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Working Paper:

Using field experiments to quantify risk and time preferences of Ugandan coffee farmers in participating in forest landscape restoration

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Harnessing the potential of trees on farms (TonF) for meeting national and global biodiversity targets

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List of Acronyms

ASC	Alternative Specific Constant
CRRA	Constant Relative Risk Aversion
CPT	Cumulative Prospect Theory
DCE	Discrete Choice Experiment
ES	Ecosystem services
FLR	Forest Landscape Restoration
P&D	Pests and diseases
PPI	Poverty Probability Index
RA	Risk-averse
RN	Risk-neutral
RS	Risk-seeking
UNHS	Uganda National Household Survey
USh	Uganda Shilling
WTR	Willingness to take risk

1. INTRODUCTION

Globally, forest loss and degradation globally have resulted in declines in multiple ecosystem services (ES) and reduced habitat for biodiversity. Forest landscape restoration (FLR) offers an opportunity to address these losses and improve human well-being (Gourevitch et al., 2016). In particular, FLR is gaining prominence as a strategy to mitigate climate change, improve water quality, and increase biodiversity (Lamb, Erskine, & Parrotta, 2005). As part of the Bonn Challenge, a global effort to restore 150 million hectares of deforested and degraded land by 2020 and 350 million hectares by 2030, 53 countries to date made commitments to national FLR (Bonn Challenge, 2019). In line with the aspiration to transition to a 'Green Economy', one of the pillars of Uganda's Vision 2040 (NPA, 2007), Uganda committed to the Bonn Challenge in 2014. This commitment is timely since, driven by agricultural expansion and increased demand for forest products (Obua, Agea, & Ogwal, 2010), Uganda has experienced widespread forest loss and degradation. Between 2000 and 2012, forest cover is estimated to have decreased by approximately 300,000 hectares, which is equal to 1.8% of the country's total land area (Hansen et al., 2013). To address these challenges, Uganda pledged to restore 2.5 million hectares of deforested and degraded land by 2020 as part of their commitments towards the Bonn Challenge (IUCN, 2016). To achieve this ambitious goal, FLR is pursued through the implementation of different restoration options, including agroforestry in key agricultural landscapes in Uganda (Dave et al., 2018; IUCN, 2016).

The Mt. Elgon landscape on the border between Kenya and Uganda has been identified by the government as a priority area for FLR (IUCN, 2016). The wider Mt. Elgon landscape can roughly be subdivided in two zones, along altitudinal lines. On the Ugandan side, the higher elevations of Mt. Elgon are covered by protected forests that are part of the Mt. Elgon National Park. In the lower altitudes, below the protected forests of Mt. Elgon, are agricultural lands that support a large population of smallholder farmers with generally intensive and mixed coffee and banana-based agricultural systems (Gram, Vaast, van der Wolf, & Jassogne, 2018). Economically, Arabica coffee is particularly important for many smallholder farmers, but its production is increasingly threatened by various effects of climate change and variability. On the one hand, increased temperature has resulted in a shift of suitable growing areas for Arabica coffee from lower to higher altitudes, and ultimately to a reduction of suitable Arabica growing areas (Bunn, Läderach, Ovalle Rivera, & Kirschke, 2015; Gram et al., 2018). On the other hand, higher temperatures improve living conditions for pests and diseases leading to higher incidences of such, and consequently to a loss of coffee quality and productivity (Liebig et al., 2016). Land degradation combined with climate change has furthermore led to increased occurrence of floods and landslides in these areas (UNDP, 2013). Against that backdrop, coffee agroforestry, or the intentional use of companion trees[1] in coffee production systems, was identified as a priority practice to address FLR and climate risk in this landscape (Bukomeko, Jassogne, Tumwebaze, Eilu, & Vaast, 2019; Dave et al., 2018; UNDP, 2013). While the benefits of agroforestry are widely acknowledged, adoption among smallholder farmers is slow (Bourne, Kimaiyo, Tanui, Catacutan, & Otiende, 2015; Jerneck & Olsson, 2013; Mercer,

[1] Companion trees directly and indirectly affect coffee production and other ES through a variety of agro-ecological processes and have productive functions in themselves.

2004). Since an increase of land under mixed agroforestry production systems is a clear target under the formulated FLR objectives, understanding the motivations of these smallholder farmers is of primary importance.

Agroforestry adoption is often compared to the adoption of a new agricultural technology, but the multiple-output, multiple-input, and multi-seasonal character of agroforestry makes such comparisons difficult (Mercer, 2004). Due to its multi-component and multi-product features, agroforestry is a challenging commitment that involves a sequence of activities which link the past to the present while aiming for the fruition of investments mainly in the distant future (Mercer, 2004; Nair, 1998). It can take several years before benefits of agroforestry systems begin to be fully realized, while it might only take a few months to evaluate a new annual crop or new farming practice (Franzel & Scherr, 2002). Since many farmers prefer direct and immediate returns for their investment, the extended time period before economic benefits can be realized discourage farmers from adopting agroforestry practices (van Asten et al., 2015).

Risk and time preferences are important factors in economic decision-making, particularly among farmers in developing countries (Binswanger, 1980; Yesuf & Bluffstone, 2009). Risk aversion has been identified as a key feature preventing farmers from adopting new technologies (e.g. Dercon & Christiaensen, 2011; Liu, 2013). Studies of time preferences in developing countries also find high levels of impatience, which may prevent farmers from making long-term investments (Duflo, Kremer, & Robinson, 2008; Nguyen, 2011; Tanaka, Camerer, & Nguyen, 2010). Recent research suggests that risk and time preferences are related and that individuals who are more risk tolerant are also more patient (Clot, Stanton, & Willinger, 2017). This might allow drawing the reverse conclusion that impatient, risk-averse individuals may rather invest in fast-growing crops that generate immediate cash than in long-term investments such as agroforestry. Despite the importance of risk and time preference for agricultural investments, very few studies address perceptions of risk and uncertainty pertaining to agroforestry (Mercer, 2004). Empirical evidence for the influence of risk and uncertainty on agroforestry adoption is scarce because risk and uncertainty are hardly included as explanatory variables in such assessments, and the few that do typically used rough proxies for farmers' risk perceptions and attitudes (Mercer, 2004; Pattanayak, Mercer, Sills, & Yang, 2003). Risk has been proxied primarily through tenure, experience, extension and training, and membership in cooperatives and community organizations (Pattanayak et al., 2003). To overcome these shortcomings, deliberately including risk and time preference in agroforestry adoption studies is important. To address the challenge that using proxies has proved dissatisfactory, while risk and time preferences cannot be observed directly, experimental designs can be used to measure risk and time preferences directly and to relate them to the agroforestry adoption decision process.

The objectives of this study hence are (1) to elicit both risk and time preferences of smallholder coffee farmers in eastern Uganda by using lottery-based experiments, and (2) to investigate key attributes or features of companion trees in coffee agroforestry systems that are preferred by farmers using a discrete choice experiment (DCE). We investigate farmer preferences related to six companion tree attributes: tree products provided, regulating ES provided, growth rate, seedling price, provision of quality shade for coffee, and maximum tree height. To demonstrate the relation between risk and time preferences and the adoption of companion trees, we couple these experimental data with the results from the DCE about farmers' preferences for companion tree attributes. To analyze potential strata in farmer preferences, our sample includes coffee farmers from different altitude zones. Our gendered research design furthermore allows exploring possible differences in preferences between men and women.

The theoretical basis of our analysis is a random utility model to analyze the preferences of coffee farmers for various characteristics of companion trees. We use cumulative prospect theory (CPT) (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992) and quasi-hyperbolic discounting (Benhabib, Bisin, & Schotter, 2010; Laibson, 1997; O'Donoghue & Rabin, 1999) to measure farmers' risk and time preferences. We use a similar experimental design as Liebenehm and Waibel (2014) and Tanaka, Camerer, and Nguyen (2010) to elicit farmers' risk and time preferences. We then apply a maximum likelihood approach to estimate the effects of risk aversion, loss aversion, and time preference on choice probabilities of hypothetical companion tree alternatives vis-à-vis the status quo.

Our contribution to the literature is threefold. First, besides contributing new data, our paper makes a methodological contribution to experimental development economics. To the authors' knowledge, no other study combines risk and time preference experiments with a DCE. By coupling farmers' behavioral parameters with data from the DCE, we can observe how farmers' risk and time preferences affect decisions to adopt companion trees in coffee agroforestry systems. This can provide new insights that can help to improve the design of agroforestry interventions and the formulation of more efficient incentives to attract reluctant farmers. More generally, planned interventions in the study area can use the results to target their programs appropriately by taking farmer interests into account.

Second, we use a DCE to analyze farmers' preferences for attributes of companion tree species. To our knowledge, there are only a few other DCE studies related to agroforestry (Blare & Useche, 2015; Cranford & Mourato, 2014; Kaczan, Swallow, & Adamowicz, 2013; Mercer & Snook, 2004). We add to this literature by examining farmers' preferences for generic, hypothetical attributes of companion trees in coffee agroforestry systems, involving economic and environmental components. Rather than eliciting preferences between actual tree species, we focus on attributes that can be found in different species depending on the context. A better understanding of farmers' preferences in terms of the features of companion trees that they like, and dislike is important to design context-specific agroforestry options that aim to increase adoption of trees on farms in a way that is in line with and responsive to farmers' needs and preferences. The elicitation of hypothetical attributes furthermore allows to use our results for similar other contexts to define contextually suitable options based on likely attribute preferences (Coe, Sinclair, & Barrios, 2014).

Third, this is the first experimental study on coffee agroforestry systems with a comprehensive gender-sensitive research methodology. Preferences and management decisions regarding companion trees are likely to be gender-specific, especially in the context of crops that are considered to be gender-specific. Coffee is one such crop, as it traditionally is a cash crop controlled by men (Kasente et al., 2002; Kelemen, Potschin, Martín-López, & Pataki, 2016; Kiptot, 2015; Kiptot, Franzel, & Degrande, 2014). Yet, according to Lecoutere and Jassogne

(2016) and Villamor et al. (2014), literature on gender-differentiated perceptions and preferences in coffee systems is scarce. Filling this gap, particularly by eliciting gender-differentiated farmer preferences, is hence important. Specifically, we build on gender-disaggregated data to capture the perspective of different individuals within each household. In each household, we interviewed a male and a female household member. We also account for gender in the econometric analysis and compare preferences of men and women. By better addressing farmers' differentiated needs and preferences in planned interventions, adoption of agroforestry may become more attractive for a larger number of farmers.

In this paper, we proceed as follows. In section 2, we describe the theoretical framework for the DCE method and the prospect theory and time discounting parameters. In section 3, we describe the study area and data collection methods and proceeding. The design and application of the risk and time preference experiments and the DCE are outlined in section 4. In section 5, we specify which econometric models we use, and in section 6 we show how we estimate risk and time preference parameters. We then present and discuss descriptive statistics and econometric results in section 6 and section 7, respectively. In the last section, we draw conclusions and discusses policy implications.

2. THEORETICAL FRAMEWORK

Specification of prospect theory parameters

In this study, we follow Tanaka et al. (2010) and use CPT to capture risk in both gain and loss situations, as well as individuals' probability weightings. Unlike expected utility theory (EUT), which considers only a single parameter characterizing responses to risky situations, cumulative prospect theory uses three parameters that characterize individual risk behavior. The first parameter (σ) represents the curvature of the prospect value function and can be interpreted as a proxy for risk aversion. The second parameter (λ) characterizes loss aversion and the third parameter (α) captures the degree to which low probability events are disproportionately weighted when valuing risky prospects. The three parameters jointly characterize the valuation of risky prospects. To elicit the three CPT parameters, we use a series of lottery-based experiments, which are elaborated in section 4. We assume that farmers behave according to the assumptions that underlie CPT (Tversky & Kahneman, 1992). Consequently, a farmer's utility under cumulative prospect theory is defined as follows:

$$PT(x,p;y,1-p) = \begin{cases} v(y) + w(p)(\big(v(x) - v(y)\big), \\ \quad x > y > 0 \; or \; x < y < 0 \\ w(p)v(x) + w(1-p)\big(v(y)\big), \\ \quad x < 0 < y \end{cases} \tag{1}$$

where $PT(x,p;y,1-p)$ is the expected value over binary prospects $(x;y)$, with corresponding probabilities $(p;1-p)$. A two-part power function assigns a value for gains $(x > 0)$ and losses $(x < 0)$ separately:

$$v(x) = \begin{cases} x^{\sigma} & if \; x \geq 0 \\ -\lambda(-x)^{\sigma} & if \; x < 0 \end{cases} \tag{2}$$

The parameter σ determines the concavity of the value function for gains and losses and can be interpreted as a proxy for risk aversion. The parameter λ reflects the degree of loss aversion. It is hypothesized that $v(x)$ is s-shaped, that is, concave above the reference point, convex below the reference point, and steeper for losses than for gains (Tversky & Kahneman, 1992). Furthermore, we assume that farmers place a decision weight on probability information p that reflects the desirability of uncertain events. Therefore, we define the probability weighting function as follows:

$$w(p) = \frac{1}{\exp\left(ln\left(\frac{1}{p}\right)\right)^{\alpha}} \tag{3}$$

where α represents a proxy for probability weighting (Prelec, 1998). We expect that $w(p)$ is an inverted s-shape, that is, a subject will overweight small probabilities and underweight large probabilities. The above specification of a utility model under prospect theory nests the expected utility model, that is, the standard expected utility specification is obtained if $\alpha = 1$ and $\lambda = 1$.

Specification of time discounting parameters

We apply the quasi-hyperbolic discounting specification, which expands exponential discounting such that it is adequate to reproduce a reversal of preferences (Benhabib et al., 2010; Laibson, 1997; O'Donoghue & Rabin, 1999). That means that in contexts where individuals must allocate a budget between a sooner date and a later date, the decision depends on temporal proximity (Thaler, 1981). When the sooner date is in the distant future, individuals will often allocate a relatively smaller share to the sooner date, and a larger share to the later date. But when the timing of the payment moves closer to the present, these preferences reverse so that a larger share is allocated to the sooner date, and a smaller share is allocated to the later date. This reversal, referred to as hyperbolic discounting or present-bias, contradicts the standard economic assumption that individuals are consistent in their time preferences (Frederick, Loewenstein, & O'Donoghue, 2002; Laibson, 1997; O'Donoghue & Rabin, 1999). We assume that farmers do not discount the future in a constant manner.

Under quasi-hyperbolic discounting, a future reward is associated with a cost that is proportional to the amount of the reward. The discount factor is then defined for present ($t = 0$) and delayed rewards ($t > 0$) as follows:

$$D(\beta, \delta, t) = \begin{cases} 1, & if\ t = 0 \\ \beta exp(-\delta t), & if\ t > 0 \end{cases} \tag{4}$$

where β is a parameter reflecting present bias, and δ is the parameter for time preference. The quasi-hyperbolic specification reduces to the exponential specification whenever ($\beta = 1$). In exponential discounting, it is assumed that individuals have constant discount rates for different time horizons, that is, $\beta = 1$. We interpret β as an individual's preference for the present, that is, the individual prefers the immediate reward over all future rewards. The smaller β is, the larger the preference for the present.

Random utility theory

The DCE approach is theoretically based on Lancaster's model of consumer choice and econometrically on random utility models (Lancaster, 1966; McFadden, 1973). The underlying assumption is that demand is determined by the characteristics or attributes of goods, rather than by the goods themselves. Therefore, choice experiments consist of different alternatives of a good, which contain various attributes with different attribute levels. That is, the respondent has to choose a certain combination of attribute levels, which, together, characterize the good, rather than the good as such. It is assumed that the respondent chooses the combination, which gives the highest subjective level of utility. In our case, for example, we use a DCE to identify which characteristics or attributes farmers prefer in companion tree species. Rather than asking them to choose between different tree species in and by themselves, we include relevant attributes, such as growth speed and shade characteristics. These attributes, then, are differentiated according to different attribute levels. Growth, for instance, is differentiated in the levels 'fast', 'medium', and 'slow' growing, while shade is differentiated in the levels 'dense' and 'light'. It is assumed then, that individual farmers will choose a tree species because of their preference for both a specific growth attribute and a specific shade attribute, rather than only one attribute, and rather than choosing the tree species in and by itself. Since we are interested in possible gender-specific differences, we consider individual preferences of male and female household members separately. Following random utility theory, an individual's utility can be expressed as follows:

$$U_{ij} = V_{ij} + \varepsilon_{ij} = X'_{ij}\beta_i + Z'_i\gamma + \varepsilon_{ij} \tag{5}$$

$$\text{where } U_{ij} = \begin{cases} U_{M_{ij}};\ \text{Utility for men} \\ U_{F_{ij}};\ \text{Utility for women} \end{cases}$$

Utility $\left(U_{ij}\right)$ for male $\left(U_{M_{ij}}\right)$ or female $\left(U_{F_{ij}}\right)$ farmer i associated with companion tree species j can be differentiated into a deterministic element $\left(V_{ij}\right)$ and a stochastic element $\left(\varepsilon_{ij}\right)$, where the latter captures unobserved factors that determine farmers' choices. The deterministic part can be further divided into a choice-specific part $\left(X_{ij}\right)$ and an individual-specific part (Z_i). X_{ij} is the vector for attributes of companion tree species j and β_i is a vector of individual taste parameters mapping these attributes into utility. Z_i is a vector for individual-specific characteristics (preferences in relation to risk, potential losses, and time), and γ_j maps these characteristics into utility associated with the choice of a particular alternative. These individual-specific preferences enter the utility function by interacting with alternative specific constants, allowing us to determine the extent to which these parameters condition the choice of hypothetical companion tree alternatives vis-à-vis the status quo. In this specific context, $Z_i = [\sigma_i, \lambda_i, \alpha_i, \delta_i, \beta_i]$.

Following Train (2009), the probability that farmer i chooses tree species j is

$$P_{ij} = \int \frac{exp\left(X'_{ij}\beta_i + Z'_i\gamma_j\right)}{\sum_k exp\left(X'_{ij}\beta_i + Z'_i\gamma_j\right)} f(\beta|\Omega)d\beta \tag{6}$$

where k defines the number of alternatives presented in each choice task, $f(\beta|\Omega)$ is the probability density function of the taste parameters conditioned by a vector of parameters characterizing the distribution. In this formulation, γ_j is a vector of non-random alternative-specific coefficients that capture the effects of σ_i, λ_i, α_i, δ_i, and β_i on choice probability P_{ij}.

3. DATA AND BACKGROUND

Study area

This study was conducted in the Mt. Elgon region of eastern Uganda in the two neighboring districts Bulambuli and Kapchorwa (Figure 1). The study area is characterized by a mountainous topography. We defined two altitude zones across the study area: the moderate zone (<1700 masl) and the high zone (>1700 masl).[2] The soils are predominantly clays and the underlying geology is dominated by basaltic parent rocks (Liebig et al., 2016; Mugagga, Kakembo, & Buyinza, 2012). The area of Mt. Elgon receives an approximately bimodal pattern of rainfall with the wettest period from March or April to October or November, a pronounced dry period from December to February and a period of less intense rain around July to August (Liebig et al., 2016).

The study area consists mainly of smallholder farms (< 2 ha) and is generally dominated by intensive coffee-banana farming systems. Arabica coffee *(Coffea arabica)* is grown under varying levels of shade provided by various companion tree and banana *(Musa* spp.*)* species. The most common companion trees are Maesopsis *(Maesopsis eminii)*, Cordia (*Cordia Africana)*, Grevillea *(Grevillea robusta),* and Albizia *(Albizia coriaria)* across the three zones. Eucalyptus *(Eucalyptus grandis)* are also widespread in the area, as well as a number of other 'exotic' fruit and timber tree species. Other crops grown include beans, peas, ground nuts, maize, cabbage, sweet and Irish potato among others. Farming is also widespread on very steep slopes in the study area, which makes the area highly susceptible to soil erosion and landslides. Loss of soil fertility through soil degradation is a major challenge in the study area (IUCN, 2015).

[2] Given the lack of Arabica coffee grown at low altitude, we defined two altitude zones across the study area as opposed to Gram, Vaast, van der Wolf, & Jassogne (2018) and (Liebig et al., 2016) who considered three zones in their study area in the Mt. Elgon region: the low zone (<1400 masl), the mid zone (1400–1700 masl) and the high zone (>1700 masl). Mean annual temperatures are about 23°, 21°C and 18°C and mean annual rainfall about 1,200 mm, 1,400 mm and 1,800 mm respectively in the low, mid and high altitudes (Hijmans, Cameron, Parra, Jones, & Jarvis, 2005).

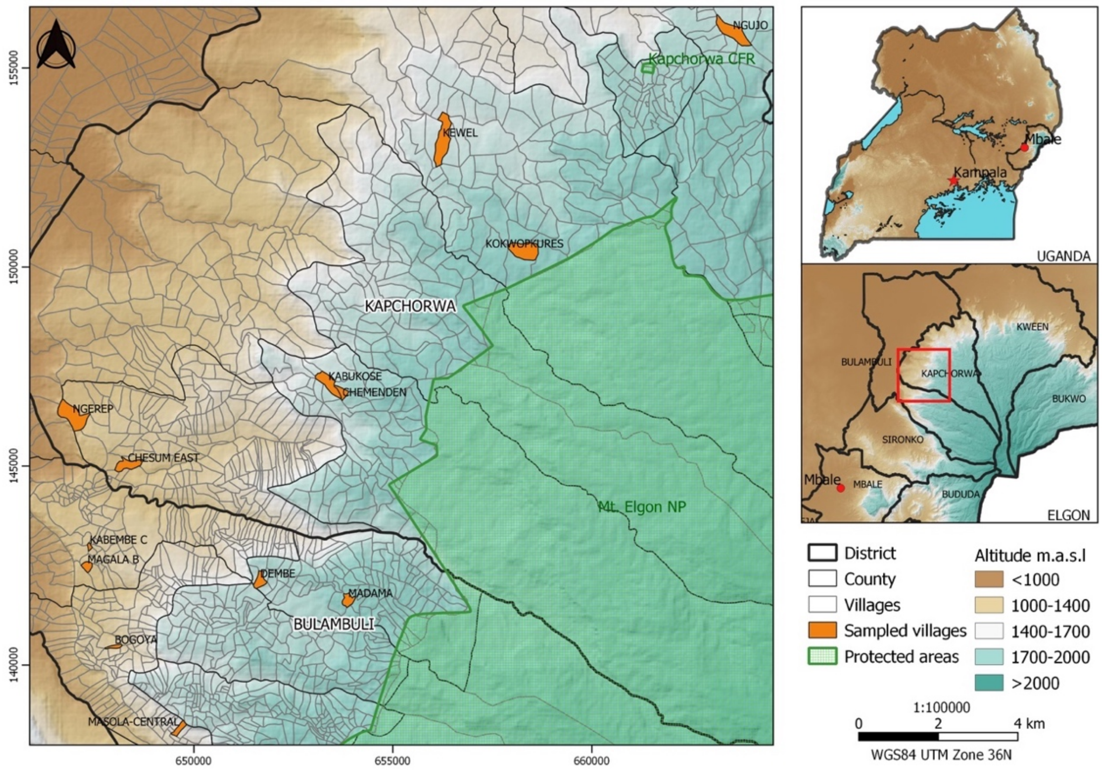

Figure 1. *Location of the study area within Uganda, Mt. Elgon area (top right), districts of the study area (Bulambuli, Kapchorwa) (down right), and study site with sampled villages across altitude zones.*

Data collection

Data used in this study were obtained from four different data collection drives carried out among coffee-producing households in the M. Elgon region of eastern Uganda in May 2019: a household survey, an experiment on risk preference, an experiment on time preference, and a DCE. We used a multi-stage sampling approach to form our survey sample. During the first stage, we purposively selected sub-counties, namely, Bulegeni TC, Central Division, Kaserem, Masiira, Sipi, Sisiyi, and Western Division, across the districts Bulambuli and Kapchorwa in which Arabica coffee is grown. During the second stage, we stratified villages according to altitude range into ‘high’ and ‘moderate’ altitude villages based on a dataset with complete lists of villages including spatial data of the Ugandan Bureau of Statistics. We then randomly selected 13 villages (Figure 1). From each of these villages, we randomly selected households using updated, village-level household lists. The households were contacted and mobilized by local extension officers and village chairpersons. In total, we included 159 households in the data collection drives.

All selected households were visited in their homesteads to conduct the face-to-face interviews and the experiments. A team of 12 local enumerators were carefully selected, trained, and supervised by the researchers and conducted all of the interviews and experiments. To ensure that respondents are able to understand and interpret the questions asked in the survey and the decisions to be made in the experiments, the dominant local languages spoken in Bulambuli and Kapchorwa districts, Lumasaaba and Kupsabiny respectively, were used during data collection. To the extent possible, both primary and secondary decision-makers, defined as household members above 18 years of age who make or influence decisions for the entire household, were targeted in each household. Decision-making, in our context, was related to agricultural production and other types of household investments or purchases. We also used the terms household head and primary decision-maker synonymously. While the primary decision-maker was typically male, the secondary decision-maker was typically the household head's spouse. In households where these structures did not apply (e.g., in cases in which households were female-headed after the demise of their husbands), we assessed whether there were other adult decision-makers of the other sex than the primary decision-maker to allow for the collection of gender-specific data in each household.

In total, we interviewed 151 primary and 168 secondary decision-makers (Table 1). Male primary decision-makers were mostly married, whereas female primary decision-makers were usually widowed, divorced, or single. Secondary decision-makers were mainly female spouses of male household heads. In some cases, secondary decision-makers were adult children or other relatives. All respondents were interviewed separately and provided consent before participating in the study. In the Ugandan context, conducting separate interviews with male and female household members was possible and socially accepted. The full data collection drive, including all four segments, took approximately two hours per household.

Table 1. *Number of individual respondents by gender and decision-making power*

Respondent category	Number of individuals interviewed
Male primary decision-maker (household heads)	141
Male secondary decision-maker (e.g., sons)	19
Female primary decision-maker (household heads)	10
Female secondary decision-maker (e.g., spouses)	149
Total	319

4. METHODS

Experiment on risk preferences

We used a series of lottery-based experiments to elicit behavioral characteristics related to risk and potential losses. The experiment used in this study is based on those introduced in Tanaka et al. (2010) and Liu (2013). This experimental design, which takes the form of a Multiple Price List (MPL) design, had previously been tested among individual respondents in different developing countries (Liebenehm & Waibel, 2014; Nguyen, 2011; Ward & Singh, 2015). According to this method, respondents are confronted with an array of paired lotteries (including options A and B) and one of these two options has to be chosen, which implies that the other has to be rejected. To enforce choices consistent with monotonic preferences, we follow Tanaka et al. (2010) and Liu (2013) and capture information only on the switching point in each series.[3] This method assumes rationality of the respondents and eliminates any inconsistent behavior (Liu & Huang, 2013). The switching points are used to estimate the respondents' risk preference parameters.[4] While our experiment maintained the general design of previous studies, a few adaptations were made to improve contextual suitability. For instance, payoffs were specifically calibrated to the context of Ugandan smallholder farmers. Furthermore, the overall experiment was framed in a way that is familiar to these farmers, rather than keeping it hypothetical. Specifically, risk preference was determined based on the respondents' choice between two types of tree species that promise different levels of income depending on the weather conditions.[5]

The risk experiment consisted of three series of paired lotteries. In each series, the respondent has to choose between two options ('Tree species A' and 'Tree species B'), where each option is a lottery (Figure 2). The probabilities were explained using a fair ten-sided dice, numbered 1 to 10, with different rewards for each option. The numbers 1 to 10 represent 10 years of weather ('good rains' or 'bad/ no rains'). The respondent makes a choice based on single picture cards illustrating each lottery pair. For example, 'Tree species A' gives 4,000 USh as income from production in times of 'good rains' (in 3 out of 10 years) and 1,000 USh in times of 'bad/ no rains' (in 7 out of 10 years). Alternatively, 'Tree species B' gives 15,000 USh as income from production in times of 'good rains' (in 1 out of 10 years) and 500 USh in times of 'bad/ no rains' (in 9 out of 10 years). One would note that 'Tree species B' pays more in times of 'good rains', but less in times of 'bad/no rains'. In total, there were 35 choices to make. These were grouped in three independent series, each of which contained between 7 and 14 choices (Table 2).

At the end of the experiment, one pair of lotteries was randomly selected to be played for real money to encourage participants to reveal their true preferences (Andersen, Harrison, Lau, & Rutström, 2006; Holt & Laury, 2002). The average reward was 7,400 USh (approximately $2). The highest amount that could have been won by the respondent was 170,000 USh

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[3] Each respondent is allowed to switch from lottery A to lottery B only once during each series. The option of choosing either all A or all B is also available.

[4] More details about the estimation method can be found in Appendix A.1 Estimation method of risk preference parameters.

[5] To increase the external validity of experiments, it has been argued that experimental instructions may be framed in a context familiar to the subjects (Alekseev, Charness, & Gneezy, 2017; Viceisza, 2016).

(approximately $45). The highest amount that could have been lost was 2,100 USh (approximately $0.6). This is the amount that was paid when the respondent agreed to participate in the experiment. More details about the experiment's procedure are provided in Appendix A.2 Instructions of experiment on risk preferences.

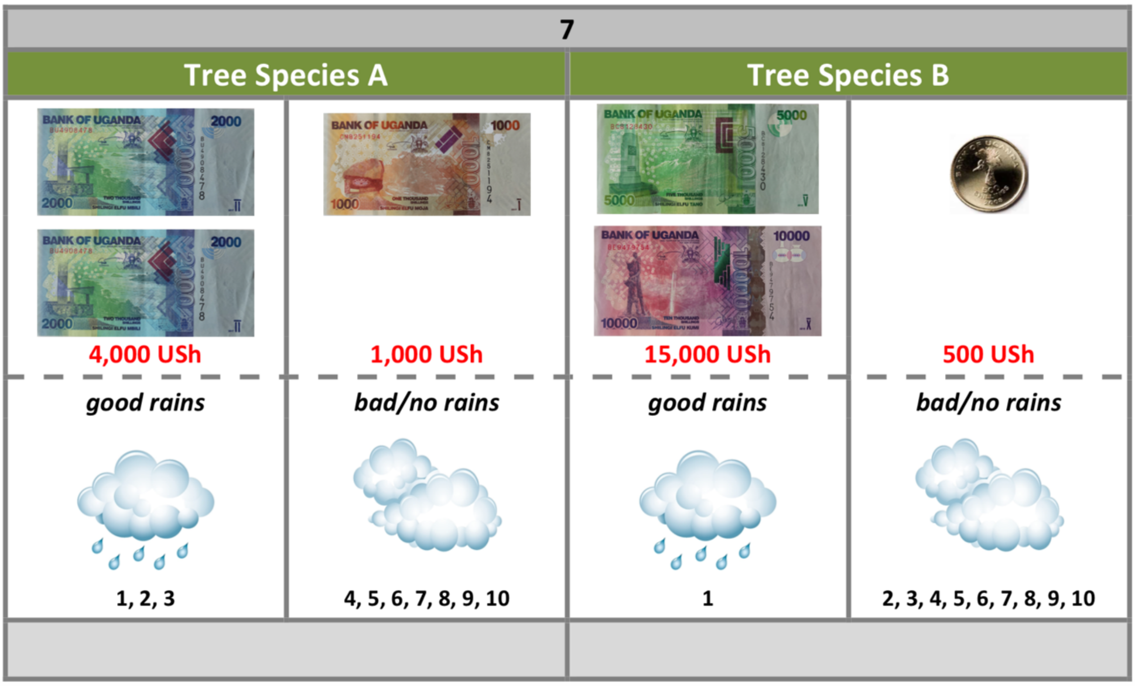

Figure 2. *Example of a picture card in the risk experiment. Source: Authors.*

Table 2. *Design of risk experiment (in Ugandan shillings)*

		Option A		Option B	
		Probability		Probability	
Series 1	Choices	30%	70%	10%	90%
	1	4,000	1,000	6,800	500
	2	4,000	1,000	7,500	500
	3	4,000	1,000	8,300	500
	4	4,000	1,000	9,300	500
	5	4,000	1,000	10,600	500
	6	4,000	1,000	12,500	500
	7	4,000	1,000	15,000	500
	8	4,000	1,000	18,500	500
	9	4,000	1,000	22,000	500
	10	4,000	1,000	30,000	500
	11	4,000	1,000	40,000	500
	12	4,000	1,000	60,000	500
	13	4,000	1,000	100,000	500
	14	4,000	1,000	170,000	500
Series 2	Choices	90%	10%	70%	30%
	1	4,000	3,000	5,400	500
	2	4,000	3,000	5,600	500
	3	4,000	3,000	5,800	500
	4	4,000	3,000	6,000	500
	5	4,000	3,000	6,200	500
	6	4,000	3,000	6,500	500
	7	4,000	3,000	6,800	500
	8	4,000	3,000	7,200	500
	9	4,000	3,000	7,700	500
	10	4,000	3,000	8,300	500
	11	4,000	3,000	9,000	500
	12	4,000	3,000	10,000	500
	13	4,000	3,000	11,000	500
	14	4,000	3,000	13,000	500
Series 3	Choices	50%	50%	50%	50%
	1	2,500	-400	3,000	-2,100
	2	400	-400	3,000	-2,100
	3	100	-400	3,000	-2,100
	4	100	-400	3,000	-1,600
	5	100	-800	3,000	-1,600
	6	100	-800	3,000	-1,400
	7	100	-800	3,000	-1,100

Experiment on time preferences

The time experiment consisted of 15 series of five choices between a smaller reward delivered immediately (Option A) and a larger reward delivered at a later specified time (Option B) (Nguyen, 2011; Tanaka et al., 2010). In total, respondents had to make 75 choices, which are partially presented in (Table 3). The table shows only the first three series in which the same range of five immediate rewards (Option A) is contrasted with the same delayed reward at three different points of time in the future (Option B). In every fourth series, the amount of the five immediate rewards x_t and that of the delayed rewards $(x_{t+\tau})$ change, but the ratio between the two options remains identical, that is, $x_t = x_{t+\tau} * \nu/6$, where $\nu = 1, \ldots, 5$ is the choice number within each series. The future reward varies between 3,000 USh (approximately \$0.8) and 30,000 USh (approximately \$8), and the delay varies between three days and three months (see Table B.1 in the Appendix). Within each series, the respondent had to decide, whether he or she preferred Option A or Option B. Respondents made choices based on single picture cards illustrating both options (Figure 3). Again, monotonic switching was enforced.

Table 3. *Design of time experiment (in Ugandan shillings)*

Series	Choices	Option A	Option B
1	1	2,000 USh today	12,000 USh in 1 week
	2	4,000 USh today	12,000 USh in 1 week
	3	6,000 USh today	12,000 USh in 1 week
	4	8,000 USh today	12,000 USh in 1 week
	5	10,000 USh today	12,000 USh in 1 week
2	6	2,000 USh today	12,000 USh in 1 month
	7	4,000 USh today	12,000 USh in 1 month
	8	6,000 USh today	12,000 USh in 1 month
	9	8,000 USh today	12,000 USh in 1 month
	10	10,000 USh today	12,000 USh in 1 month
3	11	2,000 USh today	12,000 USh in 3 months
	12	4,000 USh today	12,000 USh in 3 months
	13	6,000 USh today	12,000 USh in 3 months
	14	8,000 USh today	12,000 USh in 3 months
	15	10,000 USh today	12,000 USh in 3 months
…	…	…	…

After all 75 choices were made, the respondent was asked to blindly draw one card out of a bag. The cards in the bag were numbered from 1 to 75. The card drawn determined the decision number, and the respondent gained the reward at the respective time according to the choice he or she made during the experiment. For example, if Option A had been chosen during the choice for which the number was drawn, the respondent received the reward in cash immediately. If Option B had been chosen, the respondent received a credit voucher indicating the amount of money he or she would receive and the date of payment. The credit voucher was issued by the experimenter and approved by the main researcher. The money was sent via a mobile money transfer to the respondent's number by a finance officer of our institution exactly on the date of payment as indicated on the credit voucher. Average payoffs were 12,500 USh (approximately $3.4). More details about the experiment's procedure are provided in Appendix B.1 Instructions of experiment on time preferences.

Figure 3. *Example of a picture card in the time experiment. Source: Authors.*

Discrete choice experiment

We used a DCE to analyze farmers' preferences for different features of companion trees in coffee-banana farming systems. In a DCE, respondents are presented with alternative descriptions of a good, differentiated by their attribute levels, and are asked to choose one of the alternatives (Holmes & Adamowicz, 2003). In order to identify contextually relevant attributes and their levels, we conducted key informant interviews and focus group discussions with farmers during a preliminary field visit to the study area. Based on their feedback, we selected six attributes that they deemed important in a companion tree with two to six levels (Table 4). The first attribute relates to the products provided by companion trees, namely fruits, timber, fuelwood, and fodder. Regulating ES provided by companion trees are the second attribute. The four levels are microclimate (i.e. buffering temperature extremes and conserving soil moisture), soil fertility (i.e. producing mulch and controlling erosion) pests and diseases control (i.e. decreasing incidence of white coffee stem borer and coffee leaf rust[6]), and weed control (i.e. suppressing weed growth). As the third attribute we consider the growth rate of companion trees and define three levels: slow-, medium-, and fast-growing. The fourth attribute is the seedling price, categorized in five levels: 0 USh, 200 USh, 500 USh, 1,000 USh, and 1,500 USh. The fifth attribute concerns the provision of quality shade for coffee in two levels: light and mottled shade, as well as dense shade. The last attribute is the maximum tree height of the companion tree, either short (< 5 m) or tall (> 5 m).

[6] White coffee stem borer and coffee leaf rust are the major pests and diseases in coffee systems in the study area.

Table 4. *Overview of attributes and levels used in the choice experiment*

Attributes	Definition	Attribute levels
Tree products	Products provided by companion trees	1. Fruits 2. Timber 3. Fuelwood 4. Fodder
Ecosystem services	Regulating services provided by companion trees (i.e. microclimate, soil fertility, pests and diseases control, and weed control)	1. Buffering temperature extremes and conserving soil moisture 2. Producing mulch and controlling erosion 3. Fewer problems of White Coffee Stem Borer and Coffee Leaf Rust 4. Suppressing weed growth
Tree growth rate	Growth rate of companion tree species	1. Slow-growing 2. Medium-growing 3. Fast-growing
Seedling price	Cost of one tree seedling of companion tree species	1. 0 USh 2. 200 USh 3. 500 USh 4. 1,000 USh 5. 1,500 USh
Shade quality	Shade quality of companion tree species	1. Light, mottled shade 2. Dense shade
Tree height	Maximum tree height of companion tree species	1. Short (< 5 m) 2. Tall (> 5 m)

The six attributes and their different levels imply a full factorial design with 960 ($5^1 \times 4^2 \times 3^1 \times 2^2$) combinations. Theoretically, each unique combination of attribute levels represents a specific companion tree species. To produce a more manageable experiment, a d-optimal design was used to generate a subset of companion tree species that covers the range of variability between all possible combinations (Hensher, Rose, & Greene, 2015). In total, 32 choice sets were included in our design. The choice sets were further subdivided into four subsets containing eight choice sets each. To reduce the response burden and to avoid fatigue, respondents were randomly assigned one of these four subsets, with an even number of households allocated to each of the subsets. A choice set consisted of two alternative companion tree species (A and B) and a status quo ('none of the trees') option. The status quo option is provided because a respondent might not have a preference for either of the companion tree species listed. Moreover, illustrations were included in the choice sets to increase respondents' comprehension of the attributes and levels (Figure 4). Before conducting the DCE, we explained to the respondents that the drawings used hypothetical companion tree species rather than real ones. The attributes and levels used were carefully explained. Respondents were also informed that the choices they made in the experiment would not have any immediate consequence. It was clarified that the results would be used more generally to better understand farmers' preferences for particular characteristics of companion trees that may inform project design or future project implementation.

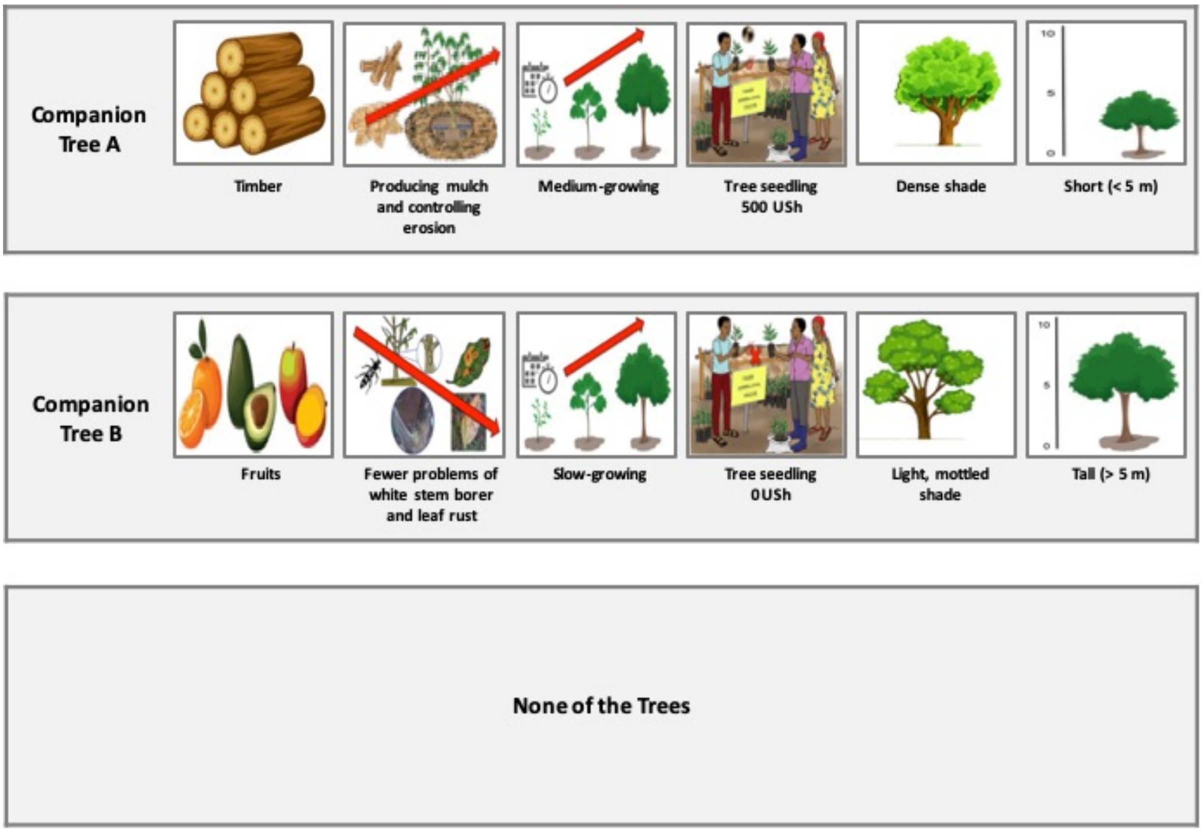

Figure 4. *Example of a choice card. Source: Authors.*

Concerning the selected attributes, our main hypotheses and conjectures are the following. We expect that farmers have positive preferences for tree products (i.e. fuelwood, fodder, timber, and fruits) and regulating ES (i.e. microclimate, soil fertility, P&D control, and weed control) provided by companion trees. Further, we expect that farmers prefer fast and medium growing companion trees, short trees, and trees that provide light, mottled shade. Shorter trees are considered to be easier to manage than taller trees, specifically to maintain appropriate shade. The branches of taller trees on the other hand may be more difficult to trim to regulate shade. Moreover, in the event of a fall, large trees may cause greater damage on coffee shrubs. Concerning the shade quality of companion trees, which refers to shade density and pattern, we expect that farmers prefer shade that permits the passage of light in a mottled pattern and contributes to a fresh microclimate; conditions that support coffee bush growth and development and sustain yields (Valencia, West, Sterling, Garcia-Barrios, & Naeem, 2015). Lastly, concerning seedling price, we expect that farmers prefer tree seedlings that are sold at a lower price. We also expect that farmers have a negative preference for slow growing companion trees.

Beyond these general hypotheses, we formulate sub-sets of hypotheses about the expected interaction between farmer preferences in relation to regulating ES and altitude. Furthermore, we formulate hypotheses about expected interactions between farmer preferences for tree attributes and behavioral preferences, as well as expected interactions between farmer preferences for provisioning and regulating ES and gender.

Table 5 summarizes how we expect the farmer preferences towards regulating ES provided by companion trees to relate with altitude. Overall, we expect that farmers whose farms are located at lower altitudes attribute a higher relative importance to regulating ES than farmers at high altitudes. According to Bunn, Läderach, Ovalle Rivera, & Kirschke (2015) and Läderach et al. (2013), climate change affects Arabica coffee most at lower altitudes, since these are exposed to higher temperatures, prolonged drought, as well as higher water and heat stresses. Coffee pests and diseases, which are already problematic, are likely to be aggravated by the effects of further climate change and variability. Specifically, more variable seasonal patterns can affect regular vegetative and reproductive growing cycle processes of the plant, and are likely to alter related biotic constraints such as pests and diseases (Davis, Gole, Baena, & Moat, 2012; Liebig et al., 2016; Schroth, Krauss, Gasparotto, Duarte, & Vohland, 2000). In this context, we hypothesize that farmers at lower altitudes need a wider set of regulating ES and hence value all regulating ES that help sustain their coffee production by buffering climate change impacts and increase the resilience of their coffee production.

Table 5. *Expected relationships between preferences for regulating ecosystem services provided by companion trees and altitude*

	Microclimate	Soil fertility	P&D[a] control	Weed control
Expected sign of preference coefficient	+	+	+	+
Expected influence of altitude	–	–	–	–

[a] Pests and diseases.

Table 6 summarizes how we expect farmer preferences in relation to companion tree attributes to relate with behavioral preferences. We expect that farmers with higher levels of risk and loss aversion put less relative importance on improving soil fertility (i.e. mulch and erosion control). This assumption is in line with Teklewold and Kohlin (2011), who showed that a high degree of risk aversion has a negative effect on the adoption of labor-intensive soil conservation practices such as erosion control. We further expect that farmers with higher levels of risk aversion prefer fast-growing companion trees compared to farmers with lower levels of risk aversion. Moreover, we expect that farmers who are impatient (i.e. high discount rate) and present-biased prefer fast-growing companion trees whose benefits are more readily available than the ones of slow-growing companion trees.

Table 6. *Expected relationships between preferences for companion tree attributes and behavioral preferences*

	Fuelwood	Soil fertility	Fast growing	Slow growing
Expected sign of preference coefficient	+	+	+	–
Expected influence of				
Risk aversion	+	+	+	–
Loss aversion		+		
Time preference			–	+

Furthermore, we expect that gender differences may exist in preferences for companion tree characteristics. Villamor, van Noordwijk, Djanibekov, Chiong-Javier, and Catacutan (2014) find that men's motivation to incorporate trees on farms is largely conditioned by financial factors, whereas women are concerned with soil conservation and household food consumption. This finding is in line with Kiptot & Franzel (2012) according to whom the agroforestry tree products that women have access to are often important for domestic use and consumption but that have little economic value. Equally, forest tree products collected by women generally serve household food security needs, while men often manage high value forest products, such as timber (Sunderland et al., 2014). Therefore, we expect that women have particularly strong preferences for tree products such as fruits and fuelwood as well as regulating ES such as soil fertility. Table 7 summarizes how we expect farmer preferences towards provisioning (i.e. fodder, fuelwood, timber, and fruits) and regulating ES (i.e. soil fertility) provided by companion trees to relate with gender.

Table 7. *Expected relationships between preferences for provisioning and regulating ecosystem services provided by companion trees and gender*

	Fodder	Fuelwood	Timber	Fruits	Soil fertility
Expected sign of preference coefficient	+	+	+	+	+
Expected influence of gender	–	+	–	+	+

5. ECONOMETRIC APPROACH

To demonstrate the effects of risk and loss aversion as well as time preference on the adoption of companion trees, we couple these experimental data with the results from the DCE, which allows evaluating farmers' preferences for the included companion tree characteristics. Since farmers are heterogenous, we expect heterogeneity in their preferences for these characteristics as well. One common way of modelling such heterogeneity is through a mixed logit model. The mixed logit model is a highly flexible model that can approximate any random utility model and relaxes assumptions on the independence of choice alternatives by allowing random taste variation within a sample according to specified distributions. Once the distributions for the taste parameters have been specified, we can estimate equation (5) using simulated maximum likelihood. For a DCE in which respondents are presented with three alternatives per choice task (as in our case), we estimate two parameters for each column of Z_i, and these parameters measure the marginal choice probability of alternative j vis-à-vis the status quo alternative.

Our models include an alternative specific constant (ASC) to account for the fact that the choice sets include a status quo ('none of the trees') option. The ASC is a dummy variable, coded 1 for the status quo alternative and 0 for the companion tree alternatives. The ASC is especially important when an opt-out option is provided, since the attributes of the opt-out alternative are usually not known or non-existent (Holmes & Adamowicz, 2003). All attribute variables were effect coded instead of dummy coded to avoid correlation of the attribute estimates with the ASC (Bech & Gyrd-Hansen, 2005; Holmes & Adamowicz, 2003).[7] Table 8 presents the effects codes associated with each attribute level. The seedling price attribute was specified as continuous in all models. Further, all attribute variables and the ASC were specified as having a random component except for the tree seedling price, which was specified as fixed in all models since we assume that farmers have a homogeneous preference for lower tree seedling prices. All model coefficients were assumed to be normally distributed.

We run different model specifications.[8] The base specification includes only the ASC and the attribute levels as explanatory variables.

$$\begin{aligned} Y_{ijk} = \beta_0 ASC + \beta_1 Price_{ijk} + \beta_2 Fuelwood_{ijk} + \beta_3 Fodder_{ijk} + \beta_4 Timber_{ijk} \\ + \beta_5 MicroCl_{ijk} + \beta_6 SoilFert_{ijk} + \beta_7 PestsDis_{ijk} \\ + \beta_8 GrowthFast_{ijk} + \beta_9 GrowthSlow_{ijk} + \beta_{10} ShadeLight_{ijk} \\ + \beta_{11} HeightShort_{ijk} + e_{ijk} \end{aligned} \tag{7}$$

where Y denotes the binary decision made by male or female farmer i for alternative j and choice set k. This base specification allows us to assess if a given attribute level increases or decreases farmers' willingness to adopt the companion tree, as indicated by the sign of the coefficient. In other model specifications, we additionally include interaction terms between specific attribute levels and individual (i.e. behavioral preferences, gender) or household (i.e. farm altitude) characteristics to explore some of the factors that drive preference heterogeneity.

[7] Since no information was available on the attribute levels for the status quo option, zeros were used to code all the attribute levels for the status quo alternative.

[8] The models are estimated by maximum simulated likelihood using 500 Halton draws (Hole, 2007).

We furthermore explore the effects of the behavioral preference factors risk aversion, loss aversion, and time preferences on preferences related to various companion tree characteristics. Furthermore, we test the relationship between households' altitudinal location and preference towards regulating ES provided by companion trees. Finally, we test gender effects.

Table 8. *Effects codes for the companion tree attributes*

Attributes	Effect code 1	Effect code 2	Effect code 3
Tree products	Fodder	Fuelwood	Timber
Fruits[a]	–1	–1	–1
Fodder	1	0	0
Fuelwood	0	1	0
Timber	0	0	1
Ecosystem services	Microclimate	Soil fertility	P&D control
Weed control[a]	–1	–1	–1
Microclimate	1	0	0
Soil fertility	0	1	0
P&D control	0	0	1
Tree growth rate	Fast growing	Slow growing	
Medium growing[a]	–1	–1	
Fast growing	1	0	
Slow growing	0	1	
Shade quality	Light shade		
Dense shade[a]	–1		
Light shade	1		
Tree height	Short tree		
Tall[a]	–1		
Short	1		
Seedling price	Quantitative variable		
0 USh (free)	0		
200 USh	200		
500 USh	500		
1,000 USh	1000		
1,500 USh	1500		

[a] Base level.

6. ESTIMATION OF RISK AND TIME PARAMETERS

Based on the analysis of the risk and time preference experiments, we derive estimates of mean values and corresponding standard errors for the underlying population.
Table *9* reports the parameter estimates for the CPT and quasi-hyperbolic specifications.[9] These parameters are all significantly different from 1 at the 1 %, implying that the data are not likely to be supported by EUT and exponential discounting.[10]

The estimated mean value of the risk aversion parameter σ is 0.67 (with a 95% confidence interval of [0.61, 0.73]), consistent with a concave utility in the gain domain and convex utility in the loss domain. The mean value of σ indicates that farmers in the sample are risk-averse. The estimated mean value of the probability weight parameter α is 0.79 (with a 95% confidence interval of [0.75, 0.83]), meaning that farmers in the sample tend to overweight small probabilities and to underweight large probabilities, which is a result associated with CPT.[11] The probability weight parameter α is estimated to be significantly different from 1. This provides some evidence of probability distortion in the expected direction. The weighting function is 'inverse S-shaped' and low probability events are overweighted. The loss aversion parameter λ is estimated to be significantly different from 1 and equal to 3.85 on average, with a 95% confidence interval between 3.36 and 4.33. Figure 5 shows the distribution of the risk aversion parameter (σ), the probability weighting parameter (α), and the loss aversion parameter (λ).

The estimated mean value of the time preference parameter δ is 0.12 (with a 95% confidence interval of [0.11, 0.12]) and of the present bias parameter β is 0.54 (with a 95% confidence interval of [0.52, 0.57]). Our estimate of β is significantly different from 1, which indicates the presence of quasi-hyperbolic discounting and a departure from exponential discounting with constant discount rates for different time horizons.[12]

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[9] Table C.1 in the Appendix compares our results with the results from applicable studies of decision-making behavior under uncertainty that have been conducted in developing countries. Tanaka et al. (2010), Nguyen (2010), Liu (2013), and Ward and Singh (2015) apply the same experimental design. Nguyen (2011) and Liebenehm and Waibel (2014) apply the same experimental design as in Tanaka et al. (2010), but use a different estimation approach. Tanaka et al. (2010) reported mean values of $(\sigma, \alpha, \lambda)$ = (0.59, 0.74, 2.63), Nguyen (2010) of $(\sigma, \alpha, \lambda)$ = (0.62, 0.75, 2.05), Nguyen (2011) of $(\sigma, \alpha, \lambda)$ = (1.01, 0.96, 3.26), Liu (2013) of $(\sigma, \alpha, \lambda)$ = (0.48, 0.69, 3.47), Liebenehm and Waibel (2014) of $(\sigma, \alpha, \lambda)$ = (0.11, 0.13, 1.35), and Ward and Singh (2015) of $(\sigma, \alpha, \lambda)$ = (0.77, 0.74, 4.46), respectively, for risk aversion, probability weighting, and loss aversion. Tanaka et al. (2010) reported mean values of (δ, β) = (0.08, 0.82), Nguyen (2011) of (δ, β) = (0.28, 0.72), and Liebenehm and Waibel (2014) of (δ, β) = (0.001, 0.94), respectively, for time preference and present bias.

[10] To test whether farmers in our study are more likely to behave according to CPT and quasi-hyperbolic discounting rather than EUT and exponential discounting, we conduct hypothesis testing: Ho: (σ, α, λ, δ, β,) = (1, 1, 1, 1, 1) where σ, α, λ, δ, and β are the common estimated means of the risk aversion, probability weighting, loss aversion, time preference, and present bias parameters, respectively.

[11] An α with a value less than 1 is associated with incorrect assessments of probability information, that is, overweighting of unlikely but desirable events and underweighting of likely but desirable events.

[12] We also use a model proposed by Benhabib et al. (2010) that allows to test exponential, hyperbolic, quasi-hyperbolic discounting, and a more general form. The three-parameter form enables a way to compare three familiar models at once. Estimation results comparing specific functions are presented in Table C.1 in the Appendix. We fitted a logistic function by using a nonlinear least-squares regression procedure. The estimated values of (δ, β, θ) are (0.101, 0.542, 4.736).

Table 9. *Estimates of risk and time preference parameters over the sample*

Parameter	Mean	Standard deviation	Lower 95% confidence interval	Upper 95% confidence interval
Risk aversion (σ)	0.671*** (0.030)	0.541	0.612	0.731
Probability weight (α)	0.790*** (0.021)	0.373	0.749	0.831
Loss aversion (λ)	3.848*** (0.247)	4.411	3.363	4.334
Time preference (δ)	0.115*** (0.004)	0.071	0.108	0.123
Present bias (β)	0.544*** (0.011)	0.199	0.522	0.566

Note: Standard errors in parentheses. Single, double and triple asterisks (*, **, and ***) denote $p < 0.10$, 0.05, and 0.01, respectively. For σ, α, λ, δ, and β, the null being tested is equivalence to 1.

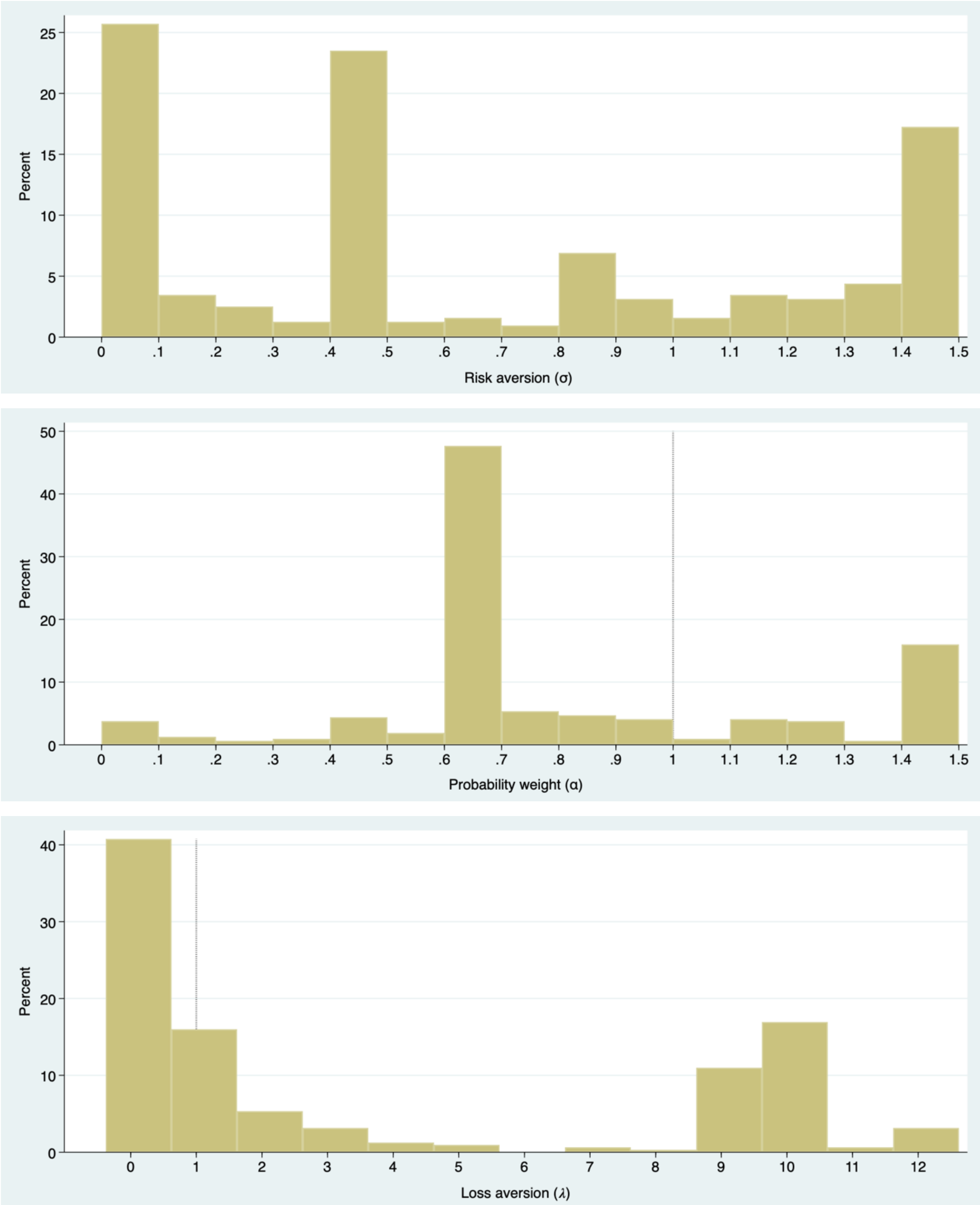

Figure 5. *Distribution of risk preference parameters. Source: Authors.*

7. DESCRIPTIVE STATISTICS

Gender-specific differences

Table 10 presents descriptive statistics. Column (1) shows the full sample of 319 individuals, whereas the other columns provide gender-disaggregated results (columns 2 and 3).[13] On average, women in our sample are younger, spent a shorter time in formal education and are less likely to be literate than men. Contrary to our expectations, we do not find significant gender differences with respect to risk aversion.[14] This result is surprising, since women are generally considered more risk-averse than men (Charness & Gneezy, 2012; Ward & Singh, 2015). With respect to probability weighting, the women in our sample tend to assess probabilities more accurately compared to men. While the literature presents mixed results about this subject, this is contrary to our expectations that respondents with more years of schooling are able to better appraise probability information (Binswanger, 1980; Nguyen, 2010, 2011; Tanaka et al., 2010; Yesuf & Bluffstone, 2009). With respect to loss aversion, we find that women have higher levels of loss aversion than men. This result suggests that women may attribute more importance to prospective losses than to equivalent prospective gains. Lower levels of loss aversion can contribute to potentially suboptimal investment decisions, particularly when combined with underweighting high probabilities (Dercon, 2008).

[13] Given the small number of male secondary decision-makers (N = 19) and female primary decision-maker (N = 10), we do not disaggregate the group of men and women in whether they are primary or secondary decision-maker.

[14] In addition to the incentivized risk preference experiment, we use two non-incentivized risk elicitation methods. The first method we use is a non-incentivized survey question adapted from Dohmen et al. (2011), which asks respondents to report their general willingness to take risks on a scale of 1 to 10 (Figure C.1). Figure C.2 shows the distribution of respondents' levels of willingness to take risks (WTR) on a scale from 1 ('not risk-seeking at all') to 10 ('very risk-seeking'). The mean response in the WTR question is 6.08 (sd = 2.28). The mean response of men is 6.38 (sd = 2.24), while the mean response of women is 5.79 (sd = 2.28). We find significant differences. Men are more willing to take risk than women in our WTR data (p = 0.02, two-tailed t-test).

The second method we use is a non-incentivized risk experiment developed by (Eckel & Grossman, 2002, 2008) (Table C.2, Figure C.3). It consists of two series of six choices. In each series, the respondent chooses the one option he/ she prefers. Each of the choices involves a 50% chance of a low or high payoff. The range of choices includes a safe alternative involving a sure payoff of 2,800 USh in series 1 (28,000 USh in series 2) with zero variance. From here, the choices increase in both expected return and risk (standard deviation) moving from Choice 1 to 5; expected return increases linearly with standard deviation. Choice 6 involves only an increase in variance, with the same expected return as Choice 5. More risk-averse respondents would choose lower risk, lower return choices; risk-neutral respondents would choose Choice 5 or 6, which have the highest rate of return; only risk-seeking respondents would choose Choice 6. Table C.2 also includes ranges of coefficients of relative risk aversion implied by each possible choice, under the assumption of constant relative risk aversion (CRRA). The mean midpoint CRRA is 1.26 (sd = 1.30), indicating that respondents are risk-averse based on the risk preference category in Table C.2. There is no significant difference between the mean midpoint CRRA in series 1, 1.27 (sd = 1.33) and in series 2, 1.24 (sd = 1.26). Women are significantly more risk-averse than men in series 2 with higher hypothetical payoffs (p = 0.01, two-tailed t-test).

Table 10. *Summary statistics by gender (individual level)*

Variables	(1) Full sample	(2) Male decision-makers[a]	(3) Female decision-makers
Age (years)	41.36	43.72	38.99***
	(14.62)	(14.90)	(13.99)
Education (years)	7.43	8.69	6.17***
	(4.28)	(4.34)	(3.83)
Literate (dummy)	0.71	0.81	0.61***
	(0.46)	(0.40)	(0.49)
Risk aversion (σ)	0.67	0.69	0.65
	(0.54)	(0.55)	(0.53)
Probability weight (α)	0.79	0.75	0.84**
	(0.37)	(0.36)	(0.39)
Loss aversion (λ)	3.85	3.12	4.58***
	(4.41)	(4.08)	(4.62)
Time preference (δ)	0.12	0.11	0.12
	(0.07)	(0.07)	(0.07)
Present bias (β)	0.54	0.55	0.54
	(0.20)	(0.21)	(0.19)
Risk payment (USh)	7373.98	8026.25	6717.61
	(11124.27)	(14568.70)	(5883.06)
Time payment (USh)	12539.18	13018.75	12056.60
	(9024.30)	(9139.54)	(8909.53)
Observations	319	160	159

Note: Mean values are shown with standard deviations in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
[a] Significance level in this column refers to the difference between male and female decision-makers.

Differences in risk aversion

Table 11 reports descriptive statistics for the entire sample of respondents, divided into sub-samples of extremely risk-averse ($\sigma \leq 0.2$), moderately risk-averse ($0.2 < \sigma \leq 1$), and risk-seeking ($\sigma > 1$). We compare the characteristics of farmers falling into each of these three categories, using the moderately risk-averse sub-sample as the comparison group against which we test for differences in these general characteristics. We find that the extremely risk-averse farmers also tend to be extremely loss averse, suggesting a strong correlation between these two behavioral characteristics within this particular sub-sample. With respect to probability weighting, we find that the extremely risk-averse farmers tend to overweight unlikely but desirable events and underweight likely but undesirable events compared to moderately risk-averse farmers. We also find that the extremely risk-averse farmers have higher discount rates (hence higher levels of impatience) and a stronger preference for the present than moderately risk-averse farmers. We find a significantly lower risk payment for extremely risk-averse farmers than for moderately risk-averse farmers.[15] We also find significant differences between risk-seeking and moderately risk-averse farmers. On average, risk-seeking farmers spent a shorter time in formal education and tend to overweight unlikely but desirable events and

[15] The variable 'risk payment' corresponds to the amount of money the respondent received in the risk experiment.

underweight likely but undesirable events compared to moderately risk-averse farmers. Risk-seeking farmers have less preference for the present compared to moderately risk-averse farmers. Further, we find significantly higher risk and time payments for risk-seeking farmers than for moderately risk-averse farmers.

Table 11. *Summary statistics by risk aversion category (individual level)*

Variables	(1) Extremely risk-averse	(2) Moderately risk-averse	(3) Risk-seeking
Age (years)	40.99	41.90	41.04
	(14.41)	(14.91)	(14.60)
Education (years)	7.69	7.77	6.73*
	(4.46)	(4.18)	(4.17)
Literate (dummy)	0.69	0.73	0.69
	(0.46)	(0.45)	(0.46)
Risk aversion (σ)	0.07***	0.60	1.39***
	(0.04)	(0.19)	(0.15)
Probability weight (α)	0.62***	1.03	0.65***
	(0.09)	(0.49)	(0.11)
Loss aversion (λ)	5.52***	3.44	2.66
	(4.83)	(3.88)	(4.15)
Time preference (δ)	0.13***	0.11	0.10
	(0.07)	(0.07)	(0.08)
Present bias (β)	0.49**	0.54	0.60**
	(0.17)	(0.18)	(0.24)
Risk payment (USh)	5195.92***	7043.65	10058.95*
	(1984.37)	(6648.33)	(18531.68)
Time payment (USh)	11346.94	11738.10	14831.58**
	(8827.50)	(8742.70)	(9079.82)
Observations	98	126	95

Note: Mean values are shown with standard deviations in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The moderately risk-averse sub-sample is the comparison group for tests of sample means.

Differences between households located at different altitudes

Table 12 also shows descriptive statistics, but now illustrating data at the household level. In addition to the full sample of 160 farm households shown in column (1), we differentiate between results from the higher (column 2) and the moderate altitude zone (column 3). There are a few significant differences between farm households that are located at higher altitude and moderate altitude. On average, high-altitude farmers spent more time in formal education, have smaller households and are less likely to live below the poverty line of $1.90 per day.[16] Most farmers indicate that banana is the main food crop that they cultivate on their land, although fewer at higher altitude (41%) than at moderate altitude (60%). Similarly, most farmers indicate that coffee is the main cash crop they cultivate on their land. Again, fewer

[16] The Poverty Probability Index (PPI) was created in 2015 using Uganda's 2012/13 National Household Survey (UNHS) by Mark Schreiner of Microfinance Risk Management, L.L.C. (www.povertyindex.org.).

farm households cultivate coffee as the main cash crop at high-altitude (76%) than at moderate altitude (88%). Slightly more than half of the interviewed households (52%) indicate that the sale of cash crops was their main source of income over the previous 12 months.[17] This source of income is less important for farm households at higher altitude (41%) than for households at moderate altitude (63%).

Table 12. *Summary statistics by altitude zone (household level)*

Variables	(1) Full sample	(2) High zone[a]	(3) Moderate zone
Household characteristics			
Male household head (dummy)	0.93	0.95	0.92
	(0.25)	(0.23)	(0.27)
Age household head (years)	46.66	46.71	46.60
	(14.15)	(14.33)	(14.07)
Education household head (years)	8.08	8.86**	7.32
	(4.37)	(4.49)	(4.12)
Household size (members)	6.64	6.24*	7.06
	(2.86)	(2.55)	(3.13)
Poverty likelihood ($1.90/day)	28.34	25.15**	31.70
	(19.30)	(20.09)	(17.95)
Farm characteristics			
Land size (acres)	2.22	2.11	2.33
	(1.75)	(1.38)	(2.07)
Farm altitude (m)	1670.75	1896.76***	1433.14
	(251.03)	(102.28)	(86.80)
Main food crop banana (dummy)	0.51	0.41**	0.60
	(0.50)	(0.50)	(0.49)
Main cash crop coffee (dummy)	0.82	0.76**	0.88
	(0.39)	(0.43)	(0.32)
Sale of food crops major income	0.59	0.56	0.62
source last 3 months (dummy)	(0.49)	(0.50)	(0.49)
Sale of cash crops major income	0.52	0.41***	0.63
source last 12 months (dummy)	(0.50)	(0.50)	(0.49)
District (1 Bulambuli 2 Kapchorwa)	1.52	1.72***	1.31
	(0.50)	(0.45)	(0.46)
Observations	160	82	78

Note: Mean values are shown with standard deviations in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.
[a] Significance levels in this column refer to the difference between households in moderate- and high-altitude zones.

[17] This is followed by the sale of food crops (38%), wages, salaries or other casual cash earnings (5%), the sale of livestock and livestock products (4%), and the sale of forest products (1%).

8. ESTIMATION RESULTS

General preferences for companion trees

The estimation results displayed in Table 13 show farmers' preferences for companion tree characteristics. The base specification of the mixed logit model that only includes attribute levels is shown in column (1) of Table 13. Since we assume that farmers have homogeneous preferences for lower tree seedling prices, we specify the price attribute to have a fixed coefficient.[18] All other attributes and the ASC are specified as random and normally distributed, assuming that preference heterogeneity exists. Positive coefficients in the model indicate a positive preference (utility) and negative coefficients indicate a negative preference (disutility) associated with a specific attribute level compared with the reference category. Non-significant attribute levels indicate respondents' indifference between the specific level and the reference level of each attribute. The standard deviation parameters, which are shown in the lower part of Table 13, confirm that significant preference heterogeneity exists. In the following, we discuss the model results in more detail before we take a closer look at factors that influence preference heterogeneity.

The ASC has a negative and significant coefficient, indicating that farmers strongly prefer the companion tree alternatives to maintaining the status quo. Concerning the different attributes, a few significant results can be reported. Surprisingly, the coefficient of the tree seedling price is positive and significant contrary to our assumption that farmers would prefer cheaper seedlings. One possible explanation might be that farmers correlate the seedling price with the quality of the tree seedling, assuming that low-priced tree seedlings might not perform as well as higher-priced ones. It might indicate that farmers are willing to pay more for a high-quality seedling. Hence, positive preferences for this attribute is not implausible. Furthermore, in terms of tree products provided by companion trees, respondents prefer companion trees that provide fodder for their livestock. As tree fodder provides a large share of animal feed, it is not surprising that farmers highly value fodder (Mukadasi, Kaboggoza, & Nabalegwa, 2007). The negative and significant coefficient for fuelwood appears counter intuitive at first. However, this might be a model effect since the tree product coded as the base level (i.e. fruits) appears to be the preferred product of this attribute. The attribute timber is insignificant. With respect to the regulating ES provided by companion trees, farmers strongly prefer microclimate regulation (i.e. temperature buffering and soil moisture conservation) and soil fertility (i.e. mulch and erosion control). Interestingly, the least preferred regulating ES provided by companion trees is P&D control. Given the high P&D pressure for coffee systems in the study area, this result is surprising and may suggest that farmers' knowledge about companion trees and their relationships to coffee P&D dynamics is low. The growth rate attribute performed as expected, with farmers preferring fast growing companion trees. The coefficient of the growth

[18] Independent of the seedling price specification, the results do not differ substantially. The estimation results displayed in Table D.1 show farmers' preferences for companion tree characteristics. In this model, all attribute levels were specified as having a random component compared to the model in
Table *13* (column 1), in which the seedling price attribute was specified as fixed. While random specifications of the seedling price may improve model fit, a fixed coefficient ensures that the estimate of price utility has the expected sign and is preferred for the calculation and interpretation of willingness to pay, as it avoids possible problems with dividing distributions on distributions.

rate attribute 'slow growing' has the expected negative sign. The coefficients of the attributes shade quality and height of the companion trees are insignificant.

Table 13. *Mixed logit model estimates – base specification and differences by altitude*

Variables	(1)	(2)	(3)
Mean parameters			
ASC[a] (for status quo alternative)	–6.82*** (0.87)	–6.80*** (0.93)	–6.81*** (0.86)
Seedling price	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)
Fodder[b]	0.16*** (0.06)	0.16*** (0.06)	0.16*** (0.06)
Fuelwood[b]	–0.20*** (0.05)	–0.20*** (0.05)	–0.20*** (0.05)
Timber[b]	0.02 (0.05)	0.02 (0.05)	0.03 (0.05)
Microclimate[c]	0.28*** (0.05)	0.28*** (0.05)	0.36*** (0.08)
Soil fertility[c]	0.09* (0.05)	0.09* (0.05)	0.01 (0.07)
P&E control[c]	–0.12*** (0.04)	–0.12*** (0.04)	0.05 (0.06)
Fast growing[d]	0.07* (0.04)	0.07* (0.04)	0.07* (0.04)
Slow growing[d]	–0.07* (0.04)	–0.07* (0.04)	–0.07* (0.04)
Light shade[e]	0.00 (0.03)	0.00 (0.03)	0.00 (0.03)
Short tree[f]	–0.02 (0.03)	–0.02 (0.03)	–0.02 (0.03)
ASC and attribute interactions			
ASC × altitude		–0.03 (0.75)	
Microclimate × altitude			–0.16* (0.11)
Soil fertility × altitude			0.15* (0.10)
P&E control × altitude			–0.12* (0.09)
Standard deviation parameters			
ASC	2.71*** (0.43)	2.71*** (0.43)	2.69*** (0.42)
Fodder	0.13 (0.18)	0.13 (0.18)	0.13 (0.17)
Fuelwood	0.22** (0.09)	0.22** (0.09)	0.22*** (0.09)
Timber	0.10 (0.13)	0.10 (0.13)	0.10 (0.12)
Microclimate	0.36*** (0.09)	0.36*** (0.09)	0.36*** (0.10)
Soil fertility	0.30*** (0.10)	0.30*** (0.10)	0.31*** (0.10)
P&E control	0.04 (0.11)	0.04 (0.11)	0.04 (0.11)
Fast growing	0.10 (0.16)	0.10 (0.16)	0.10 (0.15)
Slow growing	0.13 (0.10)	0.13 (0.10)	0.13 (0.10)
Light shade	0.01 (0.11)	0.01 (0.11)	0.01 (0.12)
Short tree	0.12 (0.13)	0.12 (0.13)	0.12 (0.13)
Log likelihood	–1826.92	–1826.92	–1823.70
Chi squared	83.33***	82.79***	83.66***
Observations	7656	7656	7656

Note: Standard errors in parentheses. The number of observations is $n = 8 * 3 * 319 = 7656$. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

[a] Alternative specific constant.

[b] Reference category is fruits.

[c] Reference category is weed control.

[d] Reference category is medium growing.

[e] Reference category is dense shade.

[f] Reference category is a tall tree.

The relative impacts of the attributes on farmers' preferences for companion trees are depicted in Figure 6. The relative attribute impact was calculated by constructing a ratio where the numerator is the difference of the maximum and minimum coefficients (i.e. utility) for the levels of that attribute; the denominator of the ratio is the sum of the values in the numerator for all attributes. Regulating ES provided by companion trees has the greatest impact on farmers' preferences. Nearly equal in importance is the tree seedling price, followed by the products provided by companion trees and the growth rate. Tree height and the quality of shade are the least important attributes among the six attributes that are captured in this study.

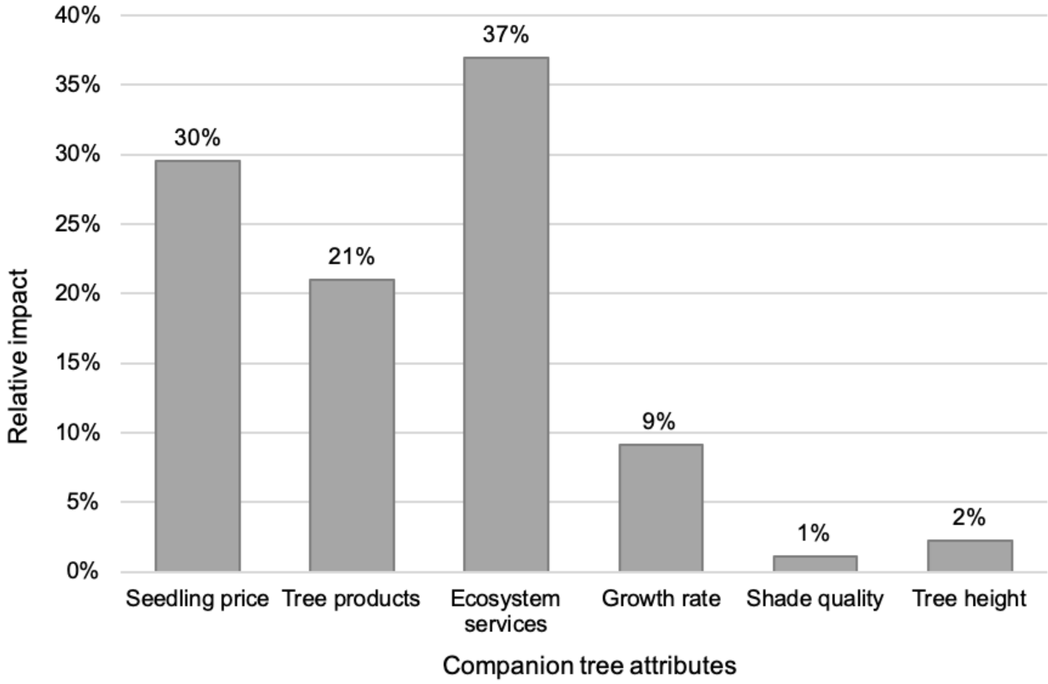

Figure 6. *Relative impact of attributes on farmers' preferences for companion trees. Source: Authors.*

Table 14 presents combinations of attributes of companion trees that are preferred by farmers.[19] These combinations are derived from the sums of parameter estimates for alternative attribute combinations to determine the total preference weight for that companion tree by the average respondent. The companion tree with the highest total preference weight is the most preferred. In our study, the most preferred companion tree is tree A with a total preference weight of 0.88. Companion tree A would provide fodder, light and mottled shade, improve the microclimate through temperature buffering and soil moisture conservation, and would be tall, fast growing, and would cost 1,000 USh. The least preferred companion tree is tree H with a total preference weight of –0.88. This tree would provide fuelwood, dense shade, weed control, and would be short, slow growing, and would be free of cost. Companion trees B–G, which were designated

[19] Based on the method described, 8 different hypothetical companion trees (A–H) were specified that combine the different attribute levels in a relevant way and that we compare respondents' relative preference based on their individual responses to attribute levels.

by the authors, range from intermediate but positive preference scores for companion trees B, C, D, and E to being perceived negatively overall (G).

Table 14. *Relative companion tree desirability with different attribute combinations*

Tree	Seedling price (USh)	Tree products	Ecosystem services	Growth rate	Shade quality	Tree height	Total preference weight	Rank
A	1,500	Fodder	Microclimate	Fast	Light	Tall	0.88	1
B	1,000	Fodder	Microclimate	Slow	Light	Tall	0.68	2
C	1,500	Fruits	Microclimate	Slow	Light	Short	0.53	3
D	200	Fruits	Soil fertility	Fast	Light	Tall	0.32	4
E	1,000	Timber	Soil fertility	Medium	Light	Tall	0.27	5
F	500	Fodder	Soil fertility	Fast	Dense	Short	0.19	6
G	200	Timber	P&D[a] control	Slow	Light	Tall	–0.08	7
H	0	Fuelwood	Weed control	Slow	Dense	Short	–0.88	8

[a] Pests and diseases control.

Differences in preferences in relation to farm altitude

In this subsection, we explore the drivers of preference heterogeneity in more detail. Specifically, we focus on the influence of farm altitude on preference. As the biophysical characteristic of altitude does not vary within a choice, it cannot be included in the regression model directly. Considering the interaction between farm altitude and attribute preferences allows slope coefficients to differ across subgroups (high-altitude vs. moderate-altitude farmers). Such variables are created by multiplying the variables of interest. For instance, since we are interested in whether preferences for regulating ES provided by companion trees vary according to the farm altitude, we create the variable 'microclimate-altitude', which is simply 'microclimate $\times$ altitude'. This can then be entered into the regression model.

In a first variation of the model's base specification we interact the ASC with the altitude dummy. Results are shown in column (2) of Table 13. The interaction term is insignificant, suggesting that altitude is not correlated with farmers' general preference for companion trees. However, altitude is correlated with preference heterogeneity for the regulating ES attribute. Results in column (3) of Table 13 reveal significant interaction terms between the regulating ES attribute and altitude. This means that high-altitude farmers have a stronger preference for soil fertility improvement through mulch and erosion control than low-altitude farmers. This could be explained by the fact that less favorable biophysical production conditions, for instance greater slope or high erosion potential, create a positive incentive to adopt technologies that will alleviate these situations (Pattanayak et al., 2003). This argument is particularly salient in the context of the multi-functionality of mulch. Mulch can provide a series of functions, such as soil moisture conservation, erosion control, yield improvement (through organic matter addition and nutrient cycling) and weed control.

On the other hand, we find that high-altitude farmers attach relatively lower importance to microclimate regulation (i.e. temperature buffering and soil moisture conservation) and P&D control (i.e. decreasing incidence of white coffee stem borer and coffee leaf rust) than moderate-altitude farmers. This might be explained by the fact that low-altitude farmers are increasingly experiencing difficulties growing Arabica coffee at low altitudes and therefore need a large set of regulating ES that support their coffee production's resilience, for instance through microclimate regulation and P&D control (Gram et al., 2018; Liebig et al., 2016).

Differences in preferences in relation to behavioral preferences

In this subsection, we look at the relation between behavioral preferences and the relative importance of companion tree characteristics. In a first variation of the model's base specification we interact the ASC with behavioral preferences. Results are shown in column (1) of Table 15. The interaction terms are insignificant, suggesting that risk aversion, loss aversion and time preference are not correlated with farmers' general preference for companion trees.

However, behavioral preferences are correlated with preference heterogeneity for several attributes. We tested all possible interaction terms, but eventually excluded those that were individually or jointly insignificant. Columns (2) to (4) of Table 15 present the results of the models that include interaction terms between companion tree attributes and farmers' behavioral preferences. Risk aversion interacts with preferences for different attributes as illustrated in column (2) of Table 15. We find that farmers with higher levels of risk aversion have a greater preference for companion trees that are associated with improving soil fertility (i.e. producing mulch and controlling soil erosion) and that provide fuelwood than farmers with lower levels of risk aversion. We also find that farmers with higher levels of risk aversion have strong preferences for fast growing, as well as particularly strong aversion to slow growing companion trees compared to farmers with lower levels of risk aversion.

In column (3), we interact soil fertility with loss aversion. The interaction term is positive and significant, implying that farmers with higher levels of loss aversion have a greater preference for the companion tree attribute soil fertility than farmers with lower levels of loss aversion.

As can be seen from the interaction between time preference and the growth rate attribute in column (4) of Table 15, farmers with a strong preference for the present prefer fast growing companion trees and the table hence shows a negative coefficient. With respect to the interpretation of the coefficient, it must be considered that the smaller the present bias parameter, the larger the preference for the present. In line with that, farmers with lower preference for the present (hence higher levels of patience) showed interest in slower growing trees.

Table 15. *Mixed logit model estimates – specifications to analyze differences in preferences for specific tree attributes in relation to behavioral preferences*

Variables	(1)	(2)	(3)	(4)
Mean parameters				
ASC[a]	–8.27*** (1.88)	–7.76*** (1.23)	–6.82*** (0.87)	–6.83*** (0.88)
Seedling price	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)
Fodder[b]	0.16*** (0.06)	0.16*** (0.06)	0.16*** (0.06)	0.16*** (0.06)
Fuelwood[b]	–0.20*** (0.05)	–0.25*** (0.05)	–0.20*** (0.05)	–0.20*** (0.05)
Timber[b]	0.02 (0.05)	0.03 (0.05)	0.02 (0.05)	0.03 (0.05)
Microclimate[c]	0.28*** (0.05)	0.29*** (0.05)	0.28*** (0.05)	0.28*** (0.05)
Soil fertility[c]	0.10* (0.05)	0.03 (0.06)	0.04 (0.06)	0.09* (0.05)
P&E control[c]	–0.12*** (0.04)	–0.12*** (0.04)	–0.12*** (0.04)	–0.12*** (0.04)
Fast growing[d]	0.07* (0.04)	0.01 (0.05)	0.07* (0.04)	0.27** (0.13)
Slow growing[d]	–0.07* (0.04)	0.01 (0.05)	–0.07* (0.04)	–0.33*** (0.11)
Light shade[e]	0.00 (0.03)	0.00 (0.03)	0.00 (0.03)	0.00 (0.03)
Short tree[f]	–0.02 (0.03)	–0.02 (0.03)	–0.02 (0.03)	–0.02 (0.03)
Interactions				
ASC × risk	0.03 (0.91)			
ASC × loss	–0.09 (0.10)			
ASC × time	2.84 (1.86)			
Fuelwood × risk		0.17** (0.008)		
Soil fertility × risk		0.22** (0.10)		
Fast growing × risk		0.20** (0.09)		
Slow growing × risk		–0.26*** (0.09)		
Soil fertility × loss			0.01* (0.01)	
Fast growing × time				–0.36* (0.22)
Slow growing × time				0.49** (0.20)
SD parameters				
ASC	2.78*** (0.47)	3.41*** (0.65)	2.70*** (0.43)	2.72*** (0.44)
Fodder	0.15 (0.15)	0.11 (0.19)	0.13 (0.17)	0.12 (0.18)
Fuelwood	0.22** (0.09)	0.21** (0.09)	0.22** (0.09)	0.23*** (0.09)
Timber	0.11 (0.12)	0.02 (0.18)	0.10 (0.12)	0.10 (0.13)
Microclimate	0.37*** (0.09)	0.37*** (0.09)	0.36*** (0.09)	0.37*** (0.09)
Soil fertility	0.31*** (0.09)	0.28*** (0.11)	0.30*** (0.10)	0.30*** (0.10)
P&E control	0.05 (0.11)	0.02 (0.13)	0.04 (0.11)	0.04 (0.11)
Fast growing	0.12 (0.12)	0.12 (0.12)	0.11 (0.15)	0.11 (0.15)
Slow growing	0.13 (0.09)	0.15* (0.08)	0.13 (0.10)	0.12 (0.10)
Light shade	0.01 (0.11)	0.02 (0.11)	0.01 (0.11)	0.01 (0.11)
Short tree	0.13 (0.12)	0.14 (0.10)	0.12 (0.13)	0.10 (0.15)
Log likelihood	–1825.19	–1816.27	–1825.90	–1823.83
Chi squared	77.29***	85.07	83.04***	83.83
Observations	7656	7656	7656	7656

Note: Standard errors in parentheses. The number of observations is $n = 8 * 3 * 319 = 7656$. *** p < 0.01, ** p < 0.05, * p < 0.1.
[a] Alternative specific constant.
[b] Reference category is fruits.
[c] Reference category is weed control.
[d] Reference category is medium growing.
[e] Reference category is dense shade.
[f] Reference category is a tall tree.

Gender-specific differences in preferences

The estimation results displayed in Table 16 show farmers' preferences for companion tree characteristics. We first examine the general companion tree preferences without covariates, displayed in column (1) and addressed in detail in subsection 'General preferences for companion trees'. To explore possible gender differences, we specify a set of additional models whose results are shown in Table 16. In column (2), we interact the ASC with a simple female dummy. The interaction term is insignificant, implying that women do not have a higher general preference for companion trees than men. In a next step, we run a model with attribute-gender interaction terms whose results are shown in column (3) of Table 16. We find significant gender differences in terms of preference for the soil fertility attribute. Women hence have greater preferences for soil fertility (i.e. mulch and erosion control) than men. This is consistent with the findings of other studies (Kiptot & Franzel, 2012; Villamor et al., 2014). While we hypothesized that men and women have different preferences for tree products, the interaction terms for the tree products attribute was insignificant. This is surprising since we expected gender-specific preferences, specifically related to the importance attributed to fuelwood. One explanation for the absence of gender differences might be that this study focused on coffee production and companion trees for coffee plantations and not on the whole farm that generally comprises plots for food crops for which women, arguably, have more management decision-making power.

Table 16. *Mixed logit model estimates – specifications to analyze gender differences*

Variables	(1)	(2)	(3)
Mean parameters			
ASC[a] (for status quo alternative)	–6.82*** (0.87)	–7.02*** (1.05)	–7.97*** (1.30)
Seedling price	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)
Fodder[b]	0.16*** (0.06)	0.16*** (0.06)	0.20** (0.08)
Fuelwood[b]	–0.20*** (0.05)	–0.20*** (0.05)	–0.25*** (0.07)
Timber[b]	0.02 (0.05)	0.02 (0.05)	-0.02 (0.07)
Microclimate[c]	0.28*** (0.05)	0.28*** (0.05)	0.28*** (0.05)
Soil fertility[c]	0.09* (0.05)	0.09* (0.05)	0.01 (0.07)
P&E control[c]	–0.12*** (0.04)	–0.11*** (0.04)	–0.12*** (0.04)
Fast growing[d]	0.07* (0.04)	0.07* (0.04)	0.07 (0.04)
Slow growing[d]	–0.07* (0.04)	–0.07* (0.04)	–0.07* (0.04)
Light shade[e]	0.00 (0.03)	0.00 (0.03)	0.00 (0.03)
Short tree[f]	–0.02 (0.03)	–0.02 (0.03)	–0.02 (0.04)
ASC and attribute interactions			
ASC × female		0.47 (0.85)	
Soil fertility × female			0.16* (0.09)
Fodder × female			–0.07 (0.11)
Fuelwood × female			0.10 (0.09)
Timber × female			0.08 (0.10)
Standard deviation parameters			
ASC	2.71*** (0.43)	2.67*** (0.46)	3.57*** (0.68)
Fodder	0.13 (0.18)	0.11 (0.22)	0.13 (0.18)
Fuelwood	0.22** (0.09)	0.22** (0.09)	0.22*** (0.08)
Timber	0.10 (0.13)	0.10 (0.13)	0.03 (0.21)
Microclimate	0.36*** (0.09)	0.36*** (0.09)	0.36*** (0.10)
Soil fertility	0.30*** (0.10)	0.30*** (0.10)	0.26** (0.12)
P&E control	0.04 (0.11)	0.04 (0.11)	0.02 (0.13)
Fast growing	0.10 (0.16)	0.08 (0.29)	0.12 (0.12)
Slow growing	0.13 (0.10)	0.14 (0.10)	0.14* (0.08)
Light shade	0.01 (0.11)	0.01 (0.11)	0.02 (0.11)
Short tree	0.12 (0.13)	0.11(0.14)	0.16* (0.09)
Log likelihood	–1826.92	–1826.75	–1823.76
Chi squared	83.33***	80.92***	84.56***
Observations	7656	7656	7656

Note: Standard errors in parentheses. The number of observations is $n = 8 * 3 * 319 = 7656$. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

[a] Alternative specific constant.

[b] Reference category is fruits.

[c] Reference category is weed control.

[d] Reference category is medium growing.

[e] Reference category is dense shade.

[f] Reference category is a tall tree.

9. CONCLUSION

Uganda has recently experienced widespread forest loss and degradation, mainly driven by increased demand for forest products and agricultural expansion. Current conservative estimates suggest a 2% deforestation for private lands and 1% for protected areas annually. Some studies have indicated a higher rate (3.3%) due to agriculture in certain sites. One of the predominating forest landscape restoration strategies is the adoption of agroforestry practices in key agricultural landscapes in Uganda. While the benefits of agroforestry have been widely acknowledged, adoption among smallholder farmers is slow. An assessment of what particular features of agroforestry systems hamper or facilitate adoption requires a better understanding of farmers' preferences.

The objective of this study were (1) to elicit both risk and time preferences of smallholder coffee farmers in the Mt. Elgon landscape of Uganda, a priority area for forest landscape restoration, by using lottery-based experiments, and (2) to investigate key attributes or features of companion trees in coffee agroforestry systems that are preferred by farmers using a discrete choice experiment. Farmers' preferences related to six companion tree attributes were investigated: tree products provided, regulating ecosystem services provided, growth rate, seedling price, provision of quality shade for coffee, and maximum tree height. To demonstrate the relation between risk and time preferences and the adoption of companion trees, these experimental data were coupled with the results from the discrete choice experiment about farmers' preferences for companion tree attributes. To analyze potential strata in farmer preferences, the sample included coffee farmers from different altitude zones. A gendered research design furthermore allowed exploring possible differences in preferences between men and women.

The theoretical basis of the analysis was a random utility model to analyze the preferences of coffee farmers for various characteristics of companion trees. Cumulative prospect theory and quasi-hyperbolic discounting were used to measure farmers' risk and time preferences. A maximum likelihood approach was then applied to estimate the effects of risk aversion, loss aversion, and time preference on choice probabilities of hypothetical companion tree alternatives vis-à-vis the status quo.

The results showed that there is a relation between behavioral preferences and the relative importance of companion tree characteristics. Specifically, farmers with higher levels of risk aversion have a greater preference for companion trees that are associated with improving soil fertility (i.e. producing mulch and controlling soil erosion) than farmers with lower levels of risk aversion. Farmers with higher levels of risk aversion also have strong preferences for fast growing, as well as particularly strong aversion to slow growing companion trees compared to farmers with lower levels of risk aversion. Further, farmers with higher levels of loss aversion have a greater preference for the companion tree attribute soil fertility than farmers with lower levels of loss aversion. Lastly, farmers with a strong preference for the present prefer fast growing companion trees. Farmers with lower preference for the present (hence higher levels of patience) showed interest in slower growing trees.

The results also suggest that preferences for regulating ecosystem services provided by companion trees vary according to farm altitude. Specifically, high-altitude farmers have a stronger preference for soil fertility improvement through mulch and erosion control than low-altitude farmers. High-altitude farmers also attach relatively lower importance to microclimate regulation (i.e. temperature buffering and soil moisture conservation) and pests and diseases control (i.e. decreasing incidence of white coffee stem borer and coffee leaf rust) than moderate-altitude farmers.

Surprisingly, the results showed that men and women do not have different preferences for tree products. However, women have greater preferences for soil fertility (i.e. mulch and erosion control) than men. These findings demonstrate that a better understanding of farmers' preferences in terms of the features of companion trees that they like, and dislike is important to design context-specific agroforestry options that aim to increase adoption of trees on farms in a way that is in line with and responsive to farmers' needs and preferences.

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APPENDIX

Appendix A.1 Estimation method of risk preference parameters

The distribution of switching points from the 319 respondents and the results disaggregated by gender is shown in Table A.1. The histograms graphically illustrate the percentage of respondents by switching points (Figure A.*1*). The switching points from series 1 and series 2 are used to estimate the curvature of the utility function (σ) and the nonlinear probability weighting parameter (α) for each respondent. Once we estimate the curvature of the utility function, we can use the switching point from series 3 to estimate the utility curvature in the loss domain (λ).

For any respondent who switches at row N, we can conclude that the respondent prefers lottery A over lottery B at row $N-1$ and prefers lottery B over lottery A at row N. Using a combination of switching points from series 1 and series 2, we will have a set of 4 inequalities, and we will be able to find the ranges of σ and α that satisfy these inequalities. In case the respondent does not switch to lottery B or switches at row 1, we have one inequality. The two series were carefully designed so that the pair of switching points from the two series (in tandem) can be used to identify the lower and upper bounds for the range of parameter tuples for which the respondents' choices are consistent under the cumulative prospect theory (Liu, 2013; Tanaka et al., 2010). For example, when a respondent switches from lottery A to lottery B at row 7 in both series 1 and series 2, the following inequalities should be satisfied:

$$1{,}000^{1-\sigma} + \exp[-(-\ln 0.3)^{\alpha}]\,(4{,}000^{1-\sigma} - 1{,}000^{1-\sigma}) > 500^{1-\sigma} + \exp[-(-\ln 0.1)^{\alpha}]\,(12{,}500^{1-\sigma} - 500^{1-\sigma})$$

$$1{,}000^{1-\sigma} + \exp[-(-\ln 0.3)^{\alpha}]\,(4{,}000^{1-\sigma} - 1{,}000^{1-\sigma}) < 500^{1-\sigma} + \exp[-(-\ln 0.1)^{\alpha}]\,(15{,}000^{1-\sigma} - 500^{1-\sigma})$$

$$3{,}000^{1-\sigma} + \exp\ [-(-\ln 0.9)^{\alpha}]\,(4{,}000^{1-\sigma} - 3{,}000^{1-\sigma}) > 500^{1-\sigma} + \exp[-(-\ln 0.7)^{\alpha}]\,(6{,}500^{1-\sigma} - 500^{1-\sigma})$$

$$3{,}000^{1-\sigma} + \exp[-(-\ln 0.9)^{\alpha}]\,(4{,}000^{1-\sigma} - 3{,}000^{1-\sigma}) < 500^{1-\sigma} + \exp[-(-\ln 0.7)^{\alpha}]\,(6{,}800^{1-\sigma} - 500^{1-\sigma})$$

In the case above, an individual switching in the seventh row in each of the two series would be assigned a parameter tuple of (σ, α) = (0.7, 0.7). For all the parameters, we calculate the midpoint of this range and use an approximation of the individuals' parameter values. After obtaining an estimate of σ, we use the switching point from series 3 to write out inequalities involving λ. Similar to σ and α, λ can be estimated only as in interval, and we use the midpoint of each interval as the point estimate. There is a range of values of λ for a particular value of σ, so an estimate for the upper bound of $\lambda(\sigma)$ is given by:

$$\lambda_j(\sigma) = \left(x_{j,A}^{\sigma} - x_{j,B}^{\sigma}\right) / \left(-y_{j,A}\right)^{\sigma} - \left(-y_{j,B}\right)^{\sigma}$$

where $x_{j,A}$ and $x_{j,B}$ are the 'winning' payoffs in choice j corresponding to lottery A and lottery B, respectively, and $y_{j,A}$ and $y_{j,B}$ are the corresponding 'losing' payoffs. Table A.2 illustrates the combinations of approximate values of σ, α, and λ for each switching point. Predications of σ, α, and λ for all possible combinations of choices are given in Table A.3.

Table A.1. Distribution of switching points (in %) in risk experiment by gender

	Series 1			Series 2			Series 3		
Switching point	Full sample	Men	Women	Full sample	Men	Women	Full sample	Men	Women
1	25.71	28.12	23.27	46.39	42.50	50.31	40.75	40.62	40.88
2	4.08	3.12	5.03	2.51	3.12	1.89	11.91	18.75	5.03
3	3.45	5.62	1.26	2.51	4.38	0.63	6.27	8.12	4.40
4	2.19	1.25	3.14	2.51	1.88	3.14	3.13	3.12	3.14
5	1.57	0.62	2.52	2.51	3.75	1.26	3.13	3.12	3.14
6	2.82	4.38	1.26	2.82	3.12	2.52	2.19	1.88	2.52
7	2.19	3.12	1.26	1.25	0.62	1.89	0.94	0.62	1.26
8	1.25	1.88	0.63	1.88	1.88	1.89	–	–	–
9	1.88	2.50	1.26	1.57	0.62	2.52	–	–	–
10	2.82	1.25	4.40	0.94	0.00	1.89	–	–	–
11	0.94	0.00	1.89	0.00	0.00	0.00	–	–	–
12	1.57	2.50	0.63	0.31	0.62	0.00	–	–	–
13	1.88	3.12	0.63	1.88	2.50	1.26	–	–	–
14	2.51	2.50	2.52	0.63	0.62	0.63	–	–	–
Never	45.14	40.00	50.31	32.29	34.38	30.19	31.66	23.75	39.62
Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Obs.	319	160	159	319	160	159	319	160	159

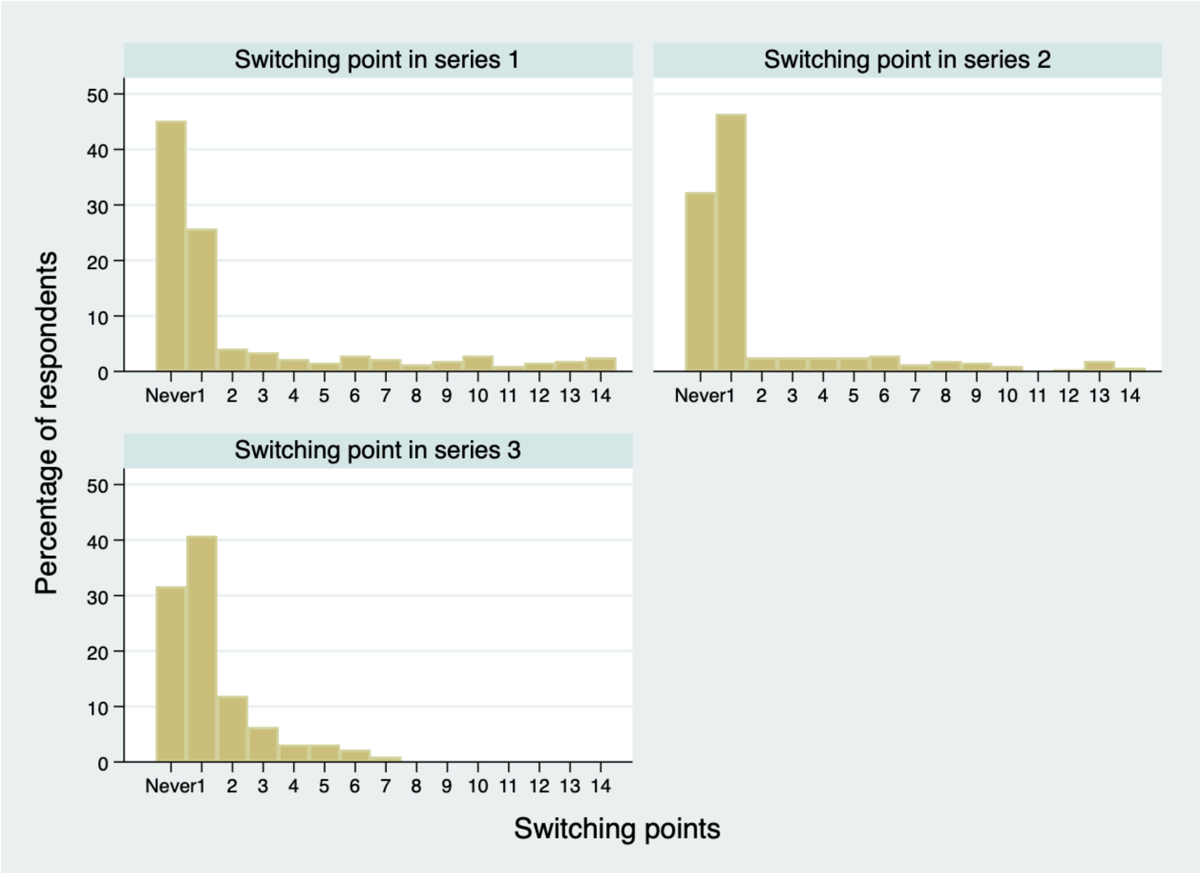

Figure A.1. Percentage of respondents by switching points in the risk experiment. Source: Authors.

Table A.2. Switching point (question at which preference switches from Option A to Option B) and approximations of the risk aversion parameter (σ), the probability weighting parameter (α), and the loss aversion parameter (λ)

Series 1 (questions 1-14)

α / σ	0.4	0.5	0.6	0.7	0.8	0.9	1.0
0.2	9	10	11	12	13	14	never
0.3	8	9	10	11	12	13	14
0.4	7	8	9	10	11	12	13
0.5	6	7	8	9	10	11	12
0.6	5	6	7	8	9	10	11
0.7	4	5	6	7	8	9	10
0.8	3	4	5	6	7	8	9
0.9	2	3	4	5	6	7	8
1.0	1	2	3	4	5	6	7

Series 2 (questions 15-28)

α / σ	0.4	0.5	0.6	0.7	0.8	0.9	1.0
0.2	never	14	13	12	11	10	9
0.3	14	13	12	11	10	9	8
0.4	13	12	11	10	9	8	7
0.5	12	11	10	9	8	7	6
0.6	11	10	9	8	7	6	5
0.7	10	9	8	7	6	5	4
0.8	9	8	7	6	5	4	3
0.9	8	7	6	5	4	3	2
1.0	7	6	5	4	3	2	1

Series 3 (questions 29-35)

Switching question	σ = 0.2	σ = 0.6	σ = 1
1	$\lambda > 0.14$	$\lambda > 0.20$	$\lambda > 0.29$
2	$0.14 < \lambda < 1.26$	$0.20 < \lambda < 1.38$	$0.29 < \lambda < 1.53$
3	$1.26 < \lambda < 1.88$	$1.38 < \lambda < 1.71$	$1.53 < \lambda < 1.71$
4	$1.88 < \lambda < 2.31$	$1.71 < \lambda < 2.25$	$1.71 < \lambda < 2.42$
5	$2.31 < \lambda < 4.32$	$2.25 < \lambda < 3.73$	$2.42 < \lambda < 3.63$
6	$4.32 < \lambda < 5.43$	$3.73 < \lambda < 4.82$	$3.63 < \lambda < 4.83$
7	$5.43 < \lambda < 9.78$	$4.82 < \lambda < 9.13$	$4.83 < \lambda < 9.67$
Never	$\lambda > 9.78$	$\lambda > 9.13$	$\lambda > 9.67$

Table A.3. Switching point (question) in Series 1, 2, and 3, and approximations of the risk aversion parameter (σ), the probability weighting parameter (α), and the loss aversion parameter (λ)

σ	Switching question in Series 1														
Series 2	1	2	3	4	5	6	7	8	9	10	11	12	13	14	Never
1	1.50	1.40	1.35	1.25	1.15	1.10	1.00	0.95	0.90	0.85	0.80	0.75	0.65	0.55	0.50
2	1.40	1.30	1.25	1.15	1.10	1.00	0.95	0.90	0.85	0.80	0.75	0.70	0.60	0.55	0.50
3	1.30	1.20	1.15	1.10	1.00	0.95	0.90	0.85	0.80	0.75	0.70	0.65	0.55	0.50	0.45
4	1.20	1.15	1.05	1.00	0.95	0.90	0.85	0.80	0.75	0.70	0.65	0.60	0.50	0.45	0.40
5	1.15	1.05	1.00	0.95	0.90	0.85	0.80	0.75	0.70	0.65	0.60	0.55	0.50	0.40	0.35
6	1.05	1.00	0.95	0.90	0.85	0.80	0.75	0.70	0.65	0.60	0.55	0.50	0.45	0.40	0.35
7	1.00	0.95	0.90	0.85	0.80	0.75	0.70	0.65	0.60	0.55	0.50	0.45	0.40	0.35	0.30
8	0.95	0.90	0.85	0.80	0.75	0.70	0.65	0.60	0.55	0.50	0.45	0.40	0.35	0.30	0.25
9	0.90	0.85	0.80	0.75	0.70	0.65	0.60	0.55	0.50	0.45	0.40	0.35	0.30	0.25	0.20
10	0.85	0.80	0.75	0.70	0.65	0.60	0.55	0.50	0.45	0.40	0.35	0.30	0.25	0.20	0.20
11	0.80	0.70	0.65	0.65	0.60	0.55	0.50	0.45	0.40	0.35	0.30	0.25	0.20	0.15	0.15
12	0.75	0.65	0.60	0.55	0.50	0.50	0.45	0.40	0.35	0.30	0.25	0.20	0.20	0.15	0.10
13	0.65	0.60	0.55	0.50	0.45	0.45	0.40	0.35	0.30	0.25	0.20	0.15	0.15	0.10	0.10
14	0.60	0.55	0.50	0.45	0.40	0.35	0.35	0.30	0.25	0.20	0.15	0.10	0.10	0.10	0.05
Never	0.50	0.45	0.40	0.40	0.35	0.30	0.30	0.25	0.20	0.15	0.10	0.10	0.05	0.05	0.05

α	Switching question in Series 1														
Series 2	1	2	3	4	5	6	7	8	9	10	11	12	13	14	Never
1	0.60	0.75	0.75	0.85	0.90	0.95	1.00	1.05	1.10	1.15	1.20	1.25	1.30	1.40	1.45
2	0.60	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05	1.10	1.15	1.20	1.25	1.35	1.40
3	0.55	0.60	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05	1.10	1.15	1.20	1.25	1.30
4	0.50	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05	1.10	1.15	1.20	1.25
5	0.45	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05	1.10	1.15	1.20
6	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05	1.10	1.15
7	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05	1.10
8	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05
9	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95	1.00
10	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95
11	0.20	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90
12	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85
13	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80
14	0.05	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75
Never	0.05	0.05	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.45	0.55	0.55	0.65	0.60

σ	Switching question in Series 3 1	2	3	4	5	6	7	Never
0.05	0.12	0.67	1.61	2.21	3.57	5.31	8.15	10.41
0.10	0.12	0.68	1.60	2.16	3.48	5.15	7.94	10.17
0.15	0.13	0.69	1.58	2.13	3.39	5.01	7.76	9.96
0.20	0.14	0.70	1.57	2.09	3.32	4.88	7.60	9.78
0.25	0.14	0.71	1.56	2.07	3.25	4.76	7.46	9.62
0.30	0.15	0.72	1.55	2.04	3.19	4.66	7.34	9.48
0.35	0.16	0.73	1.55	2.02	3.14	4.57	7.24	9.37
0.40	0.17	0.74	1.54	2.01	3.10	4.49	7.16	9.29
0.45	0.18	0.75	1.54	1.99	3.06	4.42	7.09	9.22
0.50	0.18	0.77	1.54	1.99	3.03	4.36	7.04	9.17
0.55	0.19	0.78	1.54	1.98	3.01	4.31	7.00	9.14
0.60	0.20	0.79	1.54	1.98	2.99	4.27	6.98	9.13
0.65	0.21	0.80	1.55	1.98	2.97	4.24	6.97	9.14
0.70	0.22	0.82	1.55	1.98	2.97	4.22	6.97	9.17
0.75	0.23	0.83	1.56	1.99	2.96	4.20	6.99	9.21
0.80	0.25	0.85	1.57	2.00	2.97	4.20	7.02	9.27
0.85	0.26	0.86	1.58	2.01	2.97	4.19	7.06	9.34
0.90	0.27	0.88	1.59	2.02	2.99	4.20	7.11	9.44
0.95	0.28	0.89	1.60	2.04	3.00	4.21	7.17	9.54
1.00	0.29	0.91	1.62	2.06	3.02	4.23	7.25	9.67
1.05	0.31	0.93	1.63	2.08	3.04	4.25	7.34	9.81
1.10	0.32	0.95	1.65	2.11	3.07	4.28	7.44	9.96
1.15	0.33	0.97	1.67	2.13	3.10	4.32	7.55	10.13
1.20	0.35	0.98	1.68	2.16	3.14	4.36	7.67	10.32
1.25	0.36	1.00	1.70	2.19	3.18	4.41	7.80	10.52
1.30	0.38	1.02	1.72	2.23	3.22	4.46	7.94	10.74
1.35	0.40	1.04	1.74	2.26	3.27	4.51	8.10	10.98
1.40	0.41	1.06	1.76	2.30	3.32	4.58	8.27	11.23
1.50	0.45	1.11	1.81	2.38	3.43	4.72	8.64	11.79

Appendix A.2 Instructions of experiment on risk preferences

[1] Instructions to experimenter
1. The experimenter hands out <u>choice card 1</u> of the risk game to the respondent as an example.
2. The experimenter first asks the respondent what he/she thinks the pictures on the choice card represent. i. This serves as an icebreaker. It basically enables the respondent to start thinking about the material and the decisions he/she will be presented with during the game. ii. The respondent should realize that the task has something to do with trees and 'good' or 'bad/no' rains.
[2] Experiment explanation example: Experimenter explains to respondents
1. *The brainstorming has shown that the task today has to do with trees and 'good' or 'bad/no' rains.*
2. *Specifically, we will talk about two types of tree species (we call them 'Tree species A' and 'Tree species B'). We are going to ask you which of these two tree species you prefer.*
3. *But first you have to understand how to make a difference between these two tree species? You will see that the difference has to do with how well the trees grow in different climatic conditions – specifically, you will see that some tree species grow better than others when there are good rains, but also when there bad/no rains. This is what matters. To understand that better, let's focus on the third row of the choice card.*
4. Let's start with 'Tree species A' a. *'Tree species A' gives 4,000 USh as income from production in times of 'good rains' and 1,000 USh in times of 'bad/no rains'.* i. Explain payoff and how it is associated with 'good rains' or 'bad/no rains'. ii. Quiz respondent on how high the payoff is in times of 'good rains' or 'bad/no rains'.
5. Move to explain tree species B' a. *Now, let's look at 'Tree species B'. What is different about it? Well, this tree species gives 6,800 USh as income from production in times of 'good rains' but 500 USh in times of 'bad/no rains'.*
6. *'So, the difference between the two tree species is that 'Tree Species B' pays MORE in times of 'good rains' but LESS in times of 'bad/no rains'.* i. Explain payoff and how it is associated with 'good rains' or 'bad/no rains'. ii. Quiz respondent on how much payoff is in times of 'good rains' or 'bad/no rains'.
7. <u>Recap:</u> *So, we have seen that there are two types of tree species, 'Tree Species A' and 'Tree Species B'. We also know that they are affected by the weather ('good rains' or 'bad/no rains').*
8. *What do we know about the weather*?

a. *As in real life, sometimes there are 'good rains' and sometimes there are 'bad/no rains'.* b. *These 10 numbers (1, 2, 3, …, 10) of a 10-sided dice represent 10 years of weather ('good rains' or 'bad/no rains').* c. *The numbers in the columns of 'good rains' and 'bad/no rains' of the choice card represent the years of 'good rains' or 'bad/no rains'.* d. *In the fourth row of the choice card, in 3 out of 10 years there are 'good rains' and in the 7 other years there are 'bad/no rains'* ***for 'Tree Species A'***. i. *The numbers 1, 2, 3 represent the years of 'good rains'.* ii. *The numbers 4, 5, 6, 7, 8, 9, 10 represent the years of 'bad/no rains'.* e. *Still in the fourth row of the choice card, in 1 out of 10 years there are 'good rains' and 9 out of 10 years there are 'bad/no rains'* ***for 'Tree Species B'***. iii. *The number 1 represents the year of 'good rains'.* iv. *The numbers 2, 3, 4, 5, 6, 7, 8, 9, 10 represent the years of 'bad/no rains'.*
9. Questions/quiz to test respondent's understanding of the weather factor: i. *How many years can be 'good rains' in row 4 of the choice card*? [ADD ANSWER IN BRACKETS] ii. *How many years can be 'bad/no rains'*? [ADD ANSWER IN BRACKETS] iii. *What is the income from production if there are 'good rains' (depends on whether you buy 'Tree Species A' or 'Tree Species B')*? [ADD ANSWER] iv. *Suppose, you buy 'Tree Species A' and there are 'good rains', what is your income from production? How about 'Tree Species B'*? [ADD ANSWER] v. *How about if there are 'bad/no rains'*? [ADD ANSWER IN BRACKETS]
[3] Instruction about proceedings during actual experiment: Experimenter explains to respondents
1. *We discussed only one choice card. In total, we will show 35 similar choice cards. How are the other choice cards different from choice card 1*? i. *Notice that when we go from choice card 1 to choice card 2 and continue up to choice card 14, the only aspect that changes is the income from production. The number of years of 'good rains' and 'bad/no rains' do NOT change up to choice card 14.* ii. *After choice card 14, the numbers in the columns of 'good rains' and 'bad/no rains' as well as the income from production change.* iii. The respondent is informed that during the game he/she will be notified about any changes to avoid too much prior information.
2. *So, we are going to ask you to make a decision for each of the choice cards that will be presented to you: Do you prefer 'Tree Species A' or 'Tree Species B'*?
3. *There is only one restriction in your decisions within each of the three series: you can either start with 'Tree Species A' or 'Tree Species B'. If you start with 'Tree Species A', you can continue to choose 'Tree Species A' for as long as you want, but if you choose*

	'Tree Species B' at any point, you cannot go back to 'Tree Species A'. Also, if you start with 'Tree Species B', you can only choose 'Tree Species B' for the rest of the series.
4.	*Is this clear*?
[4] Instruction to the experimenter	
1.	Examples are repeated until the experimenter feels confident about the respondent's understanding.
2.	Once the experimenter is satisfied with the respondent's understanding, actual decisions are made.
3.	The experimenter presents each series separately and after each other. <u>For each series</u> ONLY 1 switch from 'Tree Species A' to 'Tree Species B' possible. i. First, series 1: choice cards 1 – 14 ii. Second, series 2: choice cards 15 – 28 iii. Third, series 3: choice cards 29 – 35
[5] Instructions for the experiment: Experimenter explains to respondents	
1.	*In this game, you play for real money. It's a bit complicated, but you will understand.*
2.	*After you have made all 35 decisions, you are asked to blindly draw one card out of a bag. The cards in the bag are numbered from 1 to 35. The card drawn will determine the decision number that will be played for real money. So only one of the 35 decisions will be played for real money*.
3.	*For example, if you draw a card that shows a 1, then decision number 1 will be played for real money. No pair of choices is any more likely to be used than any other and you will not know in advance which one will be selected, so please think about each decision carefully*.
4.	*After the card is drawn to determine which choice pair will be played, we will refer to the questionnaire to see whether you had previously chosen 'Tree species A' or 'Tree species B'. Then, we will roll the 10-sided dice to determine which payout you will receive*.
5.	*For example, if you choose 'Tree species A', and the dice roll shows a 1, 2, or 3 then you will receive 4,000 USh and if the dice roll shows a 4, 5, 6, 7, 8, 9, or 10 then you will receive 1,000 USh*.
6.	*If you agree to participate in this game, you will receive 2,100 USh to start. What will happen with these 2,1000 USh will depend on the decisions you take and on the number you draw out of the bag. You might lose all the money or you might win some. The maximum win is to 170,000 USh*.
7.	*Do you have any questions*?

Table B.1. Design of time experiment (in Ugandan shillings)

Series	Choices	Option A	Option B
1	1	2,000 USh today	12,000 USh in 1 week
	2	4,000 USh today	12,000 USh in 1 week
	3	6,000 USh today	12,000 USh in 1 week
	4	8,000 USh today	12,000 USh in 1 week
	5	10,000 USh today	12,000 USh in 1 week
2	6	2,000 USh today	12,000 USh in 1 month
	7	4,000 USh today	12,000 USh in 1 month
	8	6,000 USh today	12,000 USh in 1 month
	9	8,000 USh today	12,000 USh in 1 month
	10	10,000 USh today	12,000 USh in 1 month
3	11	2,000 USh today	12,000 USh in 3 months
	12	4,000 USh today	12,000 USh in 3 months
	13	6,000 USh today	12,000 USh in 3 months
	14	8,000 USh today	12,000 USh in 3 months
	15	10,000 USh today	12,000 USh in 3 months
4	16	5,000 USh today	30,000 USh in 1 week
	17	10,000 USh today	30,000 USh in 1 week
	18	15,000 USh today	30,000 USh in 1 week
	19	20,000 USh today	30,000 USh in 1 week
	20	25,000 USh today	30,000 USh in 1 week
5	21	5,000 USh today	30,000 USh in 1 month
	22	10,000 USh today	30,000 USh in 1 month
	23	15,000 USh today	30,000 USh in 1 month
	24	20,000 USh today	30,000 USh in 1 month
	25	25,000 USh today	30,000 USh in 1 month
6	26	5,000 USh today	30,000 USh in 3 months
	27	10,000 USh today	30,000 USh in 3 months
	28	15,000 USh today	30,000 USh in 3 months
	29	20,000 USh today	30,000 USh in 3 months
	30	25,000 USh today	30,000 USh in 3 months
7	31	500 USh today	3,000 USh in 1 week
	32	1,000 USh today	3,000 USh in 1 week
	33	1,500 USh today	3,000 USh in 1 week
	34	2,000 USh today	3,000 USh in 1 week
	35	2,500 USh today	3,000 USh in 1 week
8	36	500 USh today	3,000 USh in 1 month
	37	1,000 USh today	3,000 USh in 1 month
	38	1,500 USh today	3,000 USh in 1 month
	39	2,000 USh today	3,000 USh in 1 month
	40	2,500 USh today	3,000 USh in 1 month
9	41	500 USh today	3,000 USh in 3 months
	42	1,000 USh today	3,000 USh in 3 months
	43	1,500 USh today	3,000 USh in 3 months
	44	2,000 USh today	3,000 USh in 3 months
	45	2,500 USh today	3,000 USh in 3 months

(Continued)

Series	Choices	Option A	Option B
10	46	4,000 USh today	24,000 USh in 3 days
	47	8,000 USh today	24,000 USh in 3 days
	48	12,000 USh today	24,000 USh in 3 days
	49	16,000 USh today	24,000 USh in 3 days
	50	20,000 USh today	24,000 USh in 3 days
11	51	4,000 USh today	24,000 USh in 2 weeks
	52	8,000 USh today	24,000 USh in 2 weeks
	53	12,000 USh today	24,000 USh in 2 weeks
	54	16,000 USh today	24,000 USh in 2 weeks
	55	20,000 USh today	24,000 USh in 2 weeks
12	56	4,000 USh today	24,000 USh in 2 months
	57	8,000 USh today	24,000 USh in 2 months
	58	12,000 USh today	24,000 USh in 2 months
	59	16,000 USh today	24,000 USh in 2 months
	60	20,000 USh today	24,000 USh in 2 months
13	61	1,000 USh today	6,000 USh in 3 days
	62	2,000 USh today	6,000 USh in 3 days
	63	3,000 USh today	6,000 USh in 3 days
	64	4,000 USh today	6,000 USh in 3 days
	65	5,000 USh today	6,000 USh in 3 days
14	66	1,000 USh today	6,000 USh in 2 weeks
	67	2,000 USh today	6,000 USh in 2 weeks
	68	3,000 USh today	6,000 USh in 2 weeks
	69	4,000 USh today	6,000 USh in 2 weeks
	70	5,000 USh today	6,000 USh in 2 weeks
15	71	1,000 USh today	6,000 USh in 2 months
	72	2,000 USh today	6,000 USh in 2 months
	73	3,000 USh today	6,000 USh in 2 months
	74	4,000 USh today	6,000 USh in 2 months
	75	5,000 USh today	6,000 USh in 2 months

Appendix B.1 Instructions of experiment on time preferences

[1] Instructions to experimenter
1. The experimenter hands out choice card 1 of the time game to the respondent as an example.
2. The experimenter first asks the respondent what he/she thinks the pictures on the choice card represent. i. This serves as an icebreaker. It basically enables the respondent to start thinking about the material and the decisions he/she will be presented with during the game. ii. The respondent should realize that the task has something to do with money and time
[2] Experiment explanation example: Experimenter explains to respondents
1. *The brainstorming has shown that the task today has to do with money and time.*
2. *Specifically, we will talk about two options (we call them 'Option A' and 'Option B'). We are going to ask you which of these two options you prefer.*
3. *But first you have to understand how to make a difference between these two options? To understand that difference, let's focus on the example.*
4. *Let's start with 'Option A'* a. *'Option A' gives 4,000 USh today.* i. The experimenter circles the exact date of payment (today's date) on the illustrated calendar of the choice card.
5. Move to explain 'Option B' a. *Now, let's look at 'Option B'. What is different about it? Well, this option gives 12,000 USh in 1 week from now.* i. The experimenter circles the exact date of payment (1 week from today's date) on the illustrated calendar of the choice card.
6. *'So, the difference between the two options is that 'Option B' pays a LARGER sum of money in the future compared to 'Option A', which pays LITTLE money today.*
7. Questions/quiz to test respondent's understanding: i. Suppose, *you choose 'Option A', how much money do you get?* [ADD ANSWER IN BRACKETS] ii. *And when?* [ADD ANSWER IN BRACKETS] iii. *Suppose, you choose 'Option B', how much money do you get?* [ADD ANSWER IN BRACKETS] iv. *And when?*
[3] Instruction about proceedings during actual experiment: Experimenter explains to respondents
1. *We discussed only one choice card. In total, we will show 75 similar choice cards. How are the other choice cards different from choice card 1?*

i. *Notice that when we go from <u>choice card 1</u> to <u>choice card 2</u> and continue up to <u>choice card 5</u>, the only aspect that changes is the amount of money in 'Option A'. The time frame of 1 week does NOT change up <u>to choice card 5</u>.* ii. *After <u>choice card 5</u>, the time frame changes between 3 days, 1 week, 2 weeks, 1 month, 2 months, and 3 months.* iii. The respondent is informed that during the game he/she will be notified about any changes to avoid too much prior information.
2. *So, we are going to ask you to make a decision for each of the choice cards that will be presented to you: Do you prefer 'Option A' or 'Option B'*?
3. *There is only one restriction in your decisions within each of the fifteen series: you can either start with 'Option A' or 'Option B'. If you start with 'Option A', you can continue to choose 'Option A' for as long as you want, but if you choose 'Option B' at any point, you cannot go back to 'Option A'. Also, if you start with 'Option B', you can only choose 'Option B' for the rest of the series*.
4. *Is this clear*?
[4] Instruction to the experimenter
1. Examples are repeated until the experimenter feels confident about the respondent's understanding.
2. Once the experimenter is satisfied with the respondent's understanding, actual decisions are made.
3. The experimenter presents each series separately and after each other. <u>For each series</u> ONLY 1 switch from 'Option A' to 'Option B' possible. i. First, series 1: choice cards 1 – 5 ii. Second, series 2: choice cards 6 – 10 iii. Third, series 3: choice cards 11 – 15 iv. … , series 4: choice cards 71 – 75
[5] Instructions for the experiment: Experimenter explains to respondents
1. *In this game, you play for real money*. The amount will be determined as follows:
2. *After you have made all 75 decisions, you are asked to blindly draw one card out of a bag. The cards in the bag are numbered from 1 to 75. The card drawn will determine the decision number, and you will gain the payoff at the respective time according to your decision. So only one of the 75 decisions will be played for real money*.
3. *For example, if you draw a card that shows a 1, then decision number 1 will be played for real money. No decision is any more likely to be used than any other and you will not know in advance which one will be selected, so please think about each decision carefully*.
4. *For example, if you choose 'Option A', you receive 2,000 USh in cash today.*
5. *If you choose 'Option B', you will receive 12,000 USh in 1 week from now. In this case, the payment will be done as follows:* *i. You receive a credit voucher in your name.* *ii. The credit voucher is issued by the experimenter and approved by our organization.*

iii. The money will be sent via a mobile money transfer to your number. *iv. This transfer will be done at the date of payment as indicated on the credit voucher.*
6. *Do you have any questions*?

Table C.1. Comparison with findings reported by selected developing country field studies

Study	Subjects	Sample size	Risk and time preference parameters				
			Risk aversion (σ)	Probability weight (α)	Loss aversion (λ)	Time preference (δ)	Present bias (β)
Own study	Coffee farmers (Uganda)	319	0.67	0.79	3.85	0.12	0.54
Tanaka, Camerer, and Nguyen (2010)	Rural villagers (Vietnam)	181	0.59	0.74	2.63	0.08	0.82
Nguyen (2010)	Livestock farmers (Vietnam)	103	0.62	0.75	2.05	–	–
Nguyen (2011)	Fishermen (Vietnam)	181	1.01	0.96	3.26	0.28	0.72
Liu (2013)	Cotton farmers (China)	320	0.48	0.69	3.47	–	–
Liebenehm and Waibel (2014)	Cattle farmers (Mali, Burkina Faso)	211	0.11	0.13	1.35	0.001	0.94
Ward and Singh (2015)	Rice farmers (India)	491	0.77	0.74	4.46	–	–

Table C.2. Comparison of exponential, hyperbolic, and quasi-hyperbolic discounting models

	(1) Exponential	(2) Hyperbolic	(3) Quasi-hyperbolic	(4) Logistic function
(μ) (x10^{-6})	0.000***	0.000***	0.000***	0.000***
	(0.258)	(0.304)	(0.317)	(0.325)
Time preference (δ)	0.114***	0.179***	0.009***	0.101
	(0.006)	(0.015)	(0.001)	(0.102)
Present bias (β)			0.404***	0.542***
			(0.020)	(0.088)
Hyperbolicity (θ)				4.736***
				(0.700)
Observations	9570	9570	9570	9570
Adjusted R-squared	0.512	0.514	0.516	0.516

Note: Robust standard errors in parentheses. Standard errors are adjusted for within-subject correlations. *** p < 0.01, ** p < 0.05, * p < 0.1.

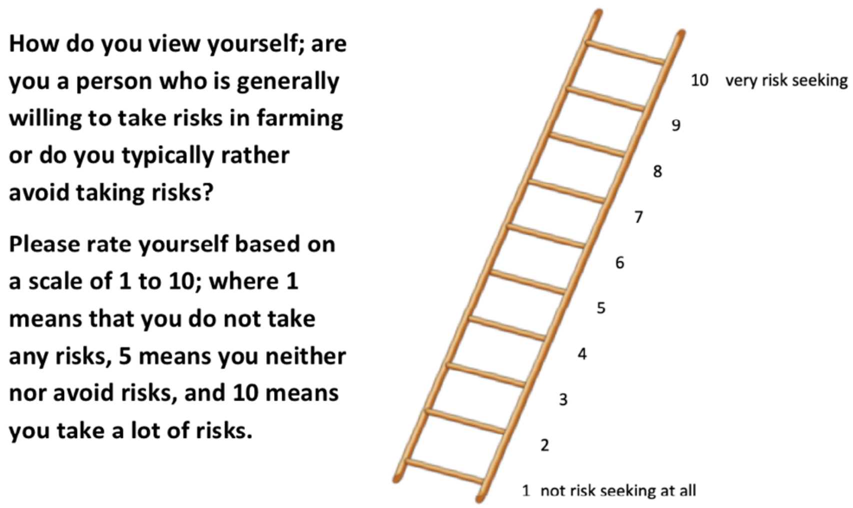

Figure C.1. Non-incentivized willingness-to-risk scale. Source: Authors.

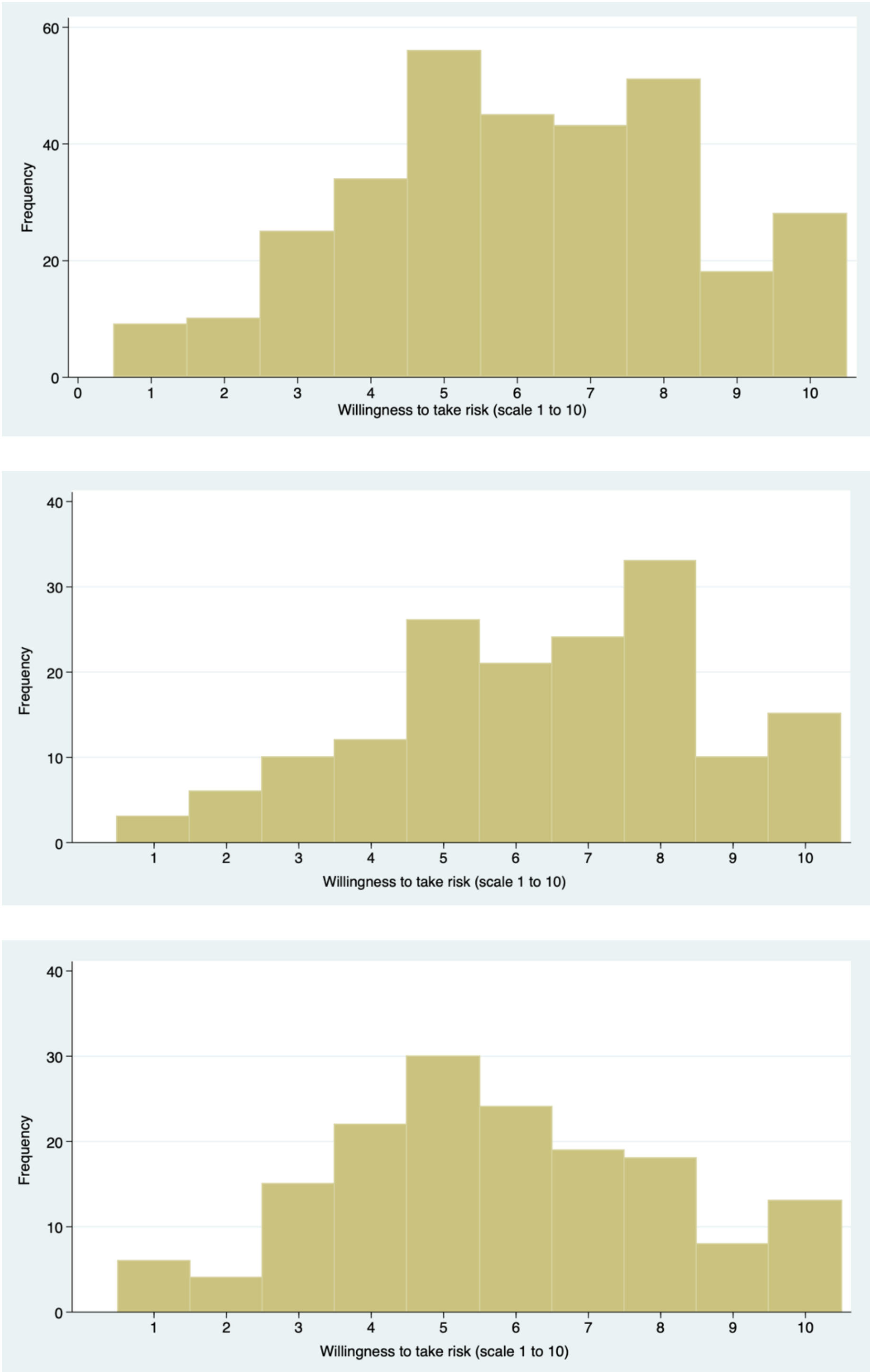

Figure C.1. Distribution of responses to the willingness to take risk scale (top panel: full sample (N = 319), middle panel: men (N = 160), bottom panel: women (N =159)). Source: Authors.

Table C.3. Design of hypothetical risk experiment (adapted from Eckel & Grossman, 2002, 2008) (in Ugandan shillings)

Series 1

Choice set (50/50)	Low payoff	High payoff	Expected return	Standard deviation	Implied CRRA[a] range	Risk category[b]	Percent of respondents
1	2,800	2,800	2,800	0	3.46 < r	RA	20.06
2	2,400	3,600	3,000	600	1.16 < r < 3.46	RA	15.67
3	2,000	4,400	3,200	1,200	0.71 < r < 1.16	RA	9.72
4	1,600	5,200	3,400	1,800	0.50 < r < 0.71	RN	14.11
5	1,200	6,000	3,600	2,400	0 < r < 0.50	RN	15.99
6	200	7,000	3,600	3,400	r < 0	RS	24.45

Series 2

Choice set (50/50)	Low payoff	High payoff	Expected return	Standard deviation	Implied CRRA[a] range	Risk category[b]	Percent of respondents
1	28,000	28,000	28,000	0	3.46 < r	RA	18.18
2	24,000	36,000	30,000	6,000	1.16 < r < 3.46	RA	13.79
3	20,000	44,000	32,000	12,000	0.71 < r < 1.16	RA	19.44
4	16,000	52,000	34,000	18,000	0.50 < r < 0.71	RN	13.17
5	12,000	60,000	36,000	24,000	0 < r < 0.50	RN	13.48
6	2,000	70,000	36,000	34,000	r < 0	RS	21.94

[a] Coefficient of relative risk aversion.
[b] Risk category RA = risk-averse, RN = risk-neutral, and RS = risk-seeking.

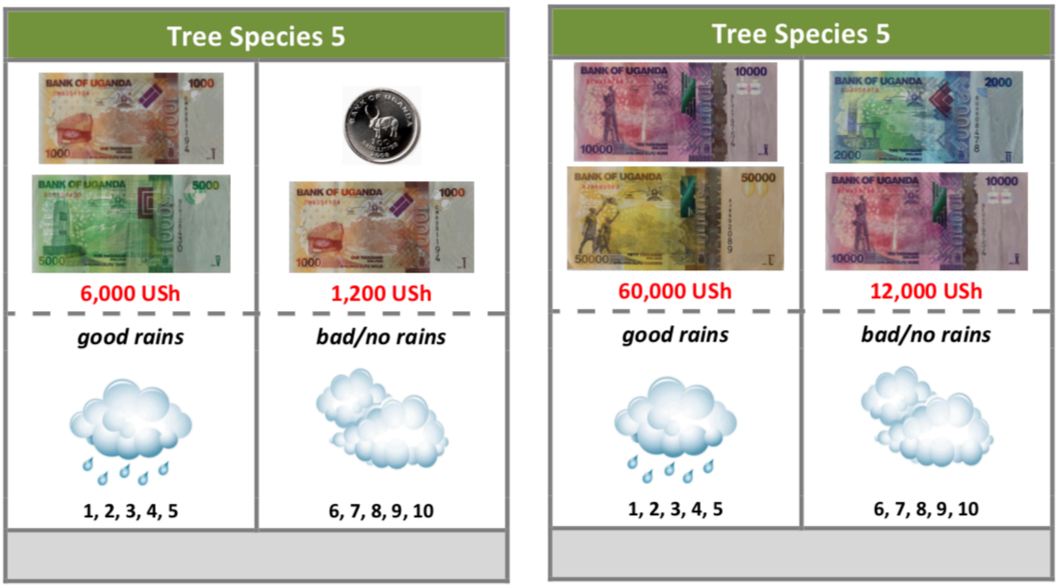

Figure C.2. Examples of choice cards in the hypothetical risk experiment (left side: low payoff task of series 1; right side: high payoff task of series 2). Source: Authors.

Table D.1. Mixed logit model estimates (base specification, seedling price random)

Variables	Coefficient	Standard error
Mean parameters		
ASC[a] (for status quo alternative)	–8.19***	1.33
Seedling price	0.00***	0.00
Fodder[b]	0.17***	0.06
Fuelwood[b]	–0.21***	0.05
Timber[b]	0.02	0.05
Microclimate[c]	0.29***	0.06
Soil fertility[c]	0.11*	0.06
P&E control[c]	–0.12***	0.05
Fast growing[d]	0.08*	0.05
Slow growing[d]	–0.07*	0.04
Light shade[e]	–0.00	0.03
Short tree[f]	–0.02	0.04
Standard deviation parameters		
ASC	3.63***	0.68
Seedling price	0.00***	0.00
Fodder	0.19	0.13
Fuelwood	0.23***	0.09
Timber	0.14	0.13
Microclimate	0.36***	0.11
Soil fertility	0.39***	0.10
P&E control	0.00	0.13
Fast growing	0.16	0.11
Slow growing	0.16	0.10
Light shade	0.08	0.11
Short tree	0.15	0.13
Log likelihood	–1820.07	
Chi squared	97.03***	
Observations	7656	

Note: The number of observations is $n = 8 * 3 * 319 = 7656$. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
[a] Alternative specific constant.
[b] Reference category is fruits.
[c] Reference category is weed control.
[d] Reference category is medium growing.
[e] Reference category is dense shade.
[f] Reference category is a tall tree.