.000	0.070 (0.019)	0.000
Total effect perceptions	2.761 (0.431)	0.041	0.129 (0.063)	0.039
N	670			

Note: Results of a weighted structural equation model. Estimator: Maximum Likelihood Robust (ML), the model was performed in Mplus

Loglikelihood user model (H0): -338.722 /Akaike (AIC): 701.445 / Bayesian (BIC): 755.621 / Sample-size adjusted Bayesian (BIC): 715.220

Marginal effects were estimated with the unstandardized estimates from Column 1. We follow the formula: $(u = 1|x = 1) = \frac{1}{1+e^{-L}}$; where $L = Thresholds\ op + \ \beta_{direct\ T1 \rightarrow actual\ adoption}$ for T1 and $Thresholds\ op + \ \beta_{direct\ T2 \rightarrow actual\ doption}$ for T2.