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ARTICLE

An experiment on the link between risk preferences and the willingness to become a farmer

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Abstract

This study investigates the link between risk preferences of agricultural students and their willingness to become a farmer. We conducted an incentivized experiment with 577 students of an agricultural university in Indonesia. Discriminating between alternative theories of decision-making under risk, we find that students' risk preferences behave in accordance with cumulative prospect theory, but risk preferences are not predictive of students' willingness to become a farmer. Framing the experimental lottery task in either an agricultural or a general entrepreneurship context does not alter the predictive power for the willingness to become a farmer. Our results contribute to the debates on risk and farm generational renewal, as well as the (lack of) parallelism in behavioral field experiments.

KEYWORDS

behavioral economics, cumulative prospect theory, expected utility theory, generation renewal, Indonesia, risk attitudes

JEL CLASSIFICATION

D81—criteria for decision-making under risk and uncertainty, Q12—micro analysis of farm firms, farm households, and farm input markets, C91—laboratory, individual behavior

1 | INTRODUCTION

Recent global crises have shifted the focus of policy debates toward a stronger emphasis on food self-sufficiency and food supply chain resilience. This shift goes hand in hand with the promotion of local food production and farm generational renewal (Coopmans et al., 2021; May et al., 2019;

Meuwissen et al., 2021; Morais et al., 2018; Rech et al., 2021; Zaremohzzabieh et al., 2021; Żmija et al., 2020). Young people often view a career in farming as unattractive (Baker et al., 2013; Miller et al., 2011; Ridha et al., 2017), which can lead to complications, as older farmers may be less efficient or productive (Hamilton et al., 2015; Rigg et al., 2016; Zagata & Sutherland, 2015). The reluctance of older farmers to embrace innovation and new technology, coupled with their diminished motivation, can contribute to the prevalence of smallholder farmers, especially in Asia (Rigg et al., 2016, 2020). Notably, younger farmers also display a greater inclination toward adopting sustainable farming practices (Pérez Urdiales et al., 2016).

Numerous investigations have focused on young people's intentions to pursue farming, with the majority of these studies pertaining to intergenerational renewal and succession within family farm contexts in Western countries (Leonard et al., 2017; May et al., 2019). Emotional attachment and positive attitudes toward farming, self-perceived competency in business management, parental support, perceived control over their actions, and social norms are driving successors' intentions to take over farms (Morais et al., 2017, 2018). Attitudes toward risks and behavioral traits more generally play a pivotal role in the decision to become a farmer (Coopmans et al., 2021; Dessart et al., 2019), and while some studies show that youths identifying as risk-takers show a greater inclination for farming (Zaremohzzabieh et al., 2021), others show that risk-takers would often avoid farming, seeking opportunities outside the agricultural sector (Arora & Slavchevska, 2021; Filloux et al., 2019). Therefore, although farming involves considerable risks, it can also attract risk-averse individuals, underscoring the consensus on the importance of risk preferences, while lacking agreement on the direction of the effect.

An ongoing discourse revolves around determining theoretical models for farmers' risk preferences and the most effective experimental designs for predicting real-world behavior (Bocquého et al., 2014; Finger et al., 2023; Menapace et al., 2016; Meraner et al., 2018; Rommel et al., 2019). While early investigations into farmers' risk preferences (Binswanger, 1980) were exclusively rooted in expected utility theory (EUT, von Neumann & Morgenstern, 1947), there is a growing tendency toward behavioral economic models (e.g., Bocquého et al., 2014; Cerroni, 2020; Sagemüller & Mußhoff, 2020; Villacis et al., 2021).

In light of these debates, the contribution of this study is two-fold: First, empirically, we contribute to the literature on risk preferences and generational renewal in farming. We focus on students of agriculture as future farmers (Filloux et al., 2019; Zaremohzzabieh et al., 2021) and representatives of the sector (Grüner et al., 2022). Second, methodologically, we contribute to the debate on how to adapt experimental designs to ensure that behaviors in the experiment are predictive of real-world behaviors (Menapace et al., 2016; Meraner et al., 2018; Rommel et al., 2019). Our case study is Indonesia, a country where the number of farmers is decreasing and which increasingly relies on food imports.

2 | THEORETICAL AND METHODOLOGICAL FRAMEWORK

2.1 | Theories of decision-making under risk and their estimation

Attitudes toward risk are of major concern to agricultural economists (Binswanger, 1980; Iyer et al., 2020). For a long time, EUT was the dominant theory for decision-making under risk in economics, although empirical violations of EUT were mounting shortly after its introduction (Allais, 1953). As a consequence, scholars formulated alternatives to EUT (Starmer, 2000; Wakker, 2010). The link between risk preferences and wealth (Lybbert & Just, 2007), status-quo effects on decision making (Samuelson & Zeckhauser, 1988), reference dependence (Farber, 2008; Fehr & Goette, 2007), and distorted perceptions of (very small and very large) probabilities (Bruhin et al., 2010) all point toward violations of EUT.

Kahneman and Tversky (1979), in the formulation of Prospect Theory, argued that people are reference-dependent and loss-averse, and that they overweight small probabilities. In contrast to EUT, Prospect Theory allows decision-makers to have different utility functions in relation to a reference point, rather than having the curvature of the utility function as a single parameter of risk aversion. Prospect theory also has a nonlinear value function, which maps objective probabilities of risky gambles to distorted subjective probabilities. The latter feature is further developed also in cumulative prospect theory (CPT, Tversky & Kahneman, 1992), combining ideas of rank-dependent EU (RDU) from Quiggin (1982) and PT.

Debates on theories in decision-making under risk are ongoing (Brown et al., 2023; Rommel et al., 2023; Wakker, 2010). Harrison et al. (2007) and Harrison and Elisabet Rutström (2008), for example, argued that there could be preference heterogeneity, in the sense that some people act more in accordance with EUT, whereas others behave in accordance with CPT. Along similar lines, List (2003) has argued that, as people become more familiar with a decision environment, they shift from CPT to EUT behavior when facing risky decisions.

A widely employed experimental design to elicit risk preferences under CPT, is the task developed by Tanaka et al. (2010) (henceforth Tanaka task). The Tanaka task uses multiple price lists in which experimental subjects must repeatedly choose between safer and riskier lottery gambles. The task also implements losses (typically participants receive an initial endowment that is, large enough to cover potential losses). By varying probabilities, one can also estimate a probability weighting function. The Tanaka study did not allow for multiple switching points to ensure transitivity and strict monotonicity by asking respondents in which row they would prefer to switch (see section 3 for more details). While showing all gambles at once and enforcing monotonous switching may compromise incentive compatibility (Brown & Healy, 2018), this procedure also reduces response time which is important in online formats.

Supporting Information: Table A1 presents an overview of the study of Tanaka et al. (2010) and other studies applying the task or modifications of the task in agriculture or rural areas. Our study combines several features of these studies: First, CPT parameters are estimated to explain farmers' behavior (e.g., as in Kreft et al., 2021; Liu, 2013); second, we estimate structural models of EUT and CPT utility functions (as for instance in Rommel et al., 2023); and third we take inspiration in framing the task from Villacis et al. (2021) or Rommel et al. (2019).

2.2 | Utility functions

We estimate risk preferences in two ways, by using (1) the so-called mid-point technique and (2) structural estimation of utility functions by maximum likelihood estimation. In what follows, we briefly describe the theoretical framework of the utility functions as presented by Bocquého et al. (2014).

2.2.1 | EUT

We follow Bocquého et al. (2014) for the specification of EUT, where utility from a risky prospect is a EUT power function with a reflected utility function at zero (the status quo used throughout this study) with parameter r:

$$u(y) = \begin{cases} y^r & \text{if} \quad y \geq 0 \\ -(-y)^r & \text{if} \quad y < 0 \end{cases}, \tag{1}$$

where y is the outcome of a lottery and $1 - r$ is the constant relative risk aversion (CRRA) parameter. An $r < 1$ implies concavity and risk aversion in the gain domain ($y \geq 0$) and convexity and risk seeking in the loss domain ($y < 0$) as gains are reflected for losses. For the structural estimation of this model, we use maximum likelihood estimation with the following log-likelihood function:

$$\ln L^{EU}(\delta, X; r) = \sum_k \left[\ln \Phi\left(\Delta_k^{\mathrm{EU}}\right) \times I(\delta_k = A) + \ln\left[1 - \Phi\left(\Delta_k^{\mathrm{EU}}\right)\right] \times I(\delta_k = B) \right], \tag{2}$$

where k indicates the choices pooled over all subjects and lottery tasks, I is the indicator function, and δ_k indexes the choice of lottery option A[B].[1] Therefore, r can be estimated as:

$$\hat{r} = \arg \quad \max \quad \ln \quad L^{\mathrm{EU}}(\delta, X; r). \tag{3}$$

To allow for varying degrees of absolute and relative risk aversion, we use the expo-power utility function of Saha (1993):

$$u(y) = \begin{cases} [1 - \exp(-\beta y^{a})]/\beta & \text{if} \quad y \geq 0 \\ [1 - \exp(-\beta(-y)^{a})]/\beta & \text{if} \quad y < 0 \end{cases}, \tag{4}$$

where α and β indicate risk aversion for gains ($y \geq 0$) and the estimation can be done as:

$$(\hat{\alpha}, \hat{\beta}) = \arg\max \ln L^{\mathrm{EP}}(\delta, X; \alpha, \beta). \tag{5}$$

2.2.2 | CPT

We work with the zero as the status quo and the single reference point, although one could use other (Barberis, 2013; Kőszegi & Rabin, 2007) or multiple reference points (Koop & Johnson, 2012). We follow Tanaka et al. (2010), Liu (2013), Bocquého et al. (2014), and Villacis et al. (2021) in defining:

$$\mathrm{PT}(y, p; z, 1-p) = \begin{cases} v(z) + w(p)[v(y) - v(z)]; y > z > 0 or \quad y < z < 0 \\ w(p)v(y) + w(1-p)v(z); y < 0 < z \end{cases}, \tag{6}$$

where $\mathrm{PT}(\cdot)$ indicates the expected value over binary prospects ($y;z$) with related probabilities ($p; \quad 1-p$). The value function ($v(y)$) is defined as a piecewise power function that assigns distinct values in the gain ($y > 0$) and loss domains ($y < 0$), as follows:

$$v(y) = \begin{cases} y^{\sigma} \quad if \quad y > 0 \\ 0 if \quad y = 0 \\ -\lambda(-y)^{\sigma} \quad if \quad y < 0 \end{cases}. \tag{7}$$

Parameter σ simultaneously defines the utility function curvatures for the gain and loss domains. Although the original theory formulation (Tversky & Kahneman, 1992) used different parameters, most empirical studies, for simplification, assume that parameter σ is equivalent in gains and losses. Parameter σ is an anti-index of concavity for gains ($\sigma > 0$) where $\sigma < 1$ indicates risk aversion. Parameter λ indicates the degree of loss aversion. People are more sensitive to losses than to gains if $\lambda > 1$. Values smaller than one imply loss-seeking behavior.

For the probability weighting function, we follow Prelec (1998):

[1]See Bocquého et al. (2014) for the full derivation.

$$\omega(p) = \exp\left[-(-\ln p)^{\gamma}\right]. \tag{8}$$

Parameter γ determines the strength of probability distortion. Values smaller than one imply distorted probability perceptions with an overweighting of small probabilities and an underweight of large probabilities. Likewise, values greater than one imply underweighting of small probabilities and overweighting of large probabilities. For $\gamma = 1$, $\omega(p) = p$, that is, probability perceptions are objectively correct. CPT implies that $\gamma < 1$. We assume that γ is a single parameter controlling the probability weighting in both the gain and loss domains.

Then, the log-likelihood function for structural estimation of CPT becomes:

$$\ln L^{\text{CPT}}(\delta, X; \sigma, \lambda, \gamma) = \sum_k \left[\ln \Phi\left(\Delta_k^{\text{CPT}}\right) \times I(\delta_k = A) + \ln\left[1 - \Phi\left(\Delta_k^{\text{CPT}}\right)\right] \times I(\delta_k = B)\right]. \tag{9}$$

with the following maximization problem:

$$(\hat{\sigma}, \hat{\lambda}, \hat{\gamma}) = \arg\max \ln L^{\text{CPT}}(\delta, X; \sigma, \lambda, \gamma). \tag{10}$$

3 | EXPERIMENTAL DESIGN AND EMPIRICAL ANALYSIS

3.1 | Experimental design and procedure

We adapted the multiple price list experiment from the Tanaka task as in Bocquého et al. (2014), who removed two gambles from the first task. In two treatments, we modify the context of the task. This was done to test whether different contexts of the tasks affect respondents' choices. As argued by Alekseev et al. (2017), framing an experimental task in a familiar context can enhance data quality. More importantly, induced context may enhance parallelism, that is how behavior in the experiment relates to real-world behavior (Hill & Viceisza, 2012; Vollmer et al., 2017).

The first scenario was an agriculturally framed task in which respondents were asked to perform a decision as if they were a farmer. In the second scenario, respondents were asked to respond as if they were entrepreneurs in a delivery-service business. Respondents performed both tasks in random order (crossover-experimental design, allowing for the between-subjects comparison of the first choice and the within subject comparison of both choices per respondent). In both scenarios, respondents were presented with payoffs and probabilities for Technology A and Technology B, that is, we framed the safer lottery (Lottery A) as Technology A and the riskier lottery (Lottery B) as Technology B. We compare tasks using comparisons in the distribution of the three CPT parameters by nonparametric tests.

Supporting Information: Table A2 displays the lottery choices that we modified to account for agricultural and nonagricultural contexts. There were three series with 33 rows in total. To ensure monotonic switching, respondents were asked in which row they want to switch to Technology B (change from Technology A to Technology B). Payoffs of the lottery choices were multiplied by 1000 Indonesian Rupiah (IDR). If participants chose Technology A in row 4 and series 1, they received 40,000 IDR with a probability of 30% or 10,000 IDR with a probability of 70%. For series 3, if respondents chose Technology B in row 1, they could have gained 30,000 IDR with a probability of 50% or lose 21,000 IDR with a probability of 50%. As illustrated in the column of the expected payoff difference (which was not shown to respondents), the values are negative and decrease, as one moves down in the table, as the expected payoff of Technology B increases.

Respondents received incentives for their choices. All respondents received a show-up fee of 30,000 IDR (approximately two US dollars). More than 80% of students who filled the questionnaire had monthly expenditures of less than 2,000,000 IDR per month, or around 66,000 IDR per day.

Therefore, we provided a salient incentive for students to participate in our online survey, which substantially exceeded the opportunity cost, as approximated by an hourly student wage. In addition to the show-up fee, 20 randomly selected respondents had a chance to receive an additional payment based on their lottery choices, which ranged from a loss of 21,000 IDR to a gain of 600,000 IDR, and which were deducted from or added to participants' show-up fee. Negative total earnings could not occur, as the highest possible loss was covered by the show-up fee. The randomization for payments was performed in Excel. A row was randomly selected with equal probability. Based on the observed choices and probabilities, the final payment was calculated.

The survey was carried out in February 2022 with students at IPB University in Bogor, Indonesia. We collected 577 responses from various bachelor and master programs at all faculties, except the Faculty of Veterinary Medicine, which we deemed unsuitable to cover participants that have a background and interest in farming. We distributed the survey online, using a Qualtrics-programmed web survey available in Supporting Information: Appendix 4. Respondents were given instructions and examples.[2] Based on comprehension questions, most of them showed a good understanding of the experiment. Seventy percent of respondents disagreed with the statement "it was difficult to understand the task" for both tasks. Almost 80% of respondents agreed that the task reminded them of real-life decision-making.

The survey was distributed with the help of student representative contacts at faculty and department levels who were asked to share links in WhatsApp groups and emails. To avoid duplicates, limit responses from outsiders, and prevent capture by bots, students had to use their university email for payment processing. The sample must still be considered a convenience sample though. Informed consent was obtained from all participants, no deception was used, a debriefing was offered, and the study's analysis followed a simple preregistered protocol (https://aspredicted.org/L2N_TBT).

First, CPT parameters are approximated based on the mid-points of the intervals in accordance with the theoretical model and implied switching points. Tanaka et al. (2010) provided the values for parameters σ and γ (note that the original paper used different symbols). The switching points in our case are the rows *after* the ones respondents indicated, as the question was: "Until which row you want to choose Technology A?" However, Tanaka et al. (2010) did not provide the mid-point values for the loss aversion parameter λ. We estimated the parameter based on switching points in series 3 and parameters for σ and γ.

To test whether CPT or EUT are better at predicting students' risk preferences, we investigate whether the confidence interval of the parameters of λ and γ overlap with the null hypothesis of $\lambda = \gamma = 1$. If one does not fall within the confidence interval, we reject the null hypothesis of students' behavior in accordance with EUT. To test for treatment effects between the two differently framed tasks for the mid-point approximations, we use the nonparametric Wilcoxon signed-rank test.

For the structural estimation, we follow the procedures described above. As our formulation of EUT is nested within CPT and estimates fewer parameters, we also judge the statistical fit based on AIC. We modified the code from Bocquého et al. (2014) to estimate the structural models in Stata (see Supporting Information: Appendix 3 for data and code).

3.2 | Empirical analysis

To investigate the link of students' risk preferences and their willingness to become a farmer (WLF), we use a simple linear regression. We assess the variable WLF by asking the students how much they would be willing to work as a farmer in the future using an 11-point scale (ranging from 0 = not

[2]Note that there is a small typo in one of the examples (see Supporting Information: Appendix 4; one of the 30 should be a 20). However, we believe that this small mistake has not substantially affected the respondent's choice (and it is not confounded with treatment). Not all respondents clicked the example, and we gave hints about the initial and additional payment in all parts of the real experiment.

willing at all to become a farmer to 10 = very much willing to become a farmer). The econometric model is:

$$\mathrm{WLF}_i = \alpha_i + \beta_{x,i}\mathrm{CPT}_i + \delta_{x,i}\mathrm{X}_i + \varepsilon_i, \quad (11)$$

where i indicates the respondent, $\beta_{x,i}$ is a parameter vector to be estimated, CPT_i are the three parameters from the mid-point approximation of respondent i, that is, σ, λ, and γ. X_i is a matrix of covariates (see Table 1) and $\delta_{x,i}$ is a parameter vector to be estimated. We use ordinary least squares (OLS) for estimation. Note that the data are ordinal, but the OLS estimator is easier to interpret (see Bloem, 2022 for a discussion of the involved trade-offs; we provide robustness tests in Supporting Information: Appendix 1). We add covariates in blocks to examine the robustness of the results and perform the same procedure for the agricultural and the nonagricultural task.

TABLE 1 List of covariates.

Groups of covariates	Name of variable	Description	Expected coefficient sign
Familiarity of farming	*Familiarity*	Familiarity with farming using 11-point scale	+
	Parents	Dummy = 1 if at least one of the parents is a farmer	+
	Origin	Dummy = 1, if origin from village	+
Attitude toward farming (5-point scale) based on statements	*Attitude 1*	"Being a farmer is for people with low education."	-
	Attitude 2	"Being a farmer is a disgraceful job."	-
	Attitude 3	"Being a farmer is very risky."	-
	Attitude 4	"Being a farmer means having a hard life."	-
Social support (5-point scale) based on statements	*Support 1*	"I do not get support from parents to become a farmer."	-
	Support 2	"I do not get support from peers to become a farmer."	-
	Support 3	"I get encouraged from teachers to become a farmer."	+
	Support 4	"I will not support my children to become a farmer."	-
Other demographic factors	*Gender*	Dummy = 1 if male	NA
	Father educ	Categorical, 0 = no schooling; 1 = primary education; 2 = lower secondary education; 3 = higher secondary education; 4 = postsecondary/higher education	NA
	Monthly expenditure in IDR	Categorical, 1 = 0 k–500 k; 2 = 500 k–1000k; 3 = 1000 k–2000 k; 4 = 2000 k–4000 k; 5 = >4000 k.	NA
	GPA	Categorical, 0 = <3; 1 = 3–3.33; 2 = 3.33–3.5; 3 = 3.5–3.77; 4 = >3.77.	NA

TABLE 2 Summary of variables of interest.

Variable	Description	Mean	St. dev	Min	Max
WLF	Willingness to become a farmer	5.65	2.59	0	10
WLE	Willingness to become an entrepreneur	8.29	2.11	0	10
Familiarity	Familiarity with farming	5.83	2.60	0	10
Attitude 1	Farming is for low educated	1.39	0.66	1	5
Attitude 2	Farming is disgraceful	1.25	0.55	1	5
Attitude 3	Farming is risky	3.18	1.00	1	5
Attitude 4	Faming means having hard life (poor)	1.64	0.79	1	5
Social 1	Not getting support from parents	2.44	1.01	1	5
Social 2	Not getting support from peers	2.31	0.94	1	5
Social 3	Getting encouragement from teachers	3.03	0.90	1	5
Social 4	Will not support their children	2.55	0.91	1	5
	N	577			

4 | RESULTS

4.1 | Summary statistics

We start by presenting summary statistics for key variables in Table 2. Additional summary statistics are available in Supporting Information: Table A3. More female students answered the survey. While 42.6% of responding students originated from rural areas, only 22% of them have parents working as farmers. Most of students have monthly expenditures between 500,000 IDR and 1,000,000 IDR, which is relatively low. Most students have a highly educated father.

The average willingness to become a farmer is 5.65, which is substantially lower than the average of willingness to become an entrepreneur in other sectors (8.29).[3] The average familiarity with farming is 5.83. On average, students disagreed with a negative statement toward being a farmer. Only agreement with the statement that farming is risky is relatively large. Students believe that they would not receive support for a farming career from teachers and peers. Many would also not support their children to become farmers. Students moderately agreed with teacher encouragement.

4.2 | CPT parameters

Table 3 displays the average of the CPT parameters obtained by the mid-point technique. Note that these data are pooled across the first and second decisions. The averages indicate that respondents act in accordance with CPT in both tasks. From the confidence intervals, we can reject the null hypotheses of $\lambda = \gamma = 1$. Students are risk averse ($\sigma < 1$), loss-averse ($\lambda > 1$), and overweight small probabilities ($\gamma < 1$). The standard error is small for parameters σ and γ, but higher for λ, which is in line with Rommel et al. (2023). Note that the greater standard error could be an indication of greater preference heterogeneity in loss aversion (Bocquého et al., 2023). The standard deviation of λ is

[3]For additional context, please consider that most people with an agricultural background in Indonesia do not work in farming (see Supporting Information: Table A4 for additional statistics).

TABLE 3 Estimates and confidence intervals of cumulative prospect theory (CPT) parameters from mid-point technique ($n = 577$).

	Mean	Std. err.	Confidence interval (95%)	
			Lower bound	Upper bound
Agricultural task				
σ	0.61	0.01	0.58	0.64
λ	2.99	0.12	2.74	3.23
γ	0.64	0.01	0.62	0.66
Nonagricultural task				
σ	0.65	0.01	0.62	0.68
λ	2.85	0.12	2.61	3.09
γ	0.66	0.01	0.64	0.68

higher than for σ and γ (see Supporting Information: Appendix 2). Although we observed a similar average, our analysis revealed no statistical significant correlation between the CPT parameters of the agricultural and Nonagricultural tasks (see Supporting Information: Appendix 5). This suggests that students exhibit distinct behavioral patterns in the two differently framed scenarios. However, note that the estimated correlation coefficients are relatively large (approximately 0.5 for the three parameters of the agricultural and nonagricultural tasks). Hence, the lack of statistical significance may stem from the large standard deviations.

Table 4 displays results from the structural estimation for the EUT, EU exponential power (EP), and CPT utility functions. The curvature r is 0.36 in the agricultural task and 0.38in the nonagricultural task. The coefficient of relative risk aversion $1 - r$ is estimated to be more than 0.5 which means the students are risk-averse in the gain domain and risk-seeking in the loss domain. For the EP utility function under the agricultural framing, α is 0.37 (less than 1) and β is 0.02 (more than 0). This means that respondents have, on average, decreasing absolute risk aversion and increasing relative risk aversion. However, these values are in contrast with the nonagricultural task for which the value of α is 0.37 (less than 1) with a β of -0.02 (less than 0). From the specification of EU and EP, we see that respondents are risk takers in the nonagricultural task.

The three risk parameters of CPT are significantly different from one at the 1% level, implying risk aversion, loss aversion, and probability weighting. The estimate of σ is 0.47 in the agricultural task and 0.48 in the nonagricultural task. Students are 1.78 times more sensitive to losses than gains for the agricultural task, while the estimate is 1.71 in the entrepreneurship task. The estimated value for γ shows the students overweight small probabilities, following an inverse S-shaped weighting function. The CPT estimates provide the best fit, as indicated also by the AIC and BIC.

4.3 | Risk preferences and the willingness to become a farmer

Table 5 presents regression results with the CPT mid-point approximations as independent variables.[4] The CPT parameters have no statistically significant relationship with students'

[4]Full results are reported in Supporting Information: Table A5. Supporting Information: Table A6 presents estimates using the same 492 observations as in Model 5. We extended the analysis by employing ordinal Logit and Probit regressions (Supporting Information: Tables A7 and A8). The conclusions hold. For an easier interpretation, we also report pairwise correlation coefficients for all variables and correlation between parameters for the two tasks in Supporting Information: Appendix 5.

TABLE 4 Structural estimates and confidence intervals for the three utility functions and two tasks.

	Mean	Std. err.	Confidence interval (95%) Lower bound	Upper bound	AIC	BIC
Agricultural task						
Expected utility					24,217.01	24,224.87
r	0.36	0.00	0.35	0.37		
EU power					24,208.80	24,224.51
α	0.37	0.01	0.36	0.38		
β	0.02	0.01	0.01	0.04		
Cumulative prospect theory					21,180.57	21,204.13
σ	0.47	0.00	0.47	0.48		
λ	1.78	0.03	1.73	1.84		
γ	0.63	0.01	0.62	0.65		
Nonagricultural task						
Expected utility					23,998.18	24,006.03
r	0.38	0.00	0.37	0.39		
EU power					23,991.64	24,007.34
α	0.37	0.01	0.36	0.38		
β	−0.02	0.00	−0.04	−0.01		
Cumulative prospect theory					21,139.02	21,162.58
σ	0.48	0.00	0.48	0.49		
λ	1.71	0.03	1.66	1.76		
γ	0.66	0.01	0.65	0.67		

willingness to become a farmer. Although λ is statistically significant in Model 5 and the parameter is positive, one should carefully interpret this in light of the large number of estimated parameters.[5]

Students' familiarity with farming increases their intention to become a farmer (see Supporting Information: Table A5), but no statistically significant relationship is found for the variables *Origin* (from a village or not) and *Parents* (any parent is a farmer). Students whose father has a higher level of education, have a lower intention to become a farmer. Other demographic and socioeconomic factors like gender, expenditure, and GPA do not show large or statistically significant linkages with the willingness to become a farmer.

Only the statement "Farming is for the low educated." has a statistically significant effect on the willingness to become a farmer. Students who agree more with the statement have a lower stated willingness to become a farmer. For the *Social* variables, support from parents and teachers appear to have an impact on students' career aspirations. Support from teachers and parents have smaller statistically significant impacts in the expected directions. Students who would not want their

[5]For example, Table 5 presents 15 parameter estimates. Using a simple Bonferroni correction of the 5% alpha error threshold by dividing 5% by 15 parameters yields a new threshold of 0.0033. Under this threshold, λ would not be statistically significant in Model 5 of Supporting Information: Table A7.

TABLE 5 Ordinary least squares (OLS) regressions on willingness to become a farmer.

	Model 1	Model 2	Model 3	Model 4	Model 5
σ	0.265	0.262	−0.0977	−0.229	−0.229
	(0.340)	(0.351)	(0.322)	(0.332)	(0.305)
λ	0.0244	0.0401	0.0108	0.0399	0.0682**
	(0.0383)	(0.0402)	(0.0365)	(0.0361)	(0.0327)
γ	−0.107	0.0637	0.0786	−0.0156	0.177
	(0.396)	(0.400)	(0.338)	(0.343)	(0.319)
Demographics	No	Yes	Yes	Yes	Yes
Familiarity	No	No	Yes	Yes	Yes
Attitude	No	No	No	Yes	Yes
Social support	No	No	No	No	Yes
Constant	5.480***	8.264***	4.331***	5.715***	5.869***
	(0.322)	(0.717)	(0.743)	(0.918)	(0.970)
N	577	520	520	496	492
R^2	0.002	0.041	0.274	0.297	0.426
Adj. R^2	−0.003	0.028	0.260	0.277	0.405
AIC	2740.1	2447.6	2308.7	2194.3	2081.6
BIC	2757.5	2481.6	2355.5	2257.4	2161.3

Note: Robust standard errors in parentheses.

$^{**}p < 0.05$; $^{***}p < 0.01$.

children to become farmers are themselves not willing to become farmers. For peer support we do not find a statistically significant effect on students' willingness to become a farmer.

To better understand the impact of domain-specific risk preferences, we asked about the propensity to take risks, using the 11-points scale developed by Dohmen et al. (2011). We distinguished between general risk preferences, risk preferences as a farmer, as an entrepreneur, related to sports, and related to health behaviors. Supporting Information: Table A9 shows the regression results. The variable risk propensity as a farmer is positively and statistically significantly related to the willingness to become a farmer. In other words, the simple statement can better predict the willingness to become a farmer than the framed task. In contrast, students who are willing to take risks as entrepreneurs in another sector have a *lower* willingness to become a farmer. That is, whenever someone has a career aspiration, it implies a willingness to take risks for that career.

4.4 | Effects of framing the task

To investigate whether there is an effect of framing the task, we investigate differences in risk preferences as elicited by the tasks. There are small differences in the distribution, but overall, these seem negligible (see Supporting Information: Appendix 2). We use the Wilcoxon signed-rank test for formal testing of differences in the distribution (due to the nonnormal distribution as seen in the histograms in Supporting Information: Appendix 2).[6] Supporting Information: Table A10 reports the test results. Two parameters have statistically significantly different distributions: σ at the 95% level and γ at the 90% level. The distribution of the parameter λ is not statistically significantly different between the tasks. This may also happen because parameter of λ is noisier. The distribution of σ in the agricultural task is to the left of σ in the nonagricultural task, that is, students are willing to take greater risks in the entrepreneurship task (albeit the differences are small overall). Small probability overweighting is stronger in the agricultural task.

To explain respondents' willingness to become a farmer, we regress the CPT parameters from the nonagricultural task on the willingness to become a farmer (see Supporting Information: Table A11). Focusing on the estimated coefficients for σ and γ, the results are unstable for the CPT parameters across different model specifications. The coefficient of σ becomes insignificant after adding more variables, while γ becomes significant. In Model 8 and Model 9, the coefficient of σ is positive and significant, which implies that students who are more risk-seeking have a higher willingness to become a farmer. Meanwhile, the coefficient of γ is positive and significant in Models 12 and 13, implying that students with less overweighting of small probabilities have a higher willingness to become a farmer. However, given the fluctuations in coefficients, these results should be interpreted with some care.

For comparison, we also investigate the willingness to become an entrepreneur. Supporting Information: Table A12 reports the regression results. Focusing on the CPT parameters, there are no coefficient estimates that are statistically significant for any of the two tasks. Risk preferences have no link to students' willingness to become an entrepreneur. In contrast, variables of risk propensity are significantly affecting the willingness. Students who are more risk-seeking in general (in the farmer and the entrepreneur domains) have a higher willingness to open a business.

5 | DISCUSSION

Risk preferences of agricultural students in Bogor, Indonesia are better described by CPT than EUT. There are small differences in parameters σ and λ between the structural estimates and the mid-point approach, as also found by Bocquého et al. (2014) or Rommel et al. (2023). Using the mid-point technique, students' risk aversion in this study is close to the average of most studies using the CPT framework, but participants are characterized as more risk-seeking than the Chinese farmers in Liu (2013) and more risk-averse than French farmers (Bocquého et al., 2014). For loss-aversion, the students are less loss averse than subjects in most studies (e.g., Brown et al., 2023), but the parameter value is reasonably close to Tanaka et al. (2010) with 2.63 and the estimation of Tversky and Kahneman (1992) which is 2.25. Bonjean (2023) found no evidence of loss aversion in a sample of entrepreneurial Belgian apple and pear farmers. However, we still find high levels of loss aversion in our sample of students of agriculture. The students' parameter value for probability distortion is close to most studies, but very different from the Ecuadorian farmers studied by Villacis et al. (2021) who found a value of 0.8.

We did not find a clear link between risk preferences and the willingness to become a farmer. In line with Rommel et al. (2019) and Kreft et al. (2021), risk preferences elicited by lotteries are at best weakly correlated with real-world behaviors at individual level, and they may also be unstable over time (Reynaud & Couture, 2012). Although some coefficients are statistically significant, the estimates are not consistent across multiple model specifications with covariates. We find the same when using the CPT parameters from the agricultural and nonagricultural tasks. These findings point toward two important limitations of the study.

[6]We also ran some normality tests such as Shapiro–Wilk test, Shapiro–Francia test, and Skewness–Kurtosis test. All of them showed that the data are not normally distributed.

First, domain-specific risk preferences might not be adequately captured by contextualized lotteries. Agricultural context may be easier to induce with psychometric scales, as for instance in Hansson and Lagerkvist (2012). While this comes at the cost of not being able to estimate a utility function, it may help in reducing measurement error (Wang & Navarro-Martinez, 2023). Likewise, focusing on a single dependent variable—here the willingness to become a farmer as measured on an ordinal scale—may also be prone to measurement error. Constructing indices across multiple statements may be a promising route for the future (Wang & Navarro-Martinez, 2023).

Second, one may focus on increasing the statistical efficiency in risk preferences elicitation for example through adaptive experimental designs (Jobjörnsson et al., 2023; Kasy & Sautmann, 2021) which may involve alternative tasks using for example certainty equivalents (e.g., as in Di Falco & Vieider, 2022). Finally, working with different specifications of the theoretical model could be promising (for instance as in Bocquého et al., 2023 who allow the curvature of the utility function to differ in the gain and loss domains).

Despite the lack of a statistically significant link between risk preferences and the willingness to become a farmer, other findings may inform the debate on generational renewal in farming. Students who identified as risk-seeking in a farming context and who had a higher familiarity with farming, were also more willing to become a farmer. In education, this could mean that universities want to offer extracurricular activities to reconnect students with farming life. Based on most students' answers about what they lack to become a farmer, we know that access to capital/assets, knowledge, and skills, as well as relevant social networks are other crucial resources for aspiring farmers. Whereas government could play a role in some of these aspects, one should not forget the lack of moral support and the negative attitudes some students had. Ultimately, the view of the farmer from society is not an easy thing to change.

6 | CONCLUSION

The objectives of this study were to investigate (1) whether there is a link between students' risk preferences and their willingness to become a farmer, (2) what the adequate theoretical framework to explain students' risk preferences is, and (3) whether differently framed experimental tasks can improve the predictive accuracy regarding students' willingness to become a farmer. We surveyed 577 students of IPB University to elicit their risk preferences using the Tanaka task with two different framings (an agricultural and a nonagricultural task) and to assess their willingness to become a farmer. While we have only focused on risk preferences, other behavioral traits such as hope, aspirations, self-efficacy, locus of control, or time preferences may also play an important role.

Although we do not find a statistically significant link between risk preferences and the willingness to become a farmer, this does not mean that there are no policy implications of our study. Promoting greater familiarity with farming among students may be an effective strategy for increasing young people's willingness to work on a farm. Educational institutions, in collaboration with government bodies, could change the prevailing perception that farming is only suitable for those who are impoverished or uneducated.

Different estimation approaches come to the same conclusion in our study: There is no strong link between students' risk preferences as measured by multiple price lists and their willingness to become a farmer, which, in our case, but in line with other studies (e.g., Lönnqvist et al., 2015), calls into question the usefulness of risky gambles as a predictive tool. We also confirmed previous studies in that decision-making under risk in multiple price lists is modeled better with CPT than EUT. While our framing has been "lighter" than what has been used for instance by Villacis et al. (2021), we also had a statistically more powerful study to detect smaller effect sizes and hence conclude that different tasks cannot substantially improve the predictive power. Some limitations such as measurement error (Wang & Navarro-Martinez, 2023) or stochastic incentives (Anderson et al., 2023) remain.

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DATA AVAILABILITY STATEMENT

All data and code are publicly available.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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