Promoting Agroforestry in Rwanda: the Effects of Policy Interventions Derived from the Theory of Planned Behaviour

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Abstract

Although agroforestry offers multiple benefits, its adoption by small-scale farmers remains low in some regions in developing countries. Besides economic motives also intrinsic motivations can influence farmers' behaviour. This study identifies farmers' intrinsic drivers to adopt agroforestry based on the Theory of Planned Behaviour. Furthermore, it compares policy instruments which address the intrinsic drivers to promote agroforestry adoption. Specifically, an agent-based simulation model investigates whether the following interventions increase adoption intentions 1) an information campaign to spread awareness of agroforestry benefits to strengthen positive attitudes, 2) informing farmers about social norms to reinforce their perception of subjective norm, and 3) providing trainings to improve farmers' perceived behavioural control. The research is applied to a case study in rural Rwanda. In line with the Theory of Planned Behaviour, a partial least squares structural equation model confirms that attitude, subjective norm, and perceived behavioural control influence farmers' adoption intention. The simulations demonstrate that all interventions significantly increase farmers' intention to adopt agroforestry, but their effectiveness is rather small. The information campaign targeting attitude causes the strongest increase. The relatively weak effectiveness of the individual interventions can be enhanced by their combined implementation. Policy-makers who aim to raise low agroforestry adoption rates should consider strategies that target intrinsic drivers as alternatives to economic incentives.

Keywords: Agroforestry, Innovation Adoption, Theory of Planned Behaviour, Policy Interventions, Small-scale Farming

JEL classification: O13, O21, Q18

1. Introduction

Scientists as well as policy-makers frequently promote agroforestry as a sustainable agricultural practice to address climate change and food security challenges (Ndlovu and Borrass, 2021; Rosenstock et al., 2019; WBGU, 2021). Agroforestry describes the integration of trees with other agricultural activities (Abbas et al., 2017). As a sustainable agricultural practice, it can produce food and non-food outputs, improve nutrient and water cycling, and contributes to soil fertilization. At the same time, agroforestry mitigates climate change through CO_2 sequestration and conserves biodiversity (Santos et al., 2019; Wangpakapattanawong et al., 2017; WBGU, 2021). This practice promotes food security and increases resilience. Hence, small-scale farmers in developing countries, whose livelihoods depend on agriculture and who are especially vulnerable towards climate change, can benefit from agroforestry in particular (Reppin et al., 2020; Wangpakapattanawong et al., 2017). However, the low uptake of agroforestry in certain regions, especially in parts of Africa, poses an obstacle to realize its numerous benefits (Amare et al., 2019; Do et al., 2020; Ndlovu and Borrass, 2021; Partey et al., 2017). Governmental support can remove barriers and encourage small-scale farmers' adoption (Baig et al., 2021; Iiyama et al., 2017, 2018b; Jacobi et al., 2017). Therefore, effective policy measures are needed to raise low agroforestry adoption rates (Hilbrand et al., 2017; Ndlovu and Borrass, 2021).

When developing effective policy interventions to support adoption, policy-makers need to consider the reasons for low uptake rates and thus account for factors that drive farmers' decision-making (Dessart et al., 2019; Meijer et al., 2015a). Numerous studies have established that economic reasons can motivate farmers to adopt new agricultural practices (e.g. Cole, 2010; Iiyama et al., 2018; Oduro et al., 2018; Staton et al., 2022). However, policy interventions that are based on financial incentives may not be effective in certain cases. For example, empirical evidence suggests that the fear of damaging their reputation may prohibit farmers from adopting promoted practices (Läpple and Kelley, 2013; Sereke et al., 2016). Thus, social norms and the desire to act in accordance with other people's behaviour can impact agricultural decisions (Buyinza et al., 2020b; Chandrasekhar et al., 2018; Kremer et al., 2019; Llewellyn and Brown, 2020; World Bank, 2015). Moreover, adoption may depend on farmer's attitudes towards on-farm tree planting, which can reflect perceived risks and subjective perceptions associated with the practice (Buyinza et al., 2020a, 2020b; Jha et al., 2021; McGinty et al., 2008; Meijer et al., 2015b; Olum et al., 2020). Furthermore, farmers' opinions regarding their abilities and control over the behaviour can influence their decision (Buyinza et al., 2020a, 2020b; McGinty et al., 2008). Complementing the empirical evidence, the Theory of Planned Behaviour (TPB) postulates that behaviour is based on a goal-directed, deliberate decision process and that behavioural intentions are formed by attitude, subjective norm (SN), and perceived behavioural control (PBC) (Ajzen, 1991). Attitude describes the extent to which a person holds a favourable or unfavourable evaluation of the respective behaviour. SN reflects the beliefs whether important reference individuals or groups approve the behaviour, and PBC describes the perceived ease or difficulty to perform the behaviour (Ajzen, 2006, 1991; Fishbein and Ajzen, 2010; Lima and Bastos, 2020). Policy-makers should consider these socio-psychological factors instead of implementing top-down supply-push approaches to develop and implement effective interventions (Dessart et al., 2019; Iiyama et al., 2018b; Jha et al., 2021; Meijer et al., 2015a).

To identify effective instruments that influence farmers' agricultural decisions, a few authors have compared different policy interventions. In the context of promoting tree planting and forest conservation among landholders, previous studies have assessed the effectiveness of financial incentives such as subsidies and payments for ecosystem services (e.g. Ruseva et al., 2015; Salvini et al., 2016; Villamor et al., 2014; West et al., 2018). Only few authors have tested behavioural, non-economic interventions to raise agroforestry adoption rates. For example, Romero et al. (2019) stated that changes in perception and intention due to an information campaign increased adoption among smallholder oil palm farmers in Indonesia. Buyinza et al. (2020b) found that farmers who participated in agroforestry projects were motivated by more positive evaluations and higher perceived capability to implement the practice, whereas social pressure was more important to farmers who did not participate in the project. The sparse literature on policy interventions based on behavioural insights in the field of agriculture reflects the limited insights on the efficiency of these instruments for behaviour change (Rose et al., 2018). Thus, more research testing different behavioural interventions is needed to investigate how effectively non-economic policy instruments promote adoption among small-scale farmers (Lourenco et al., 2016; Palm-Forster et al., 2019; Rose et al., 2018).

The purpose of this study is to identify intrinsic drivers of agroforestry adoption intentions using the TPB. Furthermore, it aims to test the effectiveness of non-economic interventions which address the identified intrinsic drivers to promote agroforestry adoption. An agent-based model (ABM) simulates three policy interventions derived from the TPB and compares their effects on small-scale farmers' intention to cultivate diverse tree species on their farms. The simulated policy strategies include 1) an information campaign to spread awareness of agroforestry benefits to strengthen positive attitudes, 2) informing farmers about social norms to reinforce their perception of subjective norms, and 3) providing trainings to improve farmers' perceived behavioural control over planting diverse tree species. The research is applied to a case study in rural Rwanda, where agroforestry offers a promising pathway for advancing livelihoods and food security as well as combating environmental problems (Mukuralinda et al., 2016). The study contributes to the limited literature on behaviourally-informed interventions in the field of agriculture. It provides insights into how interventions derived from the TPB as alternatives to financial rewards or input provision can motivate agroforestry adoption. Thus, the study supports policy-makers in evaluating cost-effective strategies addressed at intrinsic drivers to raise agroforestry adoption rates.

The study is organized as follows. The subsequent chapter introduces the TPB. Chapter 3 presents the data and describes the ABM. The results are presented in chapter 4 and discussed in chapter 5. The last section summarizes and concludes.

2. Theory of Planned Behaviour

To account for social influences and subjective perceptions when investigating agroforestry adoption decisions, this study employs the Theory of Planned Behaviour. According to this socio-cognitive theory, behaviour is directly determined by intention. The stronger the intention to perform a certain behaviour is, the more likely its execution becomes. Intention itself is formed by three TPB-constructs: attitude, SN, and PBC, as figure 1 illustrates (Ajzen, 2006, 1991; Lima and Bastos, 2020). A more favourable attitude, higher SN, and greater PBC lead to a stronger intention to perform the behaviour in question.

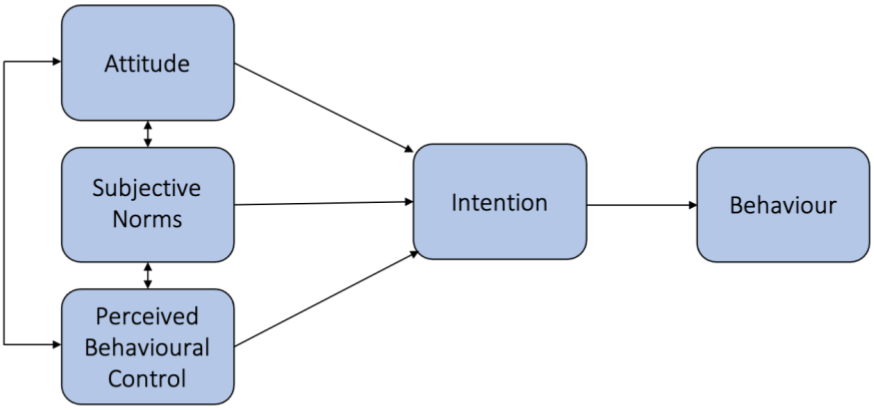

Figure 2.1: Framework: Theory of Planned Behaviour.

Source: Adapted from Ajzen (1991) and Fishbein and Ajzen (2010).

Attitude is formed by salient beliefs about the behaviours' likely outcomes and the subjective evaluation of these outcomes (Ajzen, 2006, 2005, 1991; Meijer et al., 2016). Attitude as a TPB-construct can be calculated as follows

$$Att = \sum_{i=1}^{I} b_i * e_i \qquad (1)$$

b_i reflects the strength of each salient behavioural belief i, for example to what degree a farmer believes that cultivating diverse tree species on their farm increases income. e_i describes the subjective evaluation of the belief's attribute, e.g. to what extent the farmer approves increased income. The products of the behavioural beliefs and their subjective evaluation over all I salient beliefs are summed up to compute the construct attitude (Ajzen, 1991; Ajzen and Fishbein, 2000; Meijer et al., 2016).

SN captures the perceived social pressure to engage in or refrain from the behaviour as follows

$$SN = \sum_{i=1}^{I} n_i * m_i \qquad (2)$$

For calculating SN, each normative belief strength regarding the respective reference group's approval (n_i) is multiplied by the individual's motivation to comply with the respective group's approval (m_i). Summing the products of all I salient reference groups yields the SN (Ajzen, 2006, 1991; Lima and Bastos, 2020).

The concept of PBC is related to an individual's self-efficacy and captures key skills, past experiences, and expected difficulties. Individuals perceive higher behavioural control if they are convinced to have the relevant resources and opportunities and anticipate few obstacles to perform the behaviour. The PBC can be expressed by summing up the products of each control belief and the perceived power over these control factors as follows:

$$PBC = \sum_{i=1}^{I} c_i * p_i \qquad 3$$

c_i describes the control beliefs, e.g. how likely individuals might encounter a control factor when performing the behaviour. p_i reflects the power over the respective control factor (Ajzen, 2006, 1991; Fishbein and Ajzen, 2010; Lima and Bastos, 2020).

Overall, the TPB provides a suitable framework for explaining decision-making and predicting farmers' behaviour (Buyinza et al., 2020a; Groeneveld et al., 2017; Hine et al., 2015; Maleksaeidi and Keshavarz, 2019). Researchers have applied the TPB to explain farmers' pro-environmental behaviour, including agroforestry adoption (Buyinza et al., 2020a, 2020b; McGinty et al., 2008; Meijer et al., 2016, 2015b; Sereke et al., 2016; Sood and Mitchell, 2004), related management practices (Cahyono et al., 2020), farm forestry (Zubair and Garforth, 2006), and on-farm biodiversity conservation (Zeweld et al., 2017).

3. Data and Methodology

3.1 Study area

This study is applied to a case study in rural Rwanda. Rwanda is a land-locked country located in the central African highlands occupying an area of only 26,338 km^2 (Bagstad et al., 2020; FAPDA, 2016). A mountainous relief characterizes this country, whose altitude ranges from 900 m to 4500 m. Rwanda has a tropical climate with abundant rainfalls and mean annual temperatures ranging from 16°C to 20°C (European Commission and Republic of Rwanda, 2006). With over 11 million inhabitants, Rwanda is the most densely populated country in Africa (FAPDA, 2016). This population largely depends on rain-fed agriculture for their livelihoods. Thus, agriculture is the main land use and contributes to almost 90% of total employment (FAPDA, 2016; Nishimwe et al., 2020). Most farmers cultivate plots smaller than one hectare, as the high population density makes land a scarce resource in this country (Iiyama et al., 2018a; Nishimwe et al., 2020). During the last decades, natural forests and woodland were converted into arable land, resulting in a severe loss of ecosystem services (Bagstad et al., 2020). As a result, Rwanda's agricultural sector faces major environmental challenges including biodiversity loss, land degradation, and reduced productivity (Iiyama et al., 2018a; Paul et al., 2018). Additionally, farmers in rural areas face high risks for soil erosion as most of their plots are located on slopes (Bagstad et al., 2020; Republic of Rwanda and Ministry of Agriculture and Animal Resources, 2020). Thus, agroforestry offers a promising solution to address these challenges and provide benefits to farmers and the environment (Iiyama et al., 2018a).

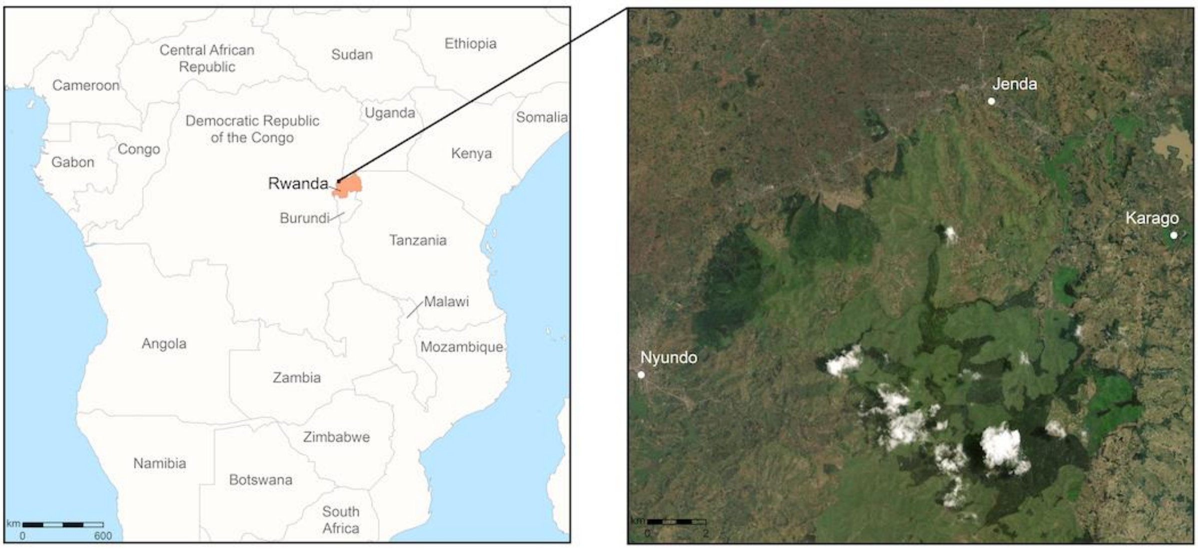

Figure 3.1: Study area

3.2 Data collection

This study focused on three study sites located in Rwanda's Western Province: Karago, Jenda, and Nyundo sector, as figure 3.1 visualizes. These sectors reflect typical characteristics of agricultural systems implemented in rural highlands of densely populated areas, where farmers operate on small hillside plots and are exposed to environmental hazards such as landslides and soil erosion. In this study area, a structured survey was conducted. The first part of the questionnaire covered socioeconomic characteristics and farming activities. The second survey section consisted of indicators to estimate the TPB-constructs. These TPB-indicators captured the behavioural beliefs and their subjective evaluation (attitude), normative beliefs and the associated motivation to comply (SN), as well as control beliefs and the perceived power over these control factors (PBC) based on a five-point Likert scale. The sample comprised a total of 145 randomly selected small-scale farmers, who were interviewed in October and November 2020.

3.3 Data analysis

The survey data were cleaned and analysed descriptively in Stata 16 (StataCorp, 2019). A partial least squares structural equation model (PLS-SEM) approach based on the software SmartPLS 3 was used to operationalize the TPB-framework and estimate the relationships between the latent TPB-constructs and the observable TPB-indicator items for identifying relevant intrinsic drivers (Ringle et al., 2015; Stein et al., 2012). This multivariate model maximizes the explained variance of the endogenous latent variables. One advantage of this approach is its ability to enable forecasts (Hair et al., 2017). These descriptive and econometric results formed the basis for the developed agent-based simulation model, which the next section describes in detail. Analysis of Variance (ANOVA) was used to compare the simulated policy scenarios using Stata 16.

3.4 Agent-based Model

Agent-based simulation models offer an advantageous tool to analyse the effectiveness of policy interventions: by providing a virtual context-specific laboratory, they can examine alternative policy options in an ethical, time-, and cost-effective way (Ahrweiler, 2017; Gilbert et al., 2018). The implemented ABM is based on the Biodiversity and Adoption of Small-scale Agroforestry in Rwanda (BASAR) model (Noeldeke et al., 2022). The following presentation of the implemented model is based on the Overview, Design Concepts and Details + Decision-making (ODD+D) protocol (Grimm et al., 2020, 2010, 2006; Müller et al., 2013). Sections that are identical to the previous model version are not presented here, but they can be found at https://www.comses.net/codebase-release/55065bfb-08ec-4a15-9357-82797a82e7f0/. The ODD+D protocol refers to the baseline scenario without any interventions. The policy scenarios are introduced subsequent to the model description.

I. Overview:

I.i Purpose: The model examines how effectively different policy interventions targeting intrinsic drivers derived from the TPB motivate Rwandan small-scale farmers to adopt agroforestry systems with diverse tree species as an alternative to potatoes and wheat rotations. It is addressed at policy-makers in the early stages of policy development. The model aims to shed light on the suitability of different non-economic policy instruments to raise low adoption rates and thus to support policy design.

I.ii Entities, state variables, and scales: The main model entities are the agents representing small-scale farming households. These farming households decide whether to implement agroforestry systems on their farms. They are characterized by variables describing their labour force, land size, number of friends, and TPB-indicators. Table 8.1 in the appendix contains further details regarding the household agents' attributes. Households can be connected with each other via links. Through these links households can exchange information about the adoption of agricultural practices. The model's spatial landscape is described by plot agents. They represent the land owned by the farming households. The household agents' behaviour determines their land cover. Table 8.2 in the appendix provides an overview over the plot agent variables. The model includes space explicitly, based on approximated land sizes calculated from the survey data. Each square grid cell represents 0.5 ha, and the model landscape represents 60 x 60 ha. One time step represents one year.

I.iii Process overview and scheduling: During every time step simulated, the following procedures take place in the order presented in figure 3.2. First, the plot agents representing the agricultural ecosystem execute the vegetation transition. Subsequently, the farming agents carry out the information exchange submodel, during which they can receive information about agroforestry. The households that know about the agricultural practice decide whether to implement agroforestry or continue to grow traditional crops. Next, farming households may harvest produced agricultural outputs depending on their land use. Farmers who adopted agroforestry on their plots must maintain the trees in certain years. Surplus family labour that was not needed for the household's farming activities is used to generate additional income. Finally, outputs are updated. Once a household has adopted agroforestry, this land use is retained for 20 years until the trees mature, and only then can households re-evaluate their decision whether to adopt agroforestry again or return to traditional crop rotations. During each procedure, the order of agents performing the respective procedure is random. The model simulates time periods of 30 years, which is sufficiently long to cover the duration until timber can be harvested from the agroforests.

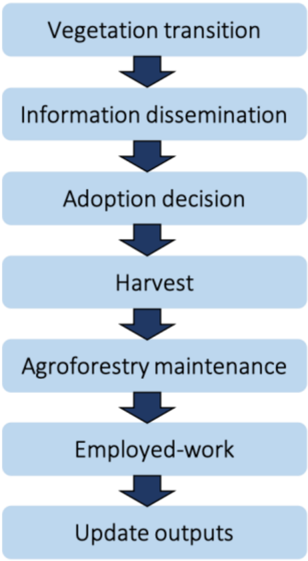

Figure 3.2: Agent-based model: process overview

II) Design concepts

II.i Theoretical and empirical background: The modified version of the BASAR model simulates farmers' decision to adopt agroforestry based on the TPB. It compares different policy interventions aimed at strengthening farmers' intention to plant diverse tree species on their farms. Land use and land cover emerge from household-level decisions. Household survey data from rural Rwanda provides the empirical basis for the model.

II.ii Individual decision-making: The farming households who have not implemented agroforestry decide about adopting this sustainable agricultural practice based on the TPB. Thus, the model includes farmers' objectives implicitly. The households compute their individual attitude, SN, and PBC based on the PLS-SEM results using the TPB-indicators from the survey. They calculate their intention as follows:

$$Intention_i = w_{Att} * Att_i + w_{SN} * SN_i + w_{PBC} * PBC_i \qquad 4$$

with the weights $w_{Att} = 0.43$, $w_{SN} = 0.18$, and $w_{PBC} = 0.13$ in line with the PLS-SEM results. Whereas the effects of attitude and PBC on intention remain constant, the influence of

SN increases over time if the household is exposed to a large share of adopters in their network. The computed value for intention is rescaled to match the model's time scale and to fall in the interval between 1 and 100 so that it can be interpreted as the adoption probability.

II.iii Individual sensing: The households are aware of their own state variables and their plot's current land cover. Additionally, they know quantities and prices of agricultural inputs and outputs. They are also aware of who in their social network has adopted the agroforestry system.

II.iv Interaction: Farmers share information regarding the agricultural practice and who has already adopted it through their social networks. Thereby, a high proportion of adopters in the network reinforces the perception of the SN to adopt.

II.v Heterogeneity: The farming households differ in terms of their state variables according to the survey. As the items used to calculate attitude, SN, and PBC are also parameterized based on the survey, farmers are heterogeneous in their intrinsic drivers and adoptions.

II.vi Stochasticity: The initialization procedure comprises stochastic elements such as random household and farm locations and establishment of connections with randomly selected households. The information dissemination procedure contains randomness as farmers receive information from an external information source or through their social network with a certain probability. Farmers' intention is implemented as an adoption probability. Furthermore, farmers receive the policy intervention with a certain likelihood.

II.vii Observation: The main model outcome is the mean adoption intention. Further outputs include land use and the proportion of households aware of the agricultural practice. The rate of households aware of the agricultural practice is computed monthly, while the other outcomes are reported annually.

III) Details

III.i Implementation details: The model was implemented in NetLogo 6.2.1 (Wilensky, 1999). The model code is available at https://www.comses.net/codebase-release/b6be1774-519e-40b4-96f0-70ff9e2f7405/.

III.ii Initialization: The model is initialised with 145 randomly located agents representing farming households in the case study area. Their state variables are parameterized according to the survey. A Watts-Strogatz network is established based on the reported number of contacts with whom the farmers discuss agricultural issues. Such a network exhibits characteristics of a small-world network such as relatively high clustering and short average distances (Borgatti et al., 2018). Based on the land size reported in the survey, the closest landscape patches are assigned to the households as their plots. Initially, all farmers cultivate potatoes and wheat crops on their plots. Finally, global variables such as prices, outputs, and parameters related to the TPB decision-making module are set up.

III.iii Submodels

Because the vegetation transition, harvest, agroforestry maintenance, and update outputs modules are identical to the original BASAR model version, the following section describes only the adjusted modules. The modified adoption decision is described in section II.ii Individual decision-making.

Information dissemination: Being aware of an innovative agricultural practice is a necessary prerequisite for adoption. Households that have access to official information sources, such as media, extension services, or their village heads, can obtain information about the agroforestry system with a certain probability. Information initially enters the community via these official information sources, but farmers may receive knowledge about agroforestry also through their social network: if households have obtained information, they share it with other households in their network with a certain likelihood. Whereas the other procedures are carried out annually, information dissemination takes place monthly.

Employed work: Households can use surplus household labour, which was not needed for their own agricultural activities, to generate additional income outside the household.

Policy intervention scenarios

The described baseline scenario is compared to three policy intervention scenarios. The first policy intervention scenario simulates an information campaign that targets farmers' attitudes. The campaign promotes benefits of planting different trees species on farms, such as increased incomes, timber availability, increased tourism, enhanced animal species diversity, and climate change mitigation. The intervention is assumed to improve farmers' behavioural beliefs. The second simulated policy measure targets SN. By spreading messages informing about social norms, this instrument aims at increasing the perceived social pressure on farmers to adopt agroforestry. This policy tool is assumed to reinforce normative beliefs by disseminating information about injunctive norms, e.g. that farmers' friends and family support agroforestry adoption, through the media or personalized messages. The third policy intervention involves trainings on on-farm tree cultivation targeting PBC. It is assumed to increase farmers' perceived power over control factors by improving their confidence in adopting agroforestry. The interventions are implemented during the whole simulation period. Randomly targeted farmers receive the interventions with a probability of 50% every year. The policy instruments are assumed to affect farmers' TPB-indicators related to behavioural beliefs, normative beliefs, or perceived power. Specifically, the interventions are assumed to result in a two-unit increase on the five-point Likert scale for the respective TPB-indicators, up to a maximum score of five (medium impact). A sensitivity analysis tests an increase of one (low impact) and three points on the Likert scale (high impact). The simulations were repeated 50 times for each scenario.

4. Results

Intrinsic determinants of agroforestry adoption intentions

This study identifies intrinsic drivers of agroforestry adoption decisions based on the TPB. A PLS-SEM is used to estimate the relationships among the TPB-constructs and farmers' intentions. According to PLS-SEM results, farmers' attitude, SN, and PBC significantly impact their adoption intentions, as figure 4.1 illustrates. Among the constructs, attitude has the largest effect with a path coefficient of 0.425 (p=0.000). This indicates that attitude is the main determinant of farmers' intention to cultivate diverse tree species on their farms. SN has a considerable, yet smaller, influence on intention, as the path coefficient of 0.182 reflects (p=0.036). PBC exerts the lowest effect with a path coefficient of 0.131 (p=0.045).

Based on the survey results, the PLS-SEM provides further details into the TPB-constructs and how they are formed. The survey responses suggest that the farmers hold generally positive attitudes towards agroforestry as they associate positive outcomes with its implementation and also value these beneficial outcomes. The factor analysis based on the survey results shows that out of the tested indicators the following aspects significantly shape farmers' attitude: income, tourism, environmental health, climate change mitigation, soil erosion protection, and animal diversity. Furthermore, most respondents believe that other people are in favour of planting diverse tree species, and farmers want to adhere to this perceived injunctive norm according to the survey. The PLS-SEM shows that family and friends constitute the significant reference groups. Consequently, the estimated SN also tends to be strong. The farmers generally believe that certain control factors are important for planting diverse trees species, and they have confidence in their abilities to control these factors. Specifically, most respondents express that they themselves control planting different tree species and that they personally feel confident to exert this control. Moreover, most farmers agree that planting different tree species is feasible despite potential obstacles, such as extreme weather events, lack of institutional support, insufficient knowledge, lack of land, and unavailability of seedlings, and that they can personally overcome these obstacles, according to the survey and the PLS-SEM results. Therefore, farmers' estimated PBC also tends to be high.

The measurement model's construct validity is evaluated as follows: composite reliability and Cronbach's α assess internal reliability, loading significances and average variance extracted confirm convergent validity, and the Heterotrait-Monotrait-Ratio, Cross loadings, and the Fornell-Larcker Criterion attest discriminant validity. Evaluating the structural model includes assessing multicollinearity using the variance inflation factor and checking significance and relevance of the constructs' path coefficients as well as R^2, f^2, and Q^2 (Hair et al., 2017). Evaluating the model's goodness-of-fit shows that the tested values are within the recommended ranges or support the underlying theoretical framework. Overall, this confirms that the model is significant.

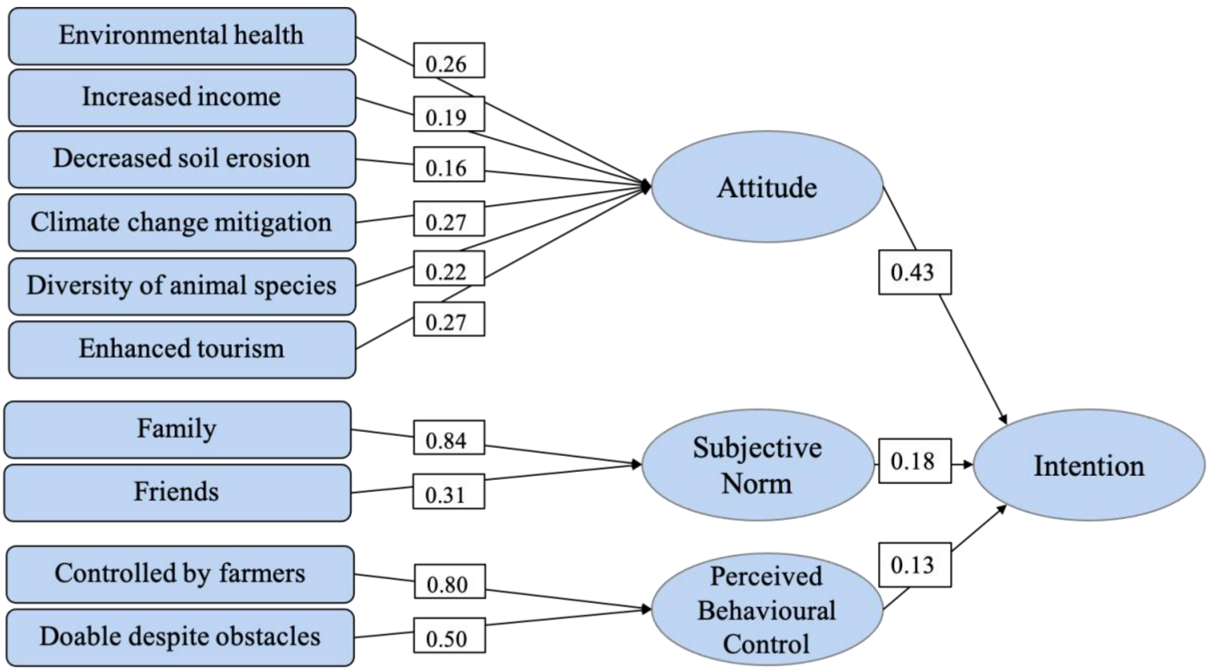

Figure 4.1: Results of the PLS-SEM.
Note: R^2=0.25. Q^2=0.212. Weights and path coefficients of all shown indicators and constructs are significant at α=5%.

Policy interventions addressing intrinsic drivers increase adoption intentions

To evaluate the impact of policy interventions derived from the TPB, an agent-based model simulates their effects on farmers' intention to adopt agroforestry. The results demonstrate that the interventions targeting attitude, SN, or PBC all increase farmers' adoption intention, as figure 4.2 illustrates. The ANOVA confirms that the policy instruments lead to significantly different intention levels (p=0.000, DF=3, F=343.25), with significant differences between all interventions compared to the baseline scenario without any intervention. However, the effects on intention are rather small. The intervention targeting attitude has the largest effect among the policy measures and improves intention by 3 percentage points (p.p.). The interventions targeting SN and PBC each increase intention by just 1 p.p. Combining policy measures to target all three TPB-constructs at the same time improves intention by as much as 5 p.p. (p=0.000, DF=7, F=712.99). Thereby, intention rises most if all three interventions are implemented simultaneously, followed by combining the attitude-intervention with targeting either PBC or SN, as figure 8.1 in the appendix visualizes.

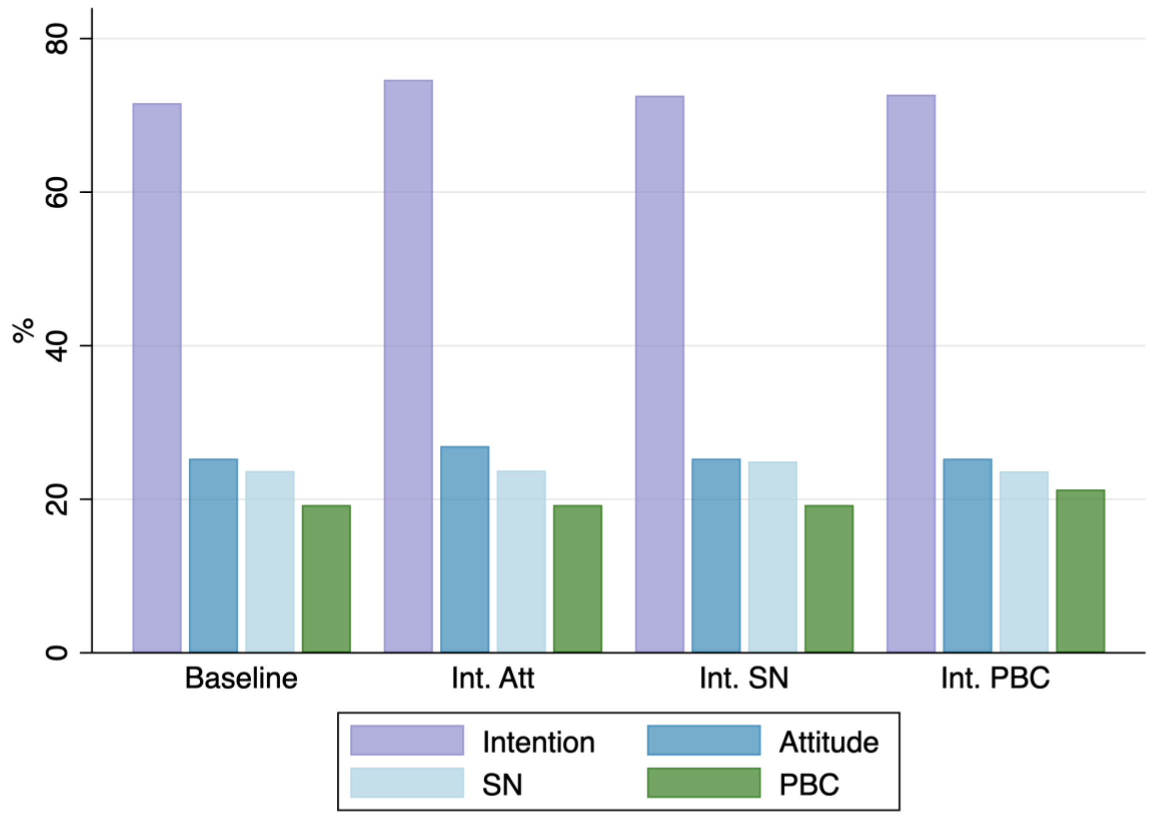

Figure 4.2: Simulation results: intervention effects

The simulation results further show that in all scenarios intention significantly increases over time (p=0.000, DF=2, F=152.45). This effect is due to the SN: when farmers are exposed to more adopters in their social network, the perceived SN intensifies and consequently increases intention. However, also this effect is rather small with an average intention increase of 1.5 p.p. over the first five years, as figure 4.2 summarizes.

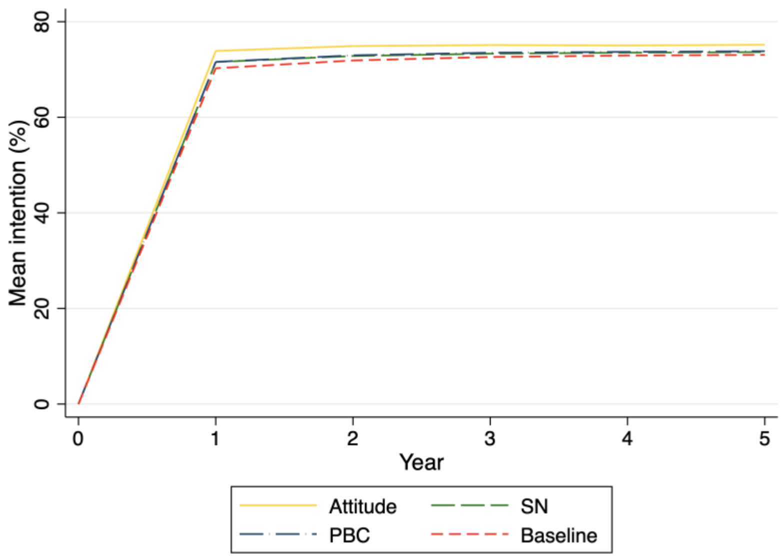

Figure 4.3: Simulation results: mean intention over the first five years

A sensitivity analysis modifies several intervention parameters to assess the robustness of the results. One change concerns strength of the policy effect on the TPB-indicators. This policy effect is reflected by the assumed increase of the TPB-indicators' Likert scale scores in response to the interventions. According to the simulations, the strength of the intervention effect on the TPB-indicators significantly affects intention, but the differences are less than 1% (p=0.0132, DF=2, F=4.34). Specifically, intention levels increase significantly when the effect strength rises from low to medium (p=0.041) or high (p=0.026). In contrast, increasing the TPB-indicator effect strength from medium to high does not significantly alter intention (p=1.000). Regardless of the effect strength, targeting attitude still provides the most effective instrument. Further parameter alterations show that implementing the intervention for shorter periods of time slightly, yet significantly, decreases intention (p=0.000, DF=3, F=37.81). Moreover, intention to cultivate diverse trees improves significantly as the likelihood of receiving the intervention increases (p=0.000, DF=8, F=136.98). However, this probability needs to rise by at least 10 p.p. to affect intention at the 5% level generally.

Whereas the previously described interventions target all TPB-indicators that form the respective TPB-construct simultaneously, measures addressing only specific beliefs also significantly increase farmers' intention (p=0.000, DF=6, F=16.36). In particular, significant impacts are obtained when interventions target behavioural beliefs related to animal species diversity (p=0.0009), climate change mitigation (p=0.000), environmental health (p=0.000), income (p=0.001), or tourism (p=0.000). However, the effects are very small (below 1 p.p.) Similarly, interventions focusing on just one specific reference group to increase normative beliefs have a very small (below 1 p.p.), yet significant, impact (p=0.000, DF=2, F=29.21). Also, interventions that target single PBC-indicators significantly improve intention, with effects below 1 p.p. (p=0.000, DF=2, F=24.03).

5. Discussion

Farmers' intentions are intrinsically motivated

This study applies the TPB to explain farmers' agroforestry adoption decisions. The PLS-SEM results indicate that attitude, SN, and PBC significantly influence farmers' adoption intentions. These findings confirm previous results that these three TPB-constructs impact farmers' decisions to cultivate and maintain trees on their farms (Buyinza et al., 2020a, 2020b; McGinty et al., 2008; Meijer et al., 2015b) and to diversify their agricultural production (Senger et al., 2017). Similarly, attitude and SN are important determinants also for on-farm biodiversity conservation (Maleksaeidi and Keshavarz, 2019). Consistent with other studies, attitude is the strongest predictor of intention in this application (Buyinza et al., 2020a; Fife-Schaw et al., 2007). Overall, the results underpin the suitability of the TPB to explain land use decisions where farmers act under the influence of social norms (Buyinza et al., 2020a; Groeneveld et al., 2017; Hine et al., 2015; Maleksaeidi and Keshavarz, 2019) and that the related intrinsic factors have high potential to explain farmers' decision to adopt agroforestry in Rwanda.

The PLS-SEM shows that farmers' attitudes are shaped by their beliefs regarding income generation but also climate change mitigation, environmental health, and soil erosion protection among others. These findings suggest that farmers do not behave as perfect rational profit maximisers. Instead, they also consider non-economic aspects in their adoption decision. Thus, these results corroborate previous findings that income motivates farmers to implement agroforestry (Mukuralinda et al., 2016; Ndayambaje et al., 2012; Oduro et al., 2018), but that their perceptions of ecosystem services are also important drivers (Djalilov et al., 2016; Mukuralinda et al., 2016). The identification of further motivational factors such as conserving animal species diversity expands previous findings. The result that income is only one of several factors motivating farmers to adopt has important implications as it suggests that financial incentives such as subsidies may not suffice to increase agroforestry uptake (Castro et al., 2020; McGinty et al., 2008). Because social and psychological factors motivate adoption as well, they should be incorporated into policy design (Dessart et al., 2019; Sereke et al., 2016; World Bank, 2015; Zubair and Garforth, 2006). Consequently, the TPB provides a helpful framework to identify entry points for changing farmers' motivations by targeting the internal antecedents of adoption intentions (Hardeman et al., 2002; Steinmetz et al., 2016).

Policy interventions derived from the TPB have potential to improve agroforestry adoption intentions

This study compares three interventions which are based on the TPB and aim at increasing farmers' intention to adopt agroforestry. The agent-based simulations reveal that the different interventions significantly increase intention. Consistent with other studies, these results confirm that changing social-psychological beliefs can change behavioural intentions (Ajzen, 2006; Fife-Schaw et al., 2007; Granco et al., 2019; Sheeran et al., 2016). Moreover, the findings support the proposition that financial incentives and input provision alone do not suffice to increase farmers' agroforestry adoption and should be complemented by non-economic measures.

Among the simulated scenarios, the information campaign targeting attitude has the largest effect on intention. This finding corroborates the frequently derived policy recommendation that calls to increase awareness regarding the advantages of on-farm tree planting and biodiversity conservation (Buyinza et al., 2020a; Djalilov et al., 2016; Jha et al., 2021; Lima and Bastos, 2020; Zubair and Garforth, 2006). Specifying previous recommendations, the present results indicate which benefits should be emphasized: policy-makers should promote agroforestry as a pathway to mitigate climate change, improve environmental health, conserve animal species diversity, increase tourism, and generate additional income. Thereby, policy-makers can expect the greatest impact on attitudes and intention if they promote all these beneficial outcomes simultaneously. Overall, the simulation results indicate the promising potential of information campaigns to reinforce positive attitudes and reverse negative attitudes.

The simulations reveal that also interventions targeting SN enhance farmers' intention. These results are consistent with previous studies showing that information about other farmers' behaviour can encourage farmers to save water or maintain environmental service provision after contracts end (Chabé-Ferret et al., 2019; Kuhfuss et al., 2016). For these studies, researchers spread messages containing descriptive norms, e.g. what other people typically do. In contrast, the norm investigated here is injunctive and thus refers to what farmers think others expect from them (Cialdini et al., 1990; Dessart et al., 2019). In a study investigating social nudges to improve tax compliance, messages containing injunctive norms had a smaller impact on payment likelihood than messages containing descriptive norms (Hallsworth et al., 2017). Also in the context of agroforestry adoption, injunctive norm messages have rather small effects, as the simulations demonstrate. In general, the findings are consistent with numerous authors who report that the social context, particularly social pressures, influences farmers' behaviour (e.g. Borges et al., 2014; Defrancesco et al., 2008; Martínez-García et al., 2013; Matuschke and Qaim, 2009; Mekonnen et al., 2018). This is because farmers may seek approval from their reference groups or want to show their commitment to values shared by these people (Martínez-García et al., 2013). Social norms can be vital for agricultural decisions because they may prevent farmers from adopting despite a positive attitude (Burton, 2004; Buyinza et al., 2020b; Sereke et al., 2016), but may encourage farmers, even if they hold a negative attitude (Borges et al., 2014). To harness the full potential of social norm messaging, policy-makers should identify relevant stakeholders that shape the norm (Dessart et al., 2019). In the case study, family and friends constitute the SN. This confirms other studies which report that farmers were mostly influenced by people close to them, including family, friends, and neighbours (Borges et al., 2014; Martínez-García et al., 2013). Overall, despite the small effects, the results support that informing about social norms has potential as a behavioural nudge to increase adoption among small-scale farmers.

The simulations further indicate that interventions targeting PBC improves intention. In this application, PBC captures farmers' confidence to control planting different tree species and to adopt agroforestry despite possible obstacles including extreme weather events, lack of institutional support, insufficient knowledge, lack of land, and seedling unavailability. This is consistent with findings from Uganda, where farmers' PBC was based on their ability to overcome economic barriers as well as their access to resources and required knowledge related to tree planting and management (Buyinza et al., 2020a). Several authors report that the lack of resources, such as seedlings and knowledge, is a common barrier to farmers' cultivation of on-farm trees (Djalilov et al., 2016; Mukuralinda et al., 2016; Oduro et al., 2018). The result that improving PBC can enhance farmers' intention is therefore consistent with other authors who state that trainings, for example, can encourage adoption (Coulibaly et al., 2017; Iiyama et al., 2017). Overall, the results underpin that reinforcing farmers' confidence to overcome possible barriers through trainings provides a promising policy instrument to increase adoption intention, but the impact might be small.

Despite their significance, the simulations reveal rather small intervention effects. Also Fife-Schaw et al. (2007) conclude that small improvements in attitude lead to negligible behavioural changes only and that modest changes in the probability of performing a behaviour require large changes in the TPB-constructs (Fife-Schaw et al., 2007). The rather small intervention effects in the case study are likely to be attributed to the fact that even without any intervention farmers report strong behavioural and normative beliefs as well as high perceived power. Positive behavioural beliefs and perceived power may origin from prior experience with agroforestry, for example through previous projects, extension services, media, or own implementation, which many farmers report in the survey. Furthermore, a lot of farmers report problems such as poor soil quality and increased occurrence of flooding and landslides due to extreme weather events. They may be aware that agroforestry can provide a solution to these challenges and consequently hold positive beliefs. Additionally, the high levels of PBC suggest that input availability is not a major barrier to most farmers, which also highlights that input provision may only have limited effects on adoption behaviour.

The results indicate that combining interventions and targeting several TPB-constructs at the same time enhances their effectiveness. Implementing several policy measures simultaneously can have a bigger impact than a single one due to additive effects (Ajzen, 1991; Chatzisarantis and Hagger, 2005; Fife-Schaw et al., 2007; Hagger et al., 2002). According to the simulations, combining the information campaign promoting agroforestry benefits with additional interventions appears especially promising. This is in line with other authors who suggest to link information provision with other behavioural interventions or material incentives such as financial rewards or inputs (Hendrie et al., 2017; Meijer et al., 2015b; Romero et al., 2019; Taghikhah et al., 2020).

Robustness tests

Confirming the findings' robustness comprised two parts. First, additional to the intervention scenarios as presented above, a sensitivity analysis investigated how changes in the model's parameters affected simulation results. The main findings were robust to changes in the social network's setup. The results were also robust to errors in the PLS-SEM estimation, as shown by changing the TPB-constructs' path coefficients and TPB-indicator weights to randomly deviate from their estimated values up to 20%. Whereas the presented simulations targeted behavioural and normative beliefs as well as perceived power over control factors, targeting the respective subjective evaluations, motivation to comply, and control beliefs instead delivered results consistent with the previous findings. Second, the non-parametric Kruskal-Wallis test confirmed the ANOVA results.

Limitations and Future research

Several limitations should be noted. This study focuses on behavioural intentions rather than agroforestry implementation because observations of the actual behaviour were not available. However, an intention does not directly translate into action if farmers are incapable to engage in the behaviour (Fife-Schaw et al., 2007; Steinmetz et al., 2016). Hence, if PBC does not coincide with actual behavioural control, the model is likely to overestimate adoption. Yet, PBC can serve as a proxy for actual control if farmers can realistically judge the behaviour's difficulty (Ajzen and Fishbein, 2000). Furthermore, the simulations did not directly address the feasibility of changing behaviour through policy measures. Instead, the simulations aimed to evaluate a “what if” scenario that investigates the suitability of successful interventions based on the TPB. Although the model is empirically based and the decision-module has been validated, the impacts of the different policy interventions on farmers’ actual attitudes, SN, PBC, and intention are only assessed in the context of the sensitivity analysis, but they are not verified against empirical observations due to data unavailability. Thereby, it is assumed that farmers exhibit homogenous responses due to the interventions.

These limitations can stimulate further research. Future work could expand the ABM to examine farmers’ heterogenous reactions to policy interventions. Another extension could relax the assumption that each intervention only affects one TPB-construct by including spill-over effects in the model. For example, farmers might discuss an information campaign and thereby reveal a social norm. Furthermore, policy interventions could introduce novel beliefs instead of altering existing ones (Ajzen, 2006). Experimental studies could empirically test the impact of the different interventions on the three TPB-constructs. Further research could validate and test the TPB-interventions in other contexts. Moreover, policy-makers should test how farmers react to interventions that combine economic and non-economic incentives and investigate associated crowding effects.

6. Summary and Conclusions

Although agroforestry systems offer numerous benefits for farmers and the environment, their uptake among small-scale farmers in certain regions of Sub-Saharan Africa is low. Because financial incentives can be limited to increase adoption rates, policy interventions targeting intrinsic drivers might provide effective and cost-efficient alternatives to motivate implementation. This study investigates intrinsic motivational factors of farmers’ agroforestry implementation decisions and how effectively policy interventions addressing these intrinsic drivers improve adoption intentions. A PLS-SEM identifies intrinsic adoption drivers based on the TPB. An ABM, which was applied to a case study in rural Rwanda, simulates the following interventions: 1) an information campaign to spread awareness of agroforestry benefits to strengthen positive attitudes, 2) informing farmers about social norms to reinforce their perception of SN, and 3) providing trainings to improve farmers' PBC. The findings demonstrate that attitude, SN, and PBC motivate farmers to plant diverse tree species on their farms. Furthermore, interventions that target these intrinsic drivers significantly increase farmers' intention to adopt agroforestry. The information campaign to strengthen positive attitudes shows the greatest potential to enhance intention. Spreading social norms to intensify normative beliefs and training provision to improve farmers' perceived control also significantly increase intention, but the effects are small. The interventions gain effectiveness when they are combined.

These findings can support policy-makers during intervention development by identifying promising and cost-effective complements or alternatives to financial incentives that motivate farmers to adopt agroforestry. Policy-makers should promote agroforestry benefits, in particular its potential to mitigate climate change, improve environmental health, increase tourism, and conserve animal species diversity. Furthermore, they should distribute messages about social norms held by farmers' family and friends related to agroforestry adoption. Policy-makers should also provide trainings to strengthen farmers' confidence in overcoming possible barriers and in their ability to cultivate diverse tree species on their farms. Overall, the findings underpin the importance of intrinsic aspects as motivational factors for agroforestry adoption as well as the promising, yet small, impacts of policy interventions targeting attitude, SN, and PBC.

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8. Appendix

Table 8.1: Farming household variables

Variable	Definition	Scale
Household ID	Household identification	Metric
Land size[a]	Land size claimed by household	Metric, in hectare
Plots	Set of plots claimed by household	Agentset
Household size[a]	Household size	Metric, in persons
Labour force[a]	Labour force based on working household members	Metric, in work-days per year
Inital labour force[a]	Initial labour force, auxiliary variable to calculate available labour force	Metric, in work-days per year
Access to Extension[a]	Access to information from extension services	Binary, 1=access, 0=no access
Access to Media[a]	Access to information from media	Binary, 1=access, 0=no access
Access to village head[a]	Access to information from village head	Binary, 1=access, 0=no access
Friends[a]	Number of contacts household discusses agricultural issues with	Metric, in persons
Tpb*belief[a]	Belief that associates agroforestry adoption with certain outcomes, how certain reference groups approve of the behaviour, or that certain control factors are present	Metric, five-point Likert scale
Tpb*scale[a]	Opinion about favourability of belief, motivation to comply, or power over control factors	Metric, five-point Likert scale
Attitude	Farmers' attitude, estimated via structural equation model (SEM)	Metric, in points
SN	Farmers' subjective norm, estimated via SEM	Metric, in points
PBC	Farmers' perceived behavioural control, estimated via SEM	Metric, in points
Intention	Intention resulting from farmers' weighted attitude, SN, and PBC	Metric, in points
Aware	Indicates whether farming agent is aware of agroforestry systems as an agricultural practice	Binary, 1=access, 0=no access
Adopter	Indicates whether farming agent has adopted agroforestry	Binary, 1=access, 0=no access

Income	Household income	Metric, in Rwandan franc (RWF)

Note: [a] parameterized according to household survey.

Table 8.2: Plot agent variables

Variable	**Definition**	**Scale**
Owner	Indicates farming household who claimed plot	HHID
Size[a]	Land size	Metric, in hectare
Potato wheat	Land cover is potato wheat rotation	Binary, 1=potato wheat rotation, 0=else
agroforestry	Land cover is agroforestry	Binary, 1=agroforestry, 0=else
Agroforestry age	Age of agroforestry system on plot	Metric, in years

Note: [a] parameterized according to household survey.

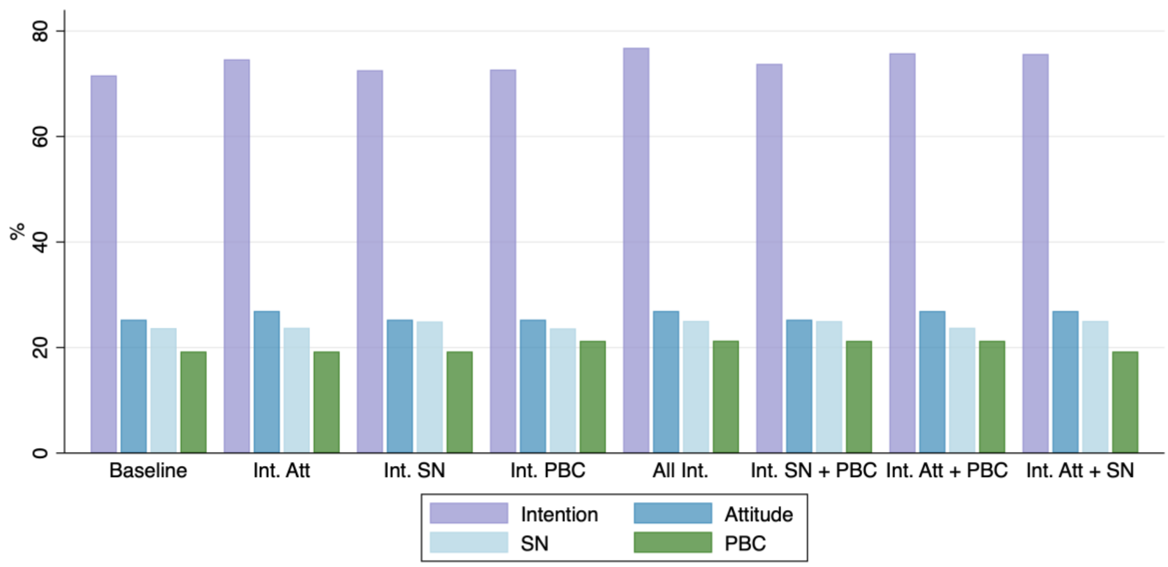

Figure 8.1: Simulation results: effects of combined interventions.

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