World Development 162 (2023) 106137

Contents lists available at ScienceDirect

World Development

journal homepage: www.elsevier.com/locate/worlddev

Relating risk preferences and risk perceptions over different agricultural risk domains: Insights from Ethiopia

Ashenafi Duguma Feyisa [a,b], Miet Maertens [a], Yann de Mey [c,*]

[a] KU Leuven, Division of Bioeconomics, Department of Earth and Environmental Sciences, Leuven, Belgium
[b] Arba Minch University, Department of Economics, College of Business and Economics, Arba Minch, Ethiopia
[c] Wageningen University & Research, Business Economics Group, Department of Social Sciences, The Netherlands

ARTICLE INFO

Article history:
Accepted 4 November 2022
Available online 21 November 2022

Keywords:
Agricultural risk
Risk preferences
Prospect theory
Risk aversion
Loss aversion
Probability weighting

ABSTRACT

Households in developing countries are exposed to various shocks and risks, which leaves them vulnerable as they typically have limited resources to cope with them. Even though a large body of development literature has focused on the role of risk in rural livelihoods, the focus is often on single sources of risk and taking a unidimensional view on risk preference. This paper explores the diversity in risk perception and risk preferences of Ethiopian households by combining incentivized field experiments with detailed primary household survey data. We disentangle the relationship between risk perception and risk preferences using an innovative combination of time framing and instrumental variable estimation approaches. We find that our respondents are exposed to multiple past shocks and perceive multiple sources of future threats across different agricultural risk domains. Our respondents can be characterized as relatively risk-averse and loss-averse, and they also overweight unlikely extreme outcomes. We find a statistically significant association between the prospect theory risk preferences parameters—risk aversion, loss aversion, and probability weighting—and overall risk perception, domain-specific risk perceptions (except for the personal domain) and the impact dimension of future risk. Our findings make an important contribution to our understanding of farm households' risk behavior, and can guide prioritizing development efforts to stimulate better informed and well-targeted risk management policy interventions.

1. Introduction

Households in developing countries are exposed to a multitude of overlapping risks, whose frequency and intensity could worsen over time (Barrett et al., 2021; Bowen et al., 2020). This leaves households vulnerable as they typically have limited resources to cope with them (Sullivan-Wiley & Short Gianotti, 2017). Making adaptive decisions under risk is therefore one of the most complex decisions a household has to make, in particular when consumption and investment decisions are inseparable, which is a common feature in most developing countries (Chaĩânov & Čajanov, 1986; Sullivan-Wiley & Short Gianotti, 2017). In order to take appropriate preventive or adaptive actions, farm households do not only need to have a clear understanding of the underlying risk, but also have the capacity to do so within their risk behavior. As farmers are diverse in their preferences towards taking risk (Iyer et al., 2020), a diversity of responses can be expected. This paper therefore explores the diversity in risk perception and risk preferences of farm households in Ethiopia, one of the Sub-Saharan African countries where vulnerability to multiple sources of risk is common. We pay specific attention to disentangle the convoluted relationship in literature between risk perception and preferences (Villacis et al., 2021) by highlighting their role in the risk behavior of farm households (Section 2.2) and explicitly discussing (Section 2.3) and estimating (Section 4.3) the directionality of their relationship.

A large body of development literature has focused on the role shocks and risks have in impacting rural livelihoods. Most studies, however focus on a single source of risk such as draughts (Janzen & Carter, 2019) or covariate shocks at the regional level such as cyclones or other natural disasters (Brown et al., 2018). While recent literature is increasingly focusing on multiple sources of risk simultaneously, these studies tend to have a domain-specific focus such as environmental risk (Sullivan-Wiley & Short Gianotti, 2017), or present evidence from Western countries (Komarek et al., 2020). International organizations are also increasingly focusing on the multitude of shocks and risks that threaten the livelihoods of

* Corresponding author at: Hollandseweg 1, 6706 KN Wageningen, The Netherlands.

E-mail address: yann.demey@wur.nl (Y. de Mey).

https://doi.org/10.1016/j.worlddev.2022.106137
0305-750X/© 2022 The Author(s). Published by Elsevier Ltd.

households in developing countries with great effort being made to increase their adaptive capacity. National risk management policies to reduce risk exposure, however, are often implemented ex-post and focus on a single source of risk (e.g., index insurance to cover drought risk). Such policies are sub-optimal for two reasons. First, they are constrained in exploiting the advantages of ex-ante mitigation measures that could be taken by the farm households themselves to prevent or reduce the impact of adverse events (Janzen & Carter, 2019). Second, they are heavily based on external sources of resources (such as aid) leading to lagged interventions. In the context of achieving the Sustainable Development Goals, the Sendai Framework for Disaster Risk Reduction was initiated (2015) with priority number one understanding disaster risk in all its dimensions. As infrastructure in developing countries is often lacking, ex-ante forecasting risk using data-driven approaches is not feasible. Evidence on how people perceive various sources of risk is therefore paramount in guiding priority of development efforts aimed at reducing the vulnerability of rural households.

Besides the central role of risk perception in guiding risk behavior, risk preferences have been identified as a key determinant in making risk management and technology adoption decisions (Marra et al., 2003). As rural households are generally considered to be risk averse, they tend to take up low-risk activities that often imply lower returns (Binswanger, 1980). From a rational perspective, these decisions often appear sub-optimal, having a direct effect on the wellbeing of the rural poor (Dercon & Christiaensen, 2011; Ellis, 2007; Holden & Quiggin, 2017; Zimmerman & Carter, 2003). As we focus on an environment that is characterized by high levels of risk and uncertainty, we go beyond the uni-dimensional view on risk preferences (i.e., risk aversion) and instead characterize risk preferences by risk aversion, loss aversion and probability weighting in line with cumulative prospect theory (Tversky & Kahneman, 1992). Even though households might perceive a particular risk source as salient (e.g., draught risk), they might refrain from adopting risk management or technology solutions (e.g., index insurance or irrigation schemes) due to their loss aversion which makes them prefer potential higher losses over a more certain smaller loss. Probability weighting might lead them to overweight unlikely extreme outcomes (e.g., extreme drought spells), further leading to a distorted perception of the situation and seemingly irrational responses. Visser et al. (2020), for example, find that risk averse South African farmers are less likely to adopt novel technologies, whereas bundling the technology with an insurance encourages loss averse farmers to adopt. Properly understanding the risk landscape of the rural population for targeted policy interventions is therefore difficult to achieve without understanding well how risk perceptions are being shaped by risk preferences.

Even though risk perception and risk preferences are widely recognized as fundamental factors in households' risk behavior (Just & Just, 2016) these terms are often confounded or used interchangeable in literature (Vlek & Stallen, 1980). In studies on risk management, they are frequently considered in isolation without further attention to which factor is most relevant or their potential relationship (van Winsen et al., 2016). A large part of the literature on agricultural risk perceptions fails to consider risk preferences as a determinant of risk perception (e.g., Brown et al., 2018; Doss et al., 2008; Huet et al., 2020; Smith et al., 2001; Sullivan-Wiley & Short Gianotti, 2017), while the studies that do consider some measure of risk preferences as an independent variable, often focus on risk aversion only (e.g. Meuwissen et al., 2001; van Winsen et al., 2016; Bishu et al., 2018). Evidence on the directionality of the relationship is also limited and tends to focus largely on developed countries (Bowen et al., 2020). A notable exception is the recent study by Villacis et al. (2021) that links risk preferences and risk perception using a prospect theory approach (Tversky & Kahneman, 1992). They focus on climate change risk perceptions only, however, using a crude 3-point scale which narrows down the focus of their results.

Our paper contributes to the growing literature on rural households' risk perception and preferences by explicitly exploring the directionality between risk perception and risk preferences using an innovative combination of time framing and instrumental variable estimation approaches, and measuring both of these behavioral traits in a holistic way. We fully explore diversity in shocks and risk by analyzing household-specific perceptions of 21 sources of risk across the two dimensions of risk (likelihood and impact) and five domains of agricultural risk (production, market, institutional, financial, and personal). Rather than characterizing risk preference as a unidimensional concept (i.e., risk aversion), as in most studies, we experimentally eliciting risk aversion, loss aversion, and probability weighting parameters for each farm household in line with cumulative prospect theory. To this end, incentivized field experiments (with 786 households) in a developing country context are combined with detailed primary household survey data. The findings make an important contribution to our understanding of farm households' risk behavior, and can guide prioritizing development efforts to stimulate better informed and well-targeted risk management policy interventions.

The next section (2) presents an extensive overview of risk concepts and a conceptual framework on how farm households' risk perceptions are shaped, explicitly focusing on the role of risk preferences. The study area and experimental design are discussed in Section 3. Next, our empirical model, details on how specific variables measured and the econometric methods used are discussed in Section 4. Descriptive and econometrics results (with robustness checks) are presented in Section 5. The last section provides a general discussion and conclusion.

2. Literature review and conceptual framework

2.1. Risk concepts

Even though risk is an innate part of life, there is no single widely agreed upon definition. In the context of this study, we define *risk* as ''uncertainty about and severity of the consequences of an event with respect to something that humans value'' (Aven et al., 2018, p. 4). We will use the word risk to refer to uncertainty faced towards the future, whereas shocks will be used to denote the occurrence and the consequences of events that were uncertain in the past.

The concepts of risk perception and risk preference are inherently linked and therefore sometimes confounded or used interchangeable in literature (Vlek & Stallen, 1980). However, as people hold different preferences towards risk, they will act differently in uncertain situations even if they share a common risk perception (Slovic, 2000). We adopt the definition of *risk perception* given by Slovic (1987, p. 280) as: ''the subjective judgment that people make when they are asked to characterize and evaluate risky activities/outcomes''. The focus here lies explicitly on subjective judgements that contrasts with the ''real'' or statistical measurement of risk (Sjöberg, 2000) and that typically has two dimensions: perceived likelihood and perceived impact (Slovic, 2000). In order to fully capture the breath of risk experienced by farm households, we explore risk across five agricultural risk domains: production risk, market risk, institutional risk, financial risk and personal risk (Hardaker et al., 2015). We follow the argumentation of Weber et al. (2002) that content domain differences matter when analyzing risk taking.

Risk preference—also commonly denoted as risk attitude, risk appetite or risk propensity—is the amount and type of risk people are willing to take on (Weber, 2010). In economics, risk preferences are commonly related to the curvature of a person's utility function and range from very unwilling to take risk (risk averse), over risk neutrality (indifferent to risk) to very willing to take risk (risk seeking). This unidimensional view on risk preference was challenged with the introduction of prospect theory, a behavioral model that is based on people thinking in terms of expected utility relative to a reference point rather than absolute outcomes (Kahneman, 1979). In 1992, Tversky and Kahneman extended this model to cumulative prospect theory (Tversky & Kahneman, 1992). There are three distinct concepts in cumulative prospect theory that relate to people's risk preference: risk aversion, loss aversion, and probability weighting (Barberis, 2013). *Risk aversion* generally reflects people's unwillingness to take on risk, and prospect theory considers people are risk averse in the domain of gains yet risk seeking in the domain of losses. *Loss aversion* indicates that in general people care more about potential losses than potential gains. *Probability weighting* pertains to individuals not weighting outcomes by their objective probabilities and overweighting unlikely extreme outcomes (a feature setting cumulative prospect theory apart from the original prospect theory). In this study we refer to these three concepts collectively as *risk preferences* and evaluate these risk preferences parameters simultaneously through an experimental approach (see Section 3.2). Note that in light of our empirical context of smallholder households that are resource constrained, we make the ex-ante assumption of working in a cumulative prospect theory rather than an expected utility framework.

2.2. Farm households' risk perception and risk preferences

A large body of literature focuses on the determinants of farm households' risk perception and risk preferences. In this section, we present a general overview of independent variables identified in literature, while the next section will tie them together in a conceptual framework on how farm households' risk perceptions are shaped.

Various farm- and farm household-related variables have been identified in literature as independent variables relating to farm households' risk perception and risk preferences. Farm characteristics relate to physical capital and include farm size, livestock ownership and ownership of various other types of assets (Just & Pope, 2003; Sullivan-Wiley & Short Gianotti, 2017; van der Linden, 2015; Wachinger et al., 2013). Capital ownership matters as it provides an upper bound on how much a household could foreseeable loose (Brown et al., 2018). Farm household variables pertain to the human capital of the farm household and comprise the age (Menapace et al., 2013) and education (Liu, 2013) of the household head, and family size (Bishu et al., 2018). Measures of social capital, such as religion and ethnicity, are also reported as determinants of risk perception, yet often with insignificant or low correlations (Lazo et al., 2000; Slimak & Dietz, 2006; Stern et al., 1998). Also the location of households and their migration background appear as a source of heterogeneous risk perception and preferences (Ullah et al., 2016; Weber & Hsee, 1998).

Two key risk-related determinants of risk perception and risk preferences include farm households' experience with shocks and self-efficacy. Direct experience with shocks can elicit strong emotions, making them more memorable and dominant in processing and thus influencing risk perception and preferences (Brown et al., 2018; Slovic, 1987; Sullivan-Wiley & Short Gianotti, 2017; van der Linden, 2015). van Winsen et al. (2016) for example finds that Flemish farmers' past experience had a significant effect on price, production and institutional risk perceptions. Self-efficacy can be defined as the belief an individual holds in their capabilities either to control or reduce adverse effects of risk (Ajzen, 2002). Cullen et al. (2018) find an important association between self-efficacy and risk perception for a sample of smallholder farm households in Mali.

Even though risk perception and risk preferences are studied as two distinct concepts (e.g., Dellavigna, 2009; Holden & Quiggin, 2017; Komarek et al., 2020; Smith et al., 2001; Tanaka et al., 2010; Tversky & Kahneman, 1992), empirical studies that identify the explicit role of risk preferences—risk aversion, loss aversion, and probability weighting—in shaping risk perception are limited or operationalize risk preferences in a unidimensional way. One exception is Villacis et al. (2021) who documented the association between the prospect theory parameters and Ecuadorian households' climate change risk perception. They identify a positive significant association of climate change risk perception with risk aversion, but not with loss aversion, and a positive association with probability distortion. Unlike Villacis et al. (2021), Meuwissen et al. (2001) for example examine the role of a binary risk preference measure (more versus less risk-averse) on different domains of risk perception for Dutch livestock farmers, and find a positive effect of risk aversion on risk perception in the institutional risk domain but not in other domains. Similarly, Bishu et al. (2018) find a correlation between a risk preference index (unidimensional) and risk perception in the production domain, but not in other domains, for Northern Ethiopian cattle farmers. Studies that ignore risk preference as a determinant of future risk perception, may suffer from omitted variable bias as the role of certain determinants may be mediated through an impact on risk preferences. For example, the role of location in risk perception may be overstated if risk-averse individuals choose to live in lower-risk areas.

2.3. Conceptual framework on shaping farm households' risk perception

Figure 1 represents our conceptual framework on how farm households' risk perception is shaped, highlighting the relations between farm households' risk preferences and perceptions and their determining factors. The framework is based on the seminal risk behavior work by Sitkin and co-authors that was proposed (Sitkin & Pablo, 1992) and validated (Sitkin & Weingart, 1995) in the field of management science. As argued by Brown et al. (2018), a lot of the literature on risk perception and risk behavior in general focusses on developed countries. We therefore contextualize the framework based on empirical literature into an agricultural and development economics context. In order to more clearly structure the relationship between different risk concepts, we explicitly add time framing in our framework with: $(t\text{-}k)$ and $(t + k)$ referring to k years prior and posterior a contemporary reference period t (in our empirical application the survey period, see Section 3.1). Time framing helps in establishing the directionality of the relationships between the various variables considered.

In this paper, our main variables of interest are *risk perception*, which we investigate in a forward-looking (t+k) fashion and using multiple dimensions, and contemporary (t) *risk preferences*. We explicitly model risk preferences as a determinant of risk perception and not *vice versa* in line with Sitkin and Pablo (1992) and as implemented in studies in diverse contexts such as Dutch (Meuwissen et al., 2001) and Ethiopian (Bishu et al., 2018) livestock farming, Flemish agriculture (van Winsen et al., 2016), Latin American indigenous villages (Villacis et al., 2021) and smallholder farmers in Mali (Cullen et al., 2018). We focus explicitly on perceptions across different risk domains as literature in this regard is thin. Both risk preferences and risk perception are influenced by past shocks or events that took place in the past (t-k) (Brown et al., 2018; Lybbert et al., 2007; Sullivan-Wiley & Short Gianotti, 2017). Two other sets of contemporary (t) covariates that correlate with risk preferences and risk perception are farm and farm household characteristics (including location). Finally, perceived future

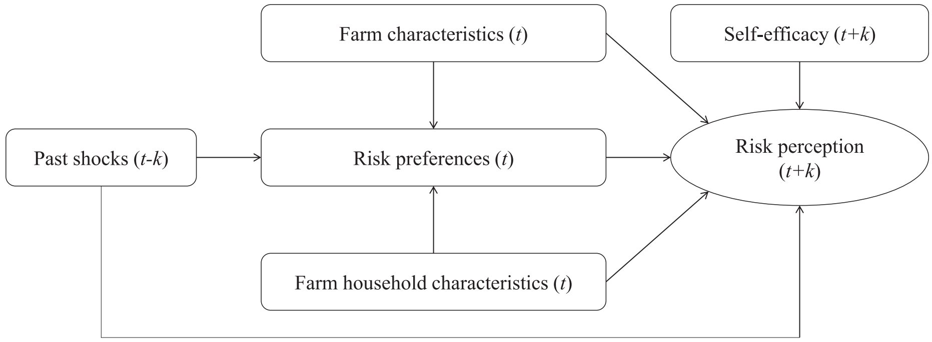

Figure 1. Conceptual framework on shaping farm households' risk preferences and risk perception with explicit time framing: *(t-k)* and *(t+k)* referring to *k* years prior and posterior a contemporary reference period *t*. Based on Sitkin and Pablo (1992) and Sitkin and Weingart (1995).

self-efficacy *(t+k)* is expected to influence future (*t+k*) risk perception, but due to time framing is assumed to not influence contemporary risk preferences (*t*).[1]

3. Study area and experimental design

3.1. Background and data collection

Our research area constitutes six rural districts, namely Arba Minch Zuriya, Bonke, Chencha, Mirab Abaya, Konso, and Derashe, in the Southern Nations, Nationalities sand Peoples Region (SNNPR) in Ethiopia (see Figure 2). The incidence of poverty and food insecurity in our study area, as in Ethiopia in general, is high. The area is diverse in terms of agro-ecology (low-land, mid-land, and high-land), livelihood base (mixed farming, off-farm, and non-farm employment), ethnicity (Gamo, Konso, Dherashe, among many other ethnicities), and religion (Orthodox, Protestant, and traditional). Apart from a new initiative on community-based health insurance, there is limited availability of formal or market-based risk management tools. For instance, the index-based crop insurance that is being promoted in two piloting regions (Oromia and Somali) in the country, has not yet been introduced in our research area (2018).

Primary data were collected through a household survey complemented with an incentivized field experiment, which were implemented in August to October 2018. A structured questionnaire was developed, with modules on risks and shocks, household demographics, crop and livestock production, off-farm and transfer income, livelihood capital and living conditions, and gender and food security. We used a two-stage stratified random sampling procedure with stratification based on agro-ecological zones within the districts. The primary sampling unit was kebele, the lowest administrative unit in Ethiopia, and the ultimate sampling unit was households in selected kebeles. In the first stage, the rural kebeles in each district were stratified based on the agro-ecological zone. From each stratum, kebeles were selected based on proportional random sampling. In the second stage, 15 households in each of the 60 selected kebeles were selected using systematic random sampling. The survey was implemented through face-to-face interviews by a team of 20 trained enumerators with prior survey experience. Computer-assisted personal interviewing techniques, based on tablets and the Survey CTO tool, were used. While the original sample included 900 households in 60 kebeles, only 877 households in 59 kebeles participated in the survey as one kebele could not be reached. From this sample, we use 786 observations in our analysis, dropping 91 households who were unable or unwilling to participate in the lottery task aimed at risk preferences elicitation (see details below in Section 3.2).

3.2. Experimental design

We elicited risk preferences based on cumulative prospect theory (Tversky & Kahneman, 1992) by applying the Tanaka et al. (2010) approach, which is commonly known as the TCN risk task. We adapted the TCN risk task in order to make it easier to understand by illiterate respondents. We used visual aids such as a game board, a luck sack, and ping pong balls to visualize outcomes, lotteries, and probability distributions respectively. The TCN risk task was incentivized in order to elicit behavior closer to real-world decisions under risk and uncertainty (Vieider et al., 2018). The final values of the parameters for risk aversion (σ), loss aversion (λ), and probability weighting (α) are inferred from the value table[2] developed by Tanaka et al. (2010) which are based on the switching points in the TCN risk task. The full details of the incentivized game are presented in Appendix A1, and below we provide a short summary with the main elements.

The TCN risk task consisted of three series of paired lotteries with a total of 35 rows. Each row is a choice between two binary lotteries, A or B. Monotonic switching was enforced by asking respondents at which question they would "switch" from Option A to Option B in each series. They were allowed to switch to Option B starting with the first question, yet they did not have the option to switch back to Option A. After they completed three series of questions with a total of 35 choices (participation phase), each respondent received a guaranteed participation amount. They were then asked whether they wanted to participate in a final game for real money linked to their previous answers. One amongst the 35 lines of the participation phase was randomly drawn using a tablet computer to determine which line would be played for real money. Based on the subject's actual choice at that particular line during the participation phase (i.e., lottery A or B), ping pong balls representing the probability of that line were placed into a luck sack and shuffled. The subject was then requested to draw one ball from the luck sack without looking into it to determine whether the drawn ball represented a win or loss.

The incentive for participating in the game had two parts: (i) a guaranteed participation amount upon completing the three tasks, and (ii) the prospect from participating in the final lottery for a real additional reward (if win) or losing part of the participation fee (if loss). The participation amount was set to ETB 25, roughly equivalent to USD 2.5,[3] and representing a half-day wage for daily labor in

[1] See also Section 4.2 for details on how our survey design motivates the directionality of this effect.

[2] See Table A1 in the web appendix (available at http://www.aeaweb.org/articles.php?doi=https://doi.org/10.1257/aer.100.1.557).

[3] 1$ ≈ 9.97 ETB in 2018 PPP.

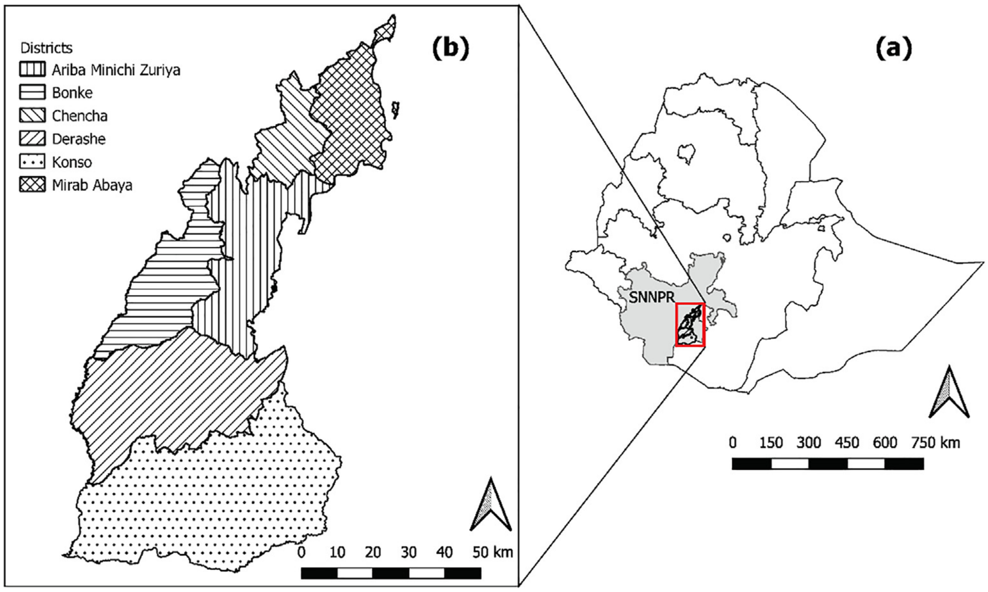

Figure 2. Map of the study area *(Source: authors' compilation)*.

the research area during the survey period. We fixed the prospect for the final game from – ETB 21 to + ETB 1,700 which is equivalent to approximately – USD 2.1 to + USD 170.5. The average prospect from the final game is around ETB 40. Combined with the guaranteed participation fee of ETB 25, the overall average payment is ETB 65, which is roughly a one-day agricultural wage at the time of the experiment. Only about 10 % of the respondents refused to participate in the final game and opted for the guaranteed pay-out, which is a plausible indication of the incentive compatibility of the reward. It should be noted, however, that the mechanism of eliciting preference based on an incentivized experiment like ours is not incentive-compatible when all decisions are shown together in a single list (Brown & Healy, 2018). Yet, we (i) presented the 35 series of lotteries on 3 different game boards (representing series 1, series 2, and series 3; see Appendix A1), and (ii) trained our enumerators in a way that they should show only one game board and one row at a time covering up the other choices in that game board. However, this cannot guarantee full incentive-compatibility as there could be a chance to look into the choices in the game board under play.

4. Empirical model and estimation strategy

4.1. Empirical model

Based on the conceptual framework depicted in Figure 1, we formulate three different sets of empirical models to explore the diversity in risk perceptions of sampled farm households. The first model explains farmers' overall risk perception (equation 1), where perception is measured as the product of the likelihood and impact of future threats. The second set of models explains domain-specific risk perception (equation 2), where perception is measured similarly as in the first model for each risk domain separately. The third set of models (equations 3 and 4) explains the two dimensions of perception—likelihood and impact—separately.

The first model explaining overall risk perception is given as follows:

$$RP_{overall,i} = \beta_0 + \beta_1 RA_i + \beta_2 LA_i + \beta_3 PW_i + \beta_4 SE_i + \beta_5 PS_i + \boldsymbol{\gamma}\boldsymbol{X}_i + \varepsilon_i \tag{1}$$

Where $RP_{overall}$ is overall risk perception of household i about the coming three years; RA_i, LA_i, and PW_i represent contemporary risk aversion, loss aversion and probability weighting;SE_i is perceived self-efficacy about the coming three years;PS_i represents experience with shocks during the past three years; $\boldsymbol{X}_i$ is a vector of farm (farm size, livestock ownership, ownership of weaving tools and access to irrigation) and farm household (family size, literacy of household head, and age of household head) covariates; ε_i is the idiosyncratic error term; and all $\beta\prime$ s and the coefficient vector γ represent parameters to be estimated.

In the second model, we decompose risk perception into five different domains D, including production, market, institutional, financial, and personal risk, and specify this as $RP_{D,i}$, the domain-specific risk perception of household i in the coming three years. The independent variables in equation (2) are the same as equation (1) except for self-efficacy $SE_{D,i}$ and past shock $PS_{D,i}$ that are now specific to their respective domains D:

$$RP_{D,i} = \beta_0 + \beta_1 RA_i + \beta_2 LA_i + \beta_3 PW_i + \beta_4 SE_{D,i} + \beta_5 PS_{D,i} + \boldsymbol{\gamma}\boldsymbol{X}_i + u_i \tag{2}$$

Finally, to disentangle the role of risk preferences separately on the two dimensions of perceived likelihood and perceived impact, we formulate two additional equations:

$$RP_{L,i} = \beta_0 + \beta_1 RA_i + \beta_2 LA_i + \beta_3 PW_i + \beta_4 SE_i + \beta_5 PS_{L,i} + \boldsymbol{\gamma}\boldsymbol{X}_i + v_i \tag{3}$$

$$RP_{I,i} = \alpha_0 + \alpha_1 RA_i + \alpha_2 LA_i + \alpha_3 PW_i + \alpha_4 SE_i + \alpha_5 PS_{I,i} + \boldsymbol{\omega}\boldsymbol{X}_i + w_i \tag{4}$$

Where $RP_{L,i}$ and $RP_{I,i}$ are perceived likelihood and perceived impact of future threats respectively. All independent variables in equations (3) and (4) are the same as in equation (1), except for past shocks which are now only considering the separate dimensions of likelihood and impact, respectively.

4.2. Measurement of risk perception, past shocks, and self-efficacy

In order to construct and classify a comprehensive list of sources of shocks and risks in our study area, we combined farmers' perspective and insights from the agricultural risk literature. We first conducted a preliminary survey with 60 regional experts (one from each selected village/kebele) in July 2018 to explore the most important sources of past shocks and future risks in the words of the experts. We re-worded and classified the identified

Table 1
Taxonomy in sources of agricultural risk in our study area.

Agricultural risk domains				
Production	*Market*	*Institutional*	*Financial*	*Personal*
Drought	Demand	Tax policy	Liquidity constraints	Illness
Flooding	Transport	Land policy	Debt crisis	Death
Pest	Input price	Input delivery		Disability
Crop disease	Output price	Local conflict/unrest		Labor shortage
Landslide				
Weeds				
Animal death				

sources based on the agricultural risk literature (see Hardaker et al., 2015) to be included in the survey. In this way, we identified 21 risk sources and classified them in five agricultural risk domains as presented in Table 1. In order to verify whether no researcher bias was present in the final list of risk sources, we cross-validated the list by comparing it with answers given in the words of the farmers to the open question "What do you consider the three major threats to your farm household?" asked at the start of the risk module in the survey. As we could not identify any source mentioned in the answers to this open question that was not in our final list of 21 risk sources, we consider the list to be exhaustive.

From the above set of risk sources, different measures of risk perception are constructed. First, the mean *overall risk perception* score for household i ($RP_{overall,i}$) is calculated by multiplying the perceived likelihood with the perceived impact divided by the total number of risk sources extending the methods proposed by Brown et al. (2018) and Meraner and Finger (2019):

$$RP_{overall,i} = \frac{\sum_{j=1}^{21} LK_{i,j} * IM_{i,j}}{\sum j} \quad (5)$$

where $LK_{i,j}$ is the perceived likelihood of the j^{th} source of risk, $IM_{i,j}$ the perceived impact on household income and $\sum j$ is the total number of risk sources (i.e., 21). The perceived occurrence of past shocks ($OC_{i,j}$, see equation 9) and the perceived likelihood of future risks ($LK_{i,j}$) are elicited using 5-point Likert scale items. We asked, "What was the occurrence of shock X in the last 3 years?" and "What is the likelihood of risk X in the coming 3 years?" for past shocks and future risks respectively, where X represents each of the 21 risk sources considered. The levels presented for occurrence and likelihood are rarely (1), less frequently (2), frequently (3), more frequently (4), and very often (5). The perceived impact on household income of past shocks and future risks[4] is also elicited with 5-point Likert scale items. We asked, "What was the effect of X on income in the last 3 years?" and "What will be the effect of X on income in the coming 3 years?" for past shock and future risks, respectively. The levels presented are no impact (1), small impact (2), moderate impact (3), large impact (4), and very large impact (5).

Second, we calculate *domain-specific risk perception* scores ($RP_{D,i}$) as the mean overall risk score in the respective domain using the same formula as in (4), now with a domain-specific denominator (Meraner & Finger, 2019):

$$RP_{D,i} = \frac{\sum_{j=1}^{Dj} LK_{i,j} * IM_{i,j}}{\sum Dj} \quad (6)$$

where $\sum Dj$ is the domain-specific total number of risk sources (see Table 1).

Third, we decompose the overall risk perception scores into two separate dimensions, i.e., *perceived likelihood* $RP_{L,i}$ and *perceived impact* $RP_{I,i}$:

$$RP_{L,i} = \frac{\sum_{j=1}^{21} LK_{i,j}}{\sum j} \quad (7)$$

$$RP_{I,i} = \frac{\sum_{j=1}^{21} IM_{i,j}}{\sum j} \quad (8)$$

In order to explore correlation between these two dimensions of risk perception, we visualize them in likelihood-impact plots for each of the five agricultural risk domains separately.

Fourth, *past shocks* (PS_i) are measured as an aggregate sum of the product of relative occurrence of each shock and its perceived impact on farm income in the past three years:

$$PS_i = \sum_{j=1}^{21} OC_{i,j} * IM_{i,j} \quad (9)$$

where $OC_{i,j}$ is the perceived occurrence of the j^{th} shock in the past three years (i.e., number of times it occurred), and $IM_{i,j}$ is the perceived impact of the j^{th} shock on household income in the past three years measured as before using a 5-point Likert scale (Brown et al., 2018; Meraner & Finger, 2019).

Finally, *self-efficacy* (SE_i) is measured as the aggregate sum of the level of perceived control over each of the 21 risk sources in the coming three years:

$$SE_i = \sum_{j=1}^{21} CT_{i,j} \quad (10)$$

where $CT_{i,j}$ is the perceived control of household i over shock j with own resources which is measured using a 5-point Likert scale item. We asked, "How do you evaluate your household's ability to control the overall impact of X in the coming 3 years using your own resources?" where X represents each of the 21 risk sources considered. The levels presented are no control (1), low control (2), moderate control (3), high control (4), and very high control (5). Note that the wording of this survey question explicitly forces respondents to evaluate their capacity to deal with a particular risk if it happens looking forward over the next three years, rather than evaluating their current capacities to do so. The self-efficacy questions were also asked before the future risk perception questions from equation 4, which allows for perceived future self-efficacy shaping future risk perceptions and limiting the potential of the reverse. It is worth recalling that both PS_i and SE_i are made domain specific while estimating equation 2 by considering only aggregate scores of past shocks and self-efficacy in their respective domains. In order to facilitate comparison between the different risk-related

[4] We elicited an impact on yield, income, overall consumption, food consumption and asset ownership. However, as a principal component analysis on the diverse sets of impacts revealed a very high correlation among the indicators, we consider only the income dimension.

independent variables, all risk perception, past shocks, and self-efficacy variables were min–max transformed prior to estimation (all other independent variables were not transformed).

4.3. Econometric estimation

We use an instrumental variable (IV) approach to estimate equations 1 to 4. Risk preferences—i.e. risk aversion, loss aversion and probability weighting—are potentially endogenous due to systematic measurement error in the joint elicitation of risk perception and risk preferences[5] or due to unobserved heterogeneity such as cognitive bias of respondents (Ariely, 2008; Simon et al., 2000). We try to limit endogeneity bias through IV estimation, using fifteen IV's: lottery pay-off, membership in a religious organization, adherence to religion, ethnicity (4 dummies), and the interaction terms ethnicity $\times$ membership religious organization (4 dummies) and ethnicity $\times$ adherence to religion (4 dummies). Below we first discuss the measurement of these IV's and then their relevance and validity. Note that we use the same set of IVs for all three risk preference parameters. Although risk preferences are considered a multi-dimensional concept, they measure behavioral traits that exist in a similar behavioral continuum and hence the reasoning below is assumed to hold for all three dimensions of risk preferences.

Lottery pay-off is the final amount paid in ETB in the TCN risk task explained in Section 3.2. It consists of the sum of (i) the guaranteed participation amount of ETB 25 and (ii) the final random payout that ranges from - ETB 21 to + ETB 1,700. This lottery pay-off is correlated with the three risk preference parameters as it depends on the history of choices by the respondent during the participation round. In other words, the switching point on which the risk preference parameters are determined correlates with the real pay-off at that particular line. As the draw for the real lottery pay-off is done by the researchers at the very end of the TCN risk task, it can be considered random and exogenous during the risk preferences elicitation task. As the lottery pay-off represents a small one-time payment which was equivalent to a half-day wage, we consider the likelihood of such a small payment directly shaping the perception of diverse future threats plausibly nil, unless mediated by risk preferences. *Membership in religious organization* is a dummy variable for being member of a religious organization. *Adherence to religion* is elicited using six questions, measured in 5-point Likert scale items and combined into an aggregate score ranging from 6 to 30.[6] *Ethnicity* is a set of dummy variables for belonging to the Gamo (reference level), Konso, Derashe, Zayise & Gidicho, or another ethnicity. We expect a correlation between the IVs membership in a religious organization, adherence to religion, and ethnicity with risk preferences as previous studies have identified these effects (see also León & Pfeifer, 2017). Ethnicity and religion are socio-culturally determined at birth and are considered exogenous as we have no evidence of religious mobility in our case study area. While theoretically-one can self-select into a particular religion, in our study region religion is mostly passed on from parents to children. Some studies include ethnicity and religiousness as direct determinants of risk perception, but then either omit risk preferences from their model or find a non-significant relationship with risk perception (Lazo et al., 2000; Slimak & Dietz, 2006; Stern et al., 1998). Furthermore, the recent study by Kahsay, Kassie, Medhin, and Hansen (2022) finds evidence that religious Ethiopian farmers are more risk-taking using a lab-in-the-field experiment complemented with survey data from 840 participants. Based on complementary focus groups discussions, the article clearly identifies trust or belief in God as the main potential reason for this effect, and makes no mention of risk perceptions playing a role. We therefore argue that religion has no plausible direct influence on risk perception, unless mediated through risk preferences. To further exploit idiosyncrasies that relate to ethnic differences in (adherence to) religion, we include interaction terms as additional IVs.

We first tested the two-stage least squares (2SLS) estimator, which is considered the most efficient IV estimator under standard assumptions (Wooldridge, 2010). According to Stock and Yogo (2005), IV estimators, however, can be inconsistent with weak IVs, and alternative estimators such as limited information maximum likelihood (LIML) are more robust in this setting. We therefore report estimates using the LIML estimator. We also re-estimate the IV model (LIML) with enumerator fixed effects added, as their assistance in completing complex experimental tasks could potentially influence the results obtained. Finally, as risk perceptions in multiple risk domains might not be mutually exclusive (van Winsen et al., 2013), the error terms of the five domain-specific equations (2) could be correlated. As a robustness check, we therefore re-estimate equations (2) using the three-stage least squares (3SLS) estimator that explicitly models the contemporaneous correlation between the five error terms (Zellner & Theil, 1992).

All data and code to replicate the results and figures of this paper are available as supplementary materials in the online version of this article.

5. Results and discussion

5.1. Descriptive results

The farm households in our study area perceive multiple sources of shocks and risks as important. Table 2 presents summary statistics of past shocks scores (sum of occurrence $\times$ impact) and future risk perception scores (average sum of likelihood $\times$ impact) for each of the 21 individual sources of risk. The variation in scores between the various sources of risk represents the heterogeneity in risk exposure in the study area. Based on two-sided t-tests, we consistently find higher mean scores for forward-looking risk perceptions than for past shocks. The top salient sources of past shocks are: droughts, liquidity constraints, pests, illness, animal death, and input prices. The top five sources of perceived future risks are: droughts, liquidity constraints, pests, input prices, and illness.

We further explore diversity in our main dependent variable future risk perceptions along the five agricultural risk domains (aggregating the individual risk scores within the domains) and two dimensions of risk (likelihood and impact). Figure 3 presents heat plots (Jann, 2019) of future risk perception for the five domains split across mean perceived impact (y-axis) and mean perceived likelihood (x-axis). These heat plots are a natural extension of traditional likelihood $\times$ impact plots, where also response frequencies are represented by color intensity. Two results are notable. First, comparing across panels, it is evident that our farm households' rankings of risk are heterogeneous with respect to the different

[5] This could happen due to systematic measurement errors that arise from eliciting risk perception and risk preference at the same time. The risk perceptions are elicited using a survey and then the risk preference experiment implemented later on the same day. The former task might inform the later which could causes systematic bias (Holden & Quiggin, 2017).

[6] The questions are adopted from the US General Social Survey (https://gss.norc.org/Get-The-Data) and include: 1) How do you evaluate your adherence to religious activities; When you encounter difficulties, to what extent does the following hold: 2) I feel that God is punishing me for my sins or lack of spirituality; 3) I look to God for strength, support and guidance; 4) I try to make sense of the situation and decide what to do without relying on God; When you are prosperous, to what extent does the following hold: 5) I believe that the prosperity comes due to God's benevolence; and 6) I think my effort plays a central role in my success. Items 1 and 2 coded as 1 = Not at all, 2 = Low, 3 = Moderate, 4 = High, and 5 = Very high; other items coded as 1 = Strongly disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly disagree (or reversed coding for items 4 and 6).

Table 2
Overall perception of past shocks (*PS*) and future risk perception (*RP*).

	Past shocks (PS)		Future risks (RP)		Difference	
	Mean	SD	Mean	SD		
Drought	10.0	7.0	11.7	7.0	1.7	**
Liquidity constraint	9.4	6.6	12.1	7.0	2.7	***
Pest	8.6	6.9	11.0	7.1	2.4	***
Illness	7.8	6.8	9.5	6.4	1.7	**
Animal death	7.0	5.9	8.6	6.1	1.6	**
Input price	6.9	6.6	9.9	7.2	2.9	***
Labor shortage	5.5	7.0	7.5	6.6	2.1	***
Transportation	5.0	6.6	9.1	7.4	4.1	***
Weeds	4.9	5.8	7.8	6.1	2.9	***
Flooding	4.6	5.6	8.9	7.1	4.3	***
Debt	4.5	5.4	8.3	6.8	3.8	***
Crop disease	4.2	6.0	6.8	6.9	2.6	***
Output price	4.0	5.2	7.3	6.4	3.3	***
Local unrest	3.9	5.8	6.5	5.5	2.6	***
Land slide	3.8	5.1	7.8	6.8	4.0	***
Input delivery	3.6	5.0	6.2	5.3	2.6	***
Output demand	3.3	4.5	6.1	5.5	2.9	***
Tax policy	2.6	3.8	6.8	5.5	4.2	***
Death	2.2	3.2	7.3	5.5	5.1	***
Land entitlement	2.1	3.9	6.3	5.7	4.2	***
Disability	1.8	3.1	6.5	5.2	4.6	***

Notes: N = 786, equality of means tested using 2-sided t-tests, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

domains of perceived risk. Second, observing the response frequencies within each panel in terms of likelihood and impact, we do not only see intensities mostly perfectly along the diagonal but rather distinct quadrants lighting up. This implies that respondents were able to disentangle the likelihood and impact dimensions of risk (i.e., they did not score both dimensions identically) and seem to care mostly about sources of risk with considerable expected impact even when the perceived probability is low. These findings underline the importance of disaggregating the results in the following sections across the two dimensions of risk (likelihood and impact) and five domains of agricultural risk.

In Table 3, we present summary statistics of the independent variables in this study. The average past shock perception is 106, with a large range from 21 to 323 (the theoretical maximum is 525). The level of perceived self-efficacy rating is low (compared to its theoretical median point of 53) with an average score of 37.9 out of 105 and a maximum score of 58. The mean land holding is 1.48 ha and livestock ownership averages 2.4 in tropical livestock units (TLU). Only 13 % of the respondents have access to weaving tools and 18 % to irrigation. The average family size is 6; the average age of the household head is 46. Half of the respondents are illiterate, while female-headed households constitute only 16 % of the total sample. The lottery payout in the TCN risk task paid out between ETB 4 and ETB 55, with an average of ETB 31. Our respondents are highly religious with a mean score of 22 out of 30, and 62 % of the respondents are members of a religious organization.

The average values of the risk preference parameters are $\sigma = 0.79$ for risk aversion, $\lambda = 3.81$ for loss aversion, and $\alpha = 0.78$ for probability weighting. The result indicates that respondents are both risk-averse and loss-averse while distorting probabilities. The average derived values of α and λ are significantly different from one at the 1 % significance level, which is often taken as evidence that respondents do not conform to Expected Utility Theory (EUT) but rather more in line with Cumulative Prospect Theory (CPT). However, these findings could also happen due to the nature of the TCN experiment where out of the 225 possible choices that respondents can select when playing the first two series that determines α and λ, only 9 of them (4 %) lead to α equal to 1. The average value of risk aversion ($\sigma = 0.79$) in our southern Ethiopian sample is relatively low compared to the study by Harrison et al. (2010) in Ethiopia ($\sigma = 0.93$), Uganda ($\sigma = 1.10$), and India ($\sigma = 0.90$). Conversely, our estimate is higher compared to the findings of Tanaka et al. (2010) and Liu (2013) who find lower levels of risk aversion for Vietnam ($\sigma = 0.59$) and China ($\sigma = 0.48$) respectively. The mean estimate of loss aversion ($\lambda = 3.81$) in our sample is lower compared to evidence from Ecuador ($\lambda = 4.64$; Villacis et al. (2021)) and Malawi ($\lambda = 4.61$; Holden and Quiggin (2017)) yet higher compared to other developing countries such as Vietnam ($\lambda = 2.63$; Tanaka et al. (2010)) and China ($\lambda = 3.47$; Liu (2013)).

Most of the respondents in our sample distort probability with a mean value of $\alpha = 0.78$. This implies a situation in which respondents overweight unlikely extreme outcomes, which is often perceived as a rationality failure (Tversky & Wakker, 1995). We find that our Ethiopian respondents relatively overweight extreme outcomes compared to Ecuadorians ($\alpha = 0.80$; Villacis et al. (2021)) and Malawians ($\alpha = 0.88$; Holden and Quiggin (2017)) yet less so compared to Vietnamese ($\alpha = 0.74$; Tanaka et al. (2010)) and Chinese ($\alpha = 0.69$; Liu (2013)) respondents. Potential reasons for the general over-weighting of unlikely outcomes could be low levels of literacy (Vieider et al., 2015) or that respondents need to make decisions from description rather than experience (Hertwig et al., 2004). We do note, however, that our result ($\alpha = 0.78$) is closer to one which contradicts the general view that there are difficulties in direct probabilities elicitation in poor countries with lower average levels of education. Our finding supports the evidence by Delavande et al. (2011) who review evidence from several developing countries and conclude that people generally understand probabilistic questions that are carefully designed yielding expectations that are useful predictors of economic decisions.

5.2. Econometric results

The econometric results on overall (model 1), domain-specific (models 2–6), and likelihood (model 7) and impact (model 8) dimensions of risk perception are presented in Table 4. The main variables of interest, i.e., the three risk preferences parameters have a significant role in shaping the various dimensions of risk perception of the Ethiopian farm households in our sample except in the personal risk domain and likelihood dimension.

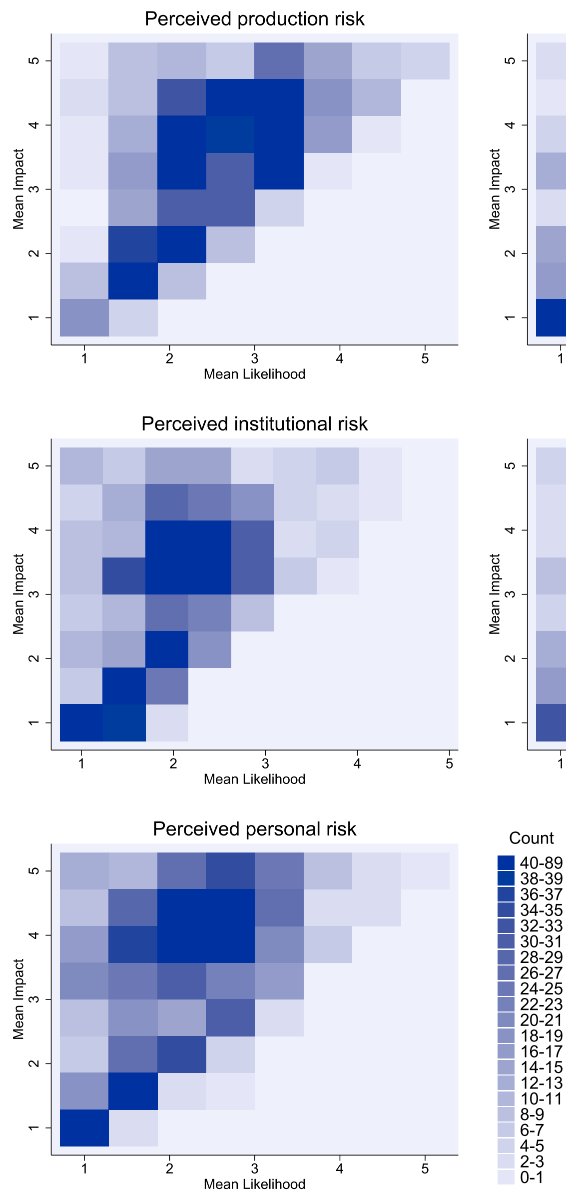

Figure 3. Heat plots of future risk perception along the five agricultural risk domains and two dimensions of risk (likelihood and impact). Color intensity represents response frequencies.

Prior to further interpreting our main results, we discuss the relevance and validity of our 15 IVs. We consider our proposed IVs relevant because of (i) their joint significance in the three first-stage regressions (see F-test in Table A2), (ii) the significance of the Kleibergen-Paap rk LM-statistics at 10 % (see Table 4) rejecting overall under identification of the model, except in the production and market domains, and (iii) the Kleibergen-Paap rk Wald F statistics exceeding the 10 % Stock-Yogo LIML critical value of 5.44 (see Table 4). In all regressions, the Hansen J statistic indicates that the null hypothesis of instrument validity is not rejected. In summary, these tests show that our proposed IVs are relevant and plausibly exogenous. Based on these IVs, we test the potential endogeneity of our three risk preferences variables. In all but one equation (7, focusing on the likelihood dimension) we reject the null hypothesis of exogeneity (see Table 4), which justifies the use of IV estimation as they likely result in the smallest bias. Hence, we base our discussion of the results on these estimates.

First, the results from LIML estimation on overall risk perception (model 1) indicate that all risk preferences parameters significantly affect overall risk perception at the 5 % significance level. A one unit change in risk aversion and loss aversion (min–max rescaled) is associated with 7.76 and 8.18 units change in overall agricultural risk perception respectively. In other words, the more risk-averse and loss-averse farm households are more pessimistic in their forward-looking perception. The interpretation of the negative coefficient for probability weighting, however, is less straightforward. Whenever α is below one, an increase in its value implies respondents improve their probability assessment. However, when α increases in value above 1, the reverse holds. Bearing this in mind, overall, a unit change in the probability weighting parameter α (min–max rescaled) is associated with a -8.06 unit change in overall risk perception. This finding implies that for the majority of our respondents (72 %) with $\alpha < 1$, discriminating probabilities better (i.e., up to $\alpha = 1$) leads to perceiving less overall risk and are hence more optimistic in their forward-looking perception. Given the magnitude of the obtained risk preference coefficients (ranging from 7.76 to 8.18 in absolute terms), their effects are significant both in a statistical and also in economic terms as

Table 3
Summary statistics.

Variables	Mean	SD	Min	Max
Risk-related				
Risk preferences				
Risk aversion (σ)	0.79	0.47	0.05	1.50
Loss aversion (λ)	3.81	3.88	0.25	9.40
Probability weighting (α)	0.78	0.40	0.05	1.45
Past shocks	105.84	46.68	21.00	323.00
Self-efficacy	38.01	8.09	21.00	58.00
Farm-related				
Farm size (hectare)	1.48	1.49	0.00	13.00
Livestock ownership (TLU)	2.37	1.93	0.00	14.10
Ownership of weaving tools (dummy)	0.13			
Access to irrigation (dummy)	0.18			
Farm household-related				
Family size (number)	6.42	2.60	1.00	19.00
Literacy of household head (dummy)	0.51			
Age of household head (years)	46.38	15.17	18.00	99.00
Sex of household head (male dummy)	0.84			
Instrumental variables				
Lottery pay-off (ETB)	30.91	12.40	4.00	55.00
Membership in religious organization (dummy)	0.62			
Adherence to religion (total score)	22.07	3.55	12.00	30.00
Ethnicity (dummies)				
Gamo	0.62			
Konso	0.21			
Derashe	0.09			
Zayse & Gidicho	0.04			
Others	0.04			

Notes: Risk perception, past shocks, and self-efficacy are presented in their original scales in this table; note that these variables were min–max transformed prior to estimation. Tropical livestock units (TLU) are calculated based on the conversion factor developed by Ghirotti (1993) where cattle = 0.70, sheep and goat = 0.10, horse = 0.80, mule = 0.70, donkey = 0.50, and chicken = 0.01. N = 786.

the dependent variable takes values between 1 and 25. Besides our main variables of interest, past shocks, farm size, and weaving tool ownership[7] also correlate positively and family size negatively with overall agricultural risk perception at the 5 % significance level.

Second, we explore heterogeneity in risk preferences shaping risk perceptions by focusing on domain-specific risk perceptions as dependent variables (models 2–6). The effect of our risk preference parameters is consistent across the five domains in terms of sign. Both risk aversion and loss aversion have a positive role in all domains, whereas probability weighting plays a negative role. In terms of magnitude, the results indicate some deviation in their relative strength. The risk preferences parameters have a relatively lower association in the market risk domain, a stronger association in the financial domain, and are not statistically significant in the personal domain.[8] These findings contrast the evidence on Northern Ethiopian cattle farmers by Bishu et al. (2018), where a significant association between risk aversion and risk perception is only found in the production risk domain and not in the others considered (financial, market and labor). This difference could be due to the risk exposure being very different for Northern Ethiopian cattle farmers compared to our respondents. However, our findings corroborate the results of Villacis et al. (2021). They find a significant link between two prospect theory parameters (risk perception and probability weighting) and climate change risk perception for Ecuadorian households, but not for loss aversion.

Third, we decompose risk perception into the likelihood and impact dimensions (models 7 & 8). The results reveal that the role risk preferences have in shaping overall risk perception originates from the perceived impact dimension. The risk aversion, loss aversion and probability weighting parameters are statistically significant only in model 8 with their signs in line with the overall risk perception model (model 1) and again with economically significant sizes (as the dependent variables takes values between 1 and 5). These results are in line with the graphical analysis in Figure 3 that highlighted more variation across the expected impact dimension compared to the perceived probability dimension. The heterogeneity in perceived likelihood and impact of future threats also significantly correlates with past shocks, perceived self-efficacy, farm size, weaving tool ownership, access to irrigation, family size, and literacy.

5.3. Robustness checks

As a first robustness check, we re-estimate the IV model (LIML) with enumerator fixed effects as their assistance in completing complex experimental tasks such as risk preference elicitations could introduce bias in particular for illiterate (51 % of our sample) or female (18 % of our sample) respondents (West & Blom, 2017). However, we find that our results are robust to the inclusion of enumerator fixed effects (see Appendix A3). In addition, we re-estimate the domain-specific risk perception equations (models 2–6 in Table 4) jointly using the 3SLS estimator (See Appendix

[7] We could not confirm our expectations that weaving tools could better buffer risk and hence lead to lower perception about future threats. We believe these findings arise for the following reasons. A farm household with a large farm size, might be relatively more prone to diverse agricultural risks such as price, land tenure, and shortage of labor in both dimensions of perceived risk (likelihood and impact). Conversely, farm households with a limited farm size produce mainly for home consumption, which makes them less exposed to market-related risks. Farm households who own weaving tools are typically those for whom weaving is an important income-generating activity. Unfortunately, in our research area such households are among the marginalized groups that are constrained in terms of livelihood capitals, which could explain why they are more pessimistic about future threats.

[8] This could be related to how risk preferences elicitation is framed in a financial context in the experimental TCN risk task. While risk preferences elicited in a financial context relate closely to the production, market, institutional, and financial risk domains (as they are to a large extent related to income and cash flows), personal risk perception likely associates better with risk preferences elicited in a health context.

Table 4
Estimation results of IV models (estimated using LIML) with risk perception as dependent variable.

Variables	IV (LIML)							
	Overall (1)	Production (2)	Market (3)	Institutional (4)	Financial (5)	Personal (6)	Likelihood (7)	Impact (8)
Risk-related								
Risk aversion (σ)	7.763**	9.928**	6.633***	8.689***	13.74***	7.441	0.299	3.511**
	(3.085)	(4.392)	(2.507)	(3.146)	(5.253)	(6.915)	(0.339)	(1.474)
Loss aversion (λ)	8.180**	11.83**	6.254**	8.840**	12.81*	7.933	0.301	4.137**
	(3.652)	(5.740)	(3.047)	(3.633)	(6.583)	(10.78)	(0.455)	(1.843)
Probability weighting (α)	−8.064**	−8.468*	−6.933**	−9.564**	−13.93**	−8.271	−0.436	−3.246**
	(3.337)	(4.630)	(3.013)	(3.849)	(6.366)	(5.789)	(0.343)	(1.515)
Past shocks	11.11***	11.50***	16.24***	9.522***	13.38***	9.571***	1.969***	1.554***
	(1.449)	(1.885)	(1.066)	(1.520)	(1.605)	(1.630)	(0.138)	(0.555)
Self-efficacy	2.665*	0.542	1.376	5.141***	−2.603	4.065**	0.672***	0.834
	(1.591)	(1.808)	(1.071)	(1.484)	(1.832)	(1.941)	(0.159)	(0.710)
Farm-related								
Farm size	0.294**	0.271	0.394***	0.411***	0.436*	0.0788	0.0325**	0.0911
	(0.139)	(0.174)	(0.137)	(0.159)	(0.244)	(0.162)	(0.0128)	(0.0576)
Livestock	−0.0456	−0.0303	−0.0472	−0.100	−0.166	0.0122	−0.00241	−0.0364
	(0.105)	(0.133)	(0.104)	(0.117)	(0.174)	(0.120)	(0.0102)	(0.0423)
Weaving tool	1.243**	1.185	0.840	1.298*	1.978*	1.827**	0.0554	0.604**
	(0.620)	(0.780)	(0.612)	(0.692)	(1.075)	(0.719)	(0.0559)	(0.263)
Irrigation	−0.929*	−1.028	−0.833*	−0.755	−1.319	−0.974*	−0.164***	−0.130
	(0.494)	(0.670)	(0.471)	(0.574)	(0.830)	(0.555)	(0.0484)	(0.216)
Farm household-related								
Family size	−0.196**	−0.216*	−0.139	−0.149	−0.266*	−0.266*	−0.0207**	−0.0752**
	(0.0869)	(0.111)	(0.0847)	(0.0985)	(0.144)	(0.145)	(0.00870)	(0.0383)
Literate	−0.714*	−0.858*	−0.568	−0.642	−1.050	−0.739	−0.0848**	−0.228
	(0.393)	(0.511)	(0.383)	(0.443)	(0.686)	(0.453)	(0.0356)	(0.173)
Age	0.00235	−0.00932	0.00571	0.00319	0.00821	0.0122	0.000857	−0.00159
	(0.0157)	(0.0215)	(0.0152)	(0.0175)	(0.0278)	(0.0262)	(0.00155)	(0.00735)
Constant	2.722	3.598	3.465	1.401	6.752*	3.076	1.356***	1.305
	(2.326)	(3.294)	(2.152)	(2.446)	(4.011)	(5.796)	(0.246)	(1.082)
Location dummies	*Included, output omitted for brevity*							
IV test statistics								
Under identification test (Kleibergen-Paaprk LM statistic)	22.410*	19.521	19.199	23.047**	19.980*	22.110*	21.211*	21.947*
Weak identification test (Kleibergen-Paap rkWald F statistic)	7.679	6.704	7.395	7.392	8.509	7.260	7.658	7.480
Overidentification test of all instruments (Hansen J statistic)	7.071	8.481	6.597	7.254	7.784	9.792	11.225	6.737
Endogeneity test of endogenous regressors	24.93***	16.017***	19.869***	29.231***	19.963***	9.338**	4.057	44.822***

Notes: N = 786. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A4). A Breusch-Pagan LM diagonal covariance matrix test rejects the null hypothesis of no contemporaneous correlation between equations. In other words, we find evidence that risk perceptions are shaped simultaneously across the five risk domains. Comparing the LIML (Table 4) and 3SLS (Appendix A4) estimates reveals consistency in the sign and magnitudes of our risk preferences parameters in shaping the risk perception of Ethiopian farm households. Using cross-equation Wald tests, we conclude that risk aversion ($Chi^2(5) = 13.09$, $P = 0.0226$) and loss aversion ($Chi^2(5) = 20.57$, $P = 0.0010$) have a significant impact across the five domains of risk, whereas probability weighting does not have a joint significant effect ($Chi^2(5) = 7.12$, $P = 0.2122$).

6. General discussion and conclusion

This paper explores the diversity in risk perception and risk preferences of Southern Ethiopian households and disentangles the convoluted relationship between both concepts in literature in a development context. We use a rich dataset of 786 observations from two of the 15 zones in the SNNPR that characterizes communities with considerable challenges. We find that respondents in the study area are exposed to multiple past shocks and perceive multiple sources of future threats across different agricultural risk domains (production, market, institutional, financial, and personal). They seem to care about sources of risk with considerable expected impact, even when the perceived probability is low. In line with cumulative prospect theory, we observe heterogeneity in their risk preferences as our respondents are relatively risk-averse and loss-averse, and overweight unlikely extreme outcomes. We find a statistically significant association between the three risk preferences parameters (risk aversion, loss aversion, and probability weighting) and overall risk perception, domain-specific risk perceptions (except for the personal domain) and the impact dimension of future risk. Below we discuss how these findings make an important contribution to our understanding of farm households' risk behavior, guiding priority of development efforts, and stimulate better informed and well-targeted risk management policy interventions.

Our main finding that risk preferences shape risk perceptions, highlights the importance of considering both variables and their interaction in a mediating/moderating fashion when analyzing behavior under risk. It is often argued that in order to steer risk behavior, it is likely easier to influence people's risk perceptions rather than their preferences (Sitkin & Weingart, 1995; Weber & Milliman, 1997) as the latter are considered relatively stable personality traits (Dellavigna, 2009; Schildberg-Hörisch, 2018). As we find that risk preferences shape risk perceptions, the extent to which risk perceptions can be easily influenced is partly limited by this indirect effect of preferences on perceptions. We observed marked heterogeneity in risk preferences across our respondents (see Section 5.1). Policy interventions aimed at increasing awareness of preparing for particular risks such as drought and floods in Ethiopia (e.g., through information campaigns or revised educational materials) would be more efficient when such heterogeneity can be taken into account. We find that the more risk-averse and loss-averse farm households in our sample are already more pessimistic in their forward-looking risk perception, and probability weighting might lead them to overweight unlikely extreme outcomes. It will be harder to persuade such farm households to take further action. Further, the results of heterogeneous risk preferences impacting risk perception call attention to the importance of eliciting multiple parameters of risk preferences in order to characterize farm households' risk behavior (Harrison et al., 2010). Attributing observed risk-responses entirely to only the curvature of a utility function (i.e. σ) can severely over-estimate risk aversion (Just & Pope, 2003) and hence lead to a misguided understanding of risk behavior. Different studies have concluded that (cumulative) prospect theory explains observed behavior in diverse contexts such as US farmers' crop insurance coverage choice (Babcock, 2015), pesticide application decisions by Chinese farmers (Pan et al., 2020), and participation in forest landscape restoration in the Ugandan coffee sector (Julia Ihli et al., 2022).

The results of our study also highlight the need to embrace context and revisit the scope of risk analyses that are often focusing on a particular source or domain of risk, and only consider formal risk management strategies in response (e.g., drought and insurance schemes (Collier et al., 2009; Janzen & Carter, 2019)). This single-risk domain bias in literature likely relates to data availability and model complexity issues. Excessive attention to a particular source of risk in a research area—despite its undoubted relevance—might marginalize other sources of risk that can be considered equally important from the rural poor's perspective. The policy implication is that a single risk management intervention might not be sufficient to address the multi-faceted agricultural risks faced by farm households in developing countries. For example, index-based crop insurance is a widely promoted formal risk management tool in most developing countries, including Ethiopia. Such a tool overlooks potential risk exposure beyond the crop production risk domain. In addition, farm households are typically constrained with resources to adopt multiple risk management tools. In such circumstances, comprehensive risk management tools that address multiple risk sources (e.g., crop insurance bundled with price contracting) could render better results.

Based on the perceived risk perception attitude framework of Rimal and Real (2003), that identifies risk behavior in relation to the combination of perceived risk and efficacy, we would expect avoidance action in our study area as risk is perceived as high and diverse, but perceived efficacy is low. As avoidance undermines risk responsiveness (Klinke & Renn, 2002) or leads to suboptimal risk management behavior (Zimmerman & Carter, 2003), our findings call for a better focus on rural farm households' perspective on risk and bi-directional learning amongst policymakers, researchers and extension agents. We identify the need to better explore to which extent risk perceptions can indeed be influenced, given that risk preferences play a clear role in shaping them, for example though policy interventions that provide relevant risk-related and risk management information. As the farm households in our study area are relatively risk-averse, loss-averse, and overweight unlikely extreme outcomes, their decision-making logic might refrain them from building their adaptive and protective capabilities by taking appropriate ex-ante measures such as adopting irrigation schemes, adjusting crop choices, promoting marketing efforts, or extending social and insurance networks.

Fertile ground for future research remains. While we make an ex-ante assumption that households make decisions in line with cumulative prospect theory, a natural progression of our work would be to run an experiment that empirically determines the fit of cumulative prospect theory versus expected utility theory. Harrison and Rutström (2009), for example noted that neither theory "wins" in their context, but rather that their data was consistent with each playing roughly an equal role. Follow-up studies could focus on investigating the underlying reasons why risk preferences only affect the perceived impact dimension of risk and not perceived likelihood, explore how risk preferences impact intra-household diversity in risk perceptions (Huet et al., 2020) or focus on the dynamics of perceptions over time using panel data (Doss et al., 2008). As we did not find any association between risk preferences and personal risk perception, our results also support the need for domain-specificity in risk preferences elicitation suggested by Weber et al. (2002) and Hansson and Lagerkvist (2012). In this paper, the possibility of time inconsistency is not taken into account (Tanaka et al., 2010). One of the nonstandard beliefs in perception about future threats is projection bias, a way in which farmers make a systematically incorrect projection about their future perception to be too close to the present one. For example, they might project current hunger levels into the future (Dellavigna, 2009). We assume uniform perception projection over the past and expected three years period. In a similar vein, our farm households might not know precisely what resources they could have after 3 years, and hence could project their current level of resources when answering the questions about perceived future self-efficacy. We did not consider in this paper how doing so would lead to a potential correlation between perceived future self-efficacy and contemporary risk preferences. Furthermore, we did not look at a convergence between perceived and objective risks due to the breath of risk sources considered. Our in-depth understanding of subjective perceptions of shocks and risk can be the starting point of developing approaches to further quantify objective sources of risk using novel tools that leverage the digital farming revolution in Africa (Oyinbo et al., 2021). The link between risk perceptions and actual decision-making is also not established in this study. Future research could explore deeper how domain-specific risk perceptions, heterogeneous risk preferences, and their interaction are guiding the ex-ante risk management decisions of farmers in developing countries.

CRediT authorship contribution statement

Ashenafi Duguma Feyisa: Conceptualization, Methodology, Investigation, Data curation, Formal analysis, Writing – original draft, Writing – review & editing, Project administration. **Miet Maertens:** Conceptualization, Methodology, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Yann de Mey:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Supervision.

Data availability

All data and code to replicate the results and figures of this paper are available as supplementary materials in the online version of this article.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This research is funded by VLIR-UOS, under the Interuniversity Cooperation Programs (IUC 2017 Phase 1 AMU), grant number ET2017IUC35A101. We thank Zonal, District, and Kebele level administrative bodies in Ethiopia for unreserved support during data collection and all household in our sample for their participation. We would also like to thank Asjad Naqvi for his heat plot Stata code and comments for Figure 3.

Appendix A. Supplementary Materials

Supplementary materials to this article, including Appendices A1–A4 and replication data and code, can be found online at https://doi.org/10.1016/j.worlddev.2022.106137.

References

Ajzen, I. (2002). Perceived behavioral control, self-efficacy, locus of control, and the theory of planned behavior. *Journal of Applied Social Psychology, 32*(4), 665–683. https://doi.org/10.1111/j.1559-1816.2002.tb00236.x.

Ariely, D. (2008). Predictably irrational: the hidden forces that shape our decisions. *Choice Reviews Online, 46*(02). https://doi.org/10.5860/choice.46-0969.

Aven, T., Ben-Haim, Y., Andersen, H. B., ... T. C.-S. for R. A., & 2018, U. (2018). Society for risk analysis glossary. *Society for Risk Analysis*, Soc. Risk Anal. (August) (2018). https://www.sra.org/wp-content/uploads/2020/04/SRA-Glossary-FINAL.pdf.

Barberis, N. C. (2013). Thirty Years of Prospect Theory in Economics: A Review and Assessment. *Journal of Economic Perspectives, 27*(1), 173–196. https://doi.org/10.1257/JEP.27.1.173.

Babcock, B. A. (2015). Using Cumulative Prospect Theory to Explain Anomalous Crop Insurance Coverage Choice. *American Journal of Agricultural Economics, 97*(5), 1371–1384. https://doi.org/10.1093/ajae/aav032.

Barrett, C. B., Ghezzi-Kopel, K., Hoddinott, J., Homami, N., Tennant, E., Upton, J., & Wu, T. (2021). A scoping review of the development resilience literature: Theory, methods and evidence. *World Development, 46*, 105612. https://doi.org/10.1016/j.worlddev.2021.105612.

Binswanger, H. P. (1980). Attitudes Toward Risk: Experimental Measurement in Rural India. *American Journal of Agricultural Economics, 62*(3), 395–407. https://doi.org/10.2307/1240194.

Bishu, K. G., O'Reilly, S., Lahiff, E., & Steiner, B. (2018). Cattle farmers' perceptions of risk and risk management strategies: Evidence from Northern Ethiopia. *Journal of Risk Research, 21*(5), 579–598. https://doi.org/10.1080/13669877.2016.1223163.

Bowen, T., Ninno, C. D., Andrews, C., & Coll-Black, S. (2020). *Adaptive social protection: Building resilience to shocks*. The World Bank.

Brown, A. L., & Healy, P. J. (2018). Separated decisions. *European Economic Review, 101*, 20–34. https://doi.org/10.1016/j.euroecorev.2017.09.014.

Brown, P., Daigneault, A. J., Tjernström, E., & Zou, W. (2018). Natural disasters, social protection, and risk perceptions. *World Development, 104*, 310–325. https://doi.org/10.1016/J.WORLDDEV.2017.12.002.

Chaîanov, A., & Čajanov, A. (1986). *AV Chayanov on the theory of peasant economy*. Manchester University Press.

Collier, B., Skees, J., & Barnett, B. (2009). Weather index insurance and climate change: Opportunities and challenges in lower income countries. *Geneva Papers on Risk and Insurance: Issues and Practice, 34*(3), 401–424. https://doi.org/10.1057/gpp.2009.11.

Cullen, A. C., Anderson, C. L., Biscaye, P., & Reynolds, T. W. (2018). Variability in Cross-Domain Risk Perception among Smallholder Farmers in Mali by Gender and Other Demographic and Attitudinal Characteristics. *Risk Analysis, 38*(7), 1361–1377. https://doi.org/10.1111/risa.12976.

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

Dellavigna, S. (2009). Psychology and economics: Evidence from the field. *Journal of Economic Literature, 47*(2), 315–372. https://doi.org/10.1257/jel.47.2.315.

Dercon, S., & Christiaensen, L. (2011). Consumption risk, technology adoption and poverty traps: Evidence from Ethiopia. *Journal of Development Economics, 96*(2), 159–173. https://doi.org/10.1016/J.JDEVECO.2010.08.003.

Doss, C., McPeak, J., & Barrett, C. B. (2008). Interpersonal, Intertemporal and Spatial Variation in Risk Perceptions: Evidence from East Africa. *World Development, 36*(8), 1453–1468. https://doi.org/10.1016/j.worlddev.2007.06.023.

Ellis, F. (2007). Household strategies and rural livelihood diversification. *The Journal of Development Studies, 35*(1), 1–38. https://doi.org/10.1080/00220389808422553.

Hansson, H., & Lagerkvist, C. J. (2012). Measuring farmers preferences for risk: A domain-specific risk preference scale. *Journal of Risk Research, 15*(7), 737–753. https://doi.org/10.1080/13669877.2012.657217.

Hardaker, J., Lien, G., Anderson, J., & Huirne, R. (2015). *Coping with risk in agriculture: applied decision analysis* (3rd ed.). CABI. 10.1079/9781780645742.0000.

Harrison, G. W., Humphrey, S. J., & Verschoor, A. (2010). Choice under uncertainty: Evidence from Ethiopia, India and Uganda. *Economic Journal, 120*(543), 80–104. https://doi.org/10.1111/j.1468-0297.2009.02303.x.

Harrison, G. W., & Rutström, E. E. (2009). Expected utility theory and prospect theory: One wedding and a decent funeral. *Experimental Economics, 12*(2), 133–158. https://doi.org/10.1007/s10683-008-9203-7.

Hertwig, R., Barron, G., Weber, E. U., & Erev, I. (2004). Decisions from experience and the effect of rare events in risky choice. *Psychological Science, 15*(8), 534–539. https://doi.org/10.1111/j.0956-7976.2004.00715.x.

Holden, S. T., & Quiggin, J. (2017). Climate risk and state-contingent technology adoption: Shocks, drought tolerance and preferences. *European Review of Agricultural Economics, 44*(2), 285–308. https://doi.org/10.1093/erae/jbw016.

Huet, E. K., Adam, M., Giller, K. E., & Descheemaeker, K. (2020). Diversity in perception and management of farming risks in southern Mali. *Agricultural Systems, 184*. https://doi.org/10.1016/j.agsy.2020.102905 102905.

Iyer, P., Bozzola, M., Hirsch, S., Meraner, M., & Finger, R. (2020). Measuring Farmer Risk Preferences in Europe: A Systematic Review. *Journal of Agricultural Economics, 71*(1), 3–26. https://doi.org/10.1111/1477-9552.12325.

Jann, B. (2019, February 3). *HEATPLOT: Stata module to create heat plots and hexagon plots*. Jann, Ben (2019). Heatplot: Stata Module to Create Heat Plots and Hexagon Plots. [Software & Other Digital Items]; Boston College Department of Economics. 10.7892/BORIS.126708.

Janzen, S. A., & Carter, M. R. (2019). After the Drought: The Impact of Microinsurance on Consumption Smoothing and Asset Protection. *American Journal of Agricultural Economics, 101*(3), 651–671. https://doi.org/10.1093/ajae/aay061.

JICA. (2018). *Rural Resilience Enhancement Project in the Federal Democratic Republic of Ethiopia*. https://www.indexinsuranceforum.org/resilience-document/rural-resilience-enhancement-project-federal-democratic-republic-ethiopia-0.

Julia Ihli, H., Chiputwa, B., Winter, E., & Gassner, A. (2022). Risk and time preferences for participating in forest landscape restoration: The case of coffee farmers in Uganda. *World Development, 150*. https://doi.org/10.1016/j.worlddev.2021.105713 105713.

Just, D. R., & Just, R. E. (2016). Empirical Identification of Behavioral Choice Models under Risk. *American Journal of Agricultural Economics, 98*(4), 1181–1194. https://doi.org/10.1093/AJAE/AAW019.

Just, R. E., & Pope, R. D. (2003). Agricultural risk analysis: Adequacy of models, data, and issues. *American Journal of Agricultural Economics, 85*(5), 1249–1256. https://doi.org/10.1111/j.0092-5853.2003.00538.x.

Kahneman, D. (1979). Prospect Theory : An Analysis of Decisions under Risk. *Econometrica, 47*, 278 https://ci.nii.ac.jp/naid/10021872180.

Kahsay, G. A., Kassie, W. A., Medhin, H., & Hansen, L. G. (2022). Are religious farmers more risk taking? Empirical evidence from Ethiopia. *Agricultural Economics*. https://doi.org/10.1111/AGEC.12697.

Klinke, A., & Renn, O. (2002). A new approach to risk evaluation and management: Risk-based, precaution-based, and discourse-based strategies. *Risk Analysis, 22*(6), 1071–1094. https://doi.org/10.1111/1539-6924.00274.

Komarek, A. M., De Pinto, A., & Smith, V. H. (2020). A review of types of risks in agriculture: What we know and what we need to know. *Agricultural Systems, 178*. https://doi.org/10.1016/J.AGSY.2019.102738 102738.

Lazo, J. K., Kinnell, J. C., & Fisher, A. (2000). Expert and layperson perceptions of ecosystem risk. *Risk Analysis, 20*(2), 179–194. https://doi.org/10.1111/0272-4332.202019.

León, A. K., & Pfeifer, C. (2017). Religious activity, risk-taking preferences and financial behaviour: Empirical evidence from German survey data. *Journal of Behavioral and Experimental Economics, 69*, 99–107. https://doi.org/10.1016/j.socec.2017.05.005.

Liu, E. M. (2013). Time to Change What to Sow: Risk Preferences and Technology Adoption Decisions of Cotton Farmers in ChinaTime to Change What to Sow. *The Review of Economics and Statistics, 95*(4), 1386–1403. https://doi.org/10.1162/REST_A_00295.

Lybbert, T. J., Barrett, C. B., McPeak, J. G., & Luseno, W. K. (2007). Bayesian Herders: Updating of Rainfall Beliefs in Response to External Forecasts. *World Development, 35*(3), 480–497. https://doi.org/10.1016/j.worlddev.2006.04.004.

Marra, M., Pannell, D. J., & Abadi Ghadim, A. (2003). The economics of risk, uncertainty and learning in the adoption of new agricultural technologies: Where are we on the learning curve? *Agricultural Systems, 75*(2–3), 215–234. https://doi.org/10.1016/S0308-521X(02)00066-5.

Menapace, L., Colson, G., & Raffaelli, R. (2013). Risk aversion, subjective beliefs, and farmer risk management strategies. *American Journal of Agricultural Economics, 95*(2), 384–389. https://doi.org/10.1093/AJAE/AAS107.

Meraner, M., & Finger, R. (2019). Risk perceptions, preferences and management strategies: Evidence from a case study using German livestock farmers. *Journal of Risk Research, 22*(1), 110–135. https://doi.org/10.1080/13669877.2017.1351476.

Meuwissen, M. P. M., Huirne, R. B. M., & Hardaker, J. B. (2001). Risk and risk management: An empirical analysis of Dutch livestock farmers. *Livestock Production Science, 69*(1), 43–53. https://doi.org/10.1016/S0301-6226(00)00247-5.

Oyinbo, O., Chamberlin, J., Abdoulaye, T., & Maertens, M. (2021). Digital Extension, Price Risk, and Farm Performance: Experimental Evidence from Nigeria. *American Journal of Agricultural Economics, 1–20*. https://doi.org/10.1111/ajae.12242.

Pan, D., He, M., & Kong, F. (2020). Risk attitude, risk perception, and farmers' pesticide application behavior in China: A moderation and mediation model. *Journal of Cleaner Production, 276*. https://doi.org/10.1016/j.jclepro.2020.124241 124241.

Rimal, R. N., & Real, K. (2003). Perceived Risk and Efficacy Beliefs as Motivators of Change. *Human Communication Research, 29*(3), 370–399. https://doi.org/10.1111/j.1468-2958.2003.tb00844.x.

Schildberg-Hörisch, H. (2018). Are risk preferences stable? *Journal of Economic Perspectives, 32*(2), 135–154. https://doi.org/10.1257/jep.32.2.135.

Simon, M., Houghton, S. M., & Aquino, K. (2000). Cognitive biases, risk perception, and venture formation: How individuals decide to start companies. *Journal of*

Business Venturing, 15(2), 113–134. https://doi.org/10.1016/S0883-9026(98)00003-2.
Sitkin, S. B., & Pablo, A. L. (1992). Reconceptualizing the Determinants of Risk Behavior. *Academy of Management Review, 17*(1), 9–38. https://doi.org/10.5465/amr.1992.4279564.
Sitkin, S. B., & Weingart, L. R. (1995). Determinants of Risky Decision-Making Behavior: A Test of the Mediating Role of Risk Perceptions and Propensity. *Academy of Management Journal, 38*(6), 1573–1592. https://doi.org/10.5465/256844.
Sjöberg, L. (2000). Factors in Risk Perception. *Risk Analysis, 20*(1), 1–12. https://doi.org/10.1111/0272-4332.00001.
Slimak, M. W., & Dietz, T. (2006). Personal values, beliefs, and ecological risk perception. *Risk Analysis, 26*(6), 1689–1705. https://doi.org/10.1111/j.1539-6924.2006.00832.x.
Slovic, P. (1987). Perception of risk. *Science, 236*(4799), 280–285. https://doi.org/10.1126/SCIENCE.3563507.
Slovic, P. (2000). The perception of risk. *Earthscan Publications.* https://psycnet.apa.org/record/2001-01329-000.
Smith, K., Barrett, C. B., & Box, P. W. (2001). Not necessarily in the same boat: Heterogeneous risk assessment among east African pastoralists. *Journal of Development Studies, 37*(5), 1–30. https://doi.org/10.1080/00220380412331322101.
Stern, P. C., Dietz, T., & Guagnano, G. A. (1998). A brief inventory of values. *Educational and Psychological Measurement, 58*(6), 984–1001. https://doi.org/10.1177/0013164498058006008.
Stock, J., & Yogo, M. (2005). Asymptotic distributions of instrumental variables statistics with many instruments. In J. H. S. Andrews, Donald W. K. (Ed.), *Identification and Inference for Econometric Models*. Cambridge University Press.
Sullivan-Wiley, K. A., & Short Gianotti, A. G. (2017). Risk Perception in a Multi-Hazard Environment. *World Development, 97*, 138–152. https://doi.org/10.1016/J.WORLDDEV.2017.04.002.
Tanaka, T., Camerer, C. F., & Nguyen, Q. (2010). Risk and time preferences: Linking experimental and household survey data from Vietnam. In. *American Economic Review, Vol. 100(1*, 557–571. https://doi.org/10.1257/aer.100.1.557.
Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty, 5(4),*, 297–323. https://doi.org/10.1007/BF00122574.
Tversky, A., & Wakker, P. (1995). Risk Attitudes and Decision Weights. *Econometrica, 63*(6), 1255. https://doi.org/10.2307/2171769.
Ullah, R., Shivakoti, G. P., Zulfiqar, F., & Kamran, M. A. (2016). Farm risks and uncertainties: Sources, impacts and management. *Outlook on Agriculture, 45*(3), 199–205. https://doi.org/10.1177/0030727016665440.
UN. (2015). *Reading the Sendai Framework for Disaster Risk Reduction 2015 - 2030 | UNDRR*. https://www.undrr.org/publication/reading-sendai-framework-disaster-risk-reduction-2015-2030.
van der Linden, S. (2015). The social-psychological determinants of climate change risk perceptions: Towards a comprehensive model. *Journal of Environmental Psychology, 41*, 112–124. https://doi.org/10.1016/J.JENVP.2014.11.012.
van Winsen, F., de Mey, Y., Lauwers, L., Van Passel, S., Vancauteren, M., & Wauters, E. (2016). Determinants of risk behaviour: Effects of perceived risks and risk attitude on farmers adoption of risk management strategies. *Journal of Risk Research, 19*(1), 56–78. https://doi.org/10.1080/13669877.2014.940597.
van Winsen, F., de Mey, Y., Lauwers, L., Van Passel, S., Vancauteren, M., & Wauters, E. (2013). Cognitive mapping: A method to elucidate and present farmers' risk perception. *Agricultural Systems, 122*, 42–52. https://doi.org/10.1016/j.agsy.2013.08.003.
Vieider, F. M., Beyene, A., Bluffstone, R., Dissanayake, S., Gebreegziabher, Z., Martinsson, P., & Mekonnen, A. (2018). Measuring risk preferences in rural Ethiopia. *Economic Development and Cultural Change, 66*(3), 417–446. https://doi.org/10.1086/696106.
Vieider, F. M., Lefebvre, M., Bouchouicha, R., Chmura, T., Hakimov, R., Krawczyk, M., & Martinsson, P. (2015). Common components of risk and uncertainty attitudes across contexts and domains: Evidence from 30 countries. *Journal of the European Economic Association, 13*(3), 421–452. https://doi.org/10.1111/jeea.12102.
Villacis, A. H., Alwang, J. R., & Barrera, V. (2021). Linking risk preferences and risk perceptions of climate change: A prospect theory approach. *Agricultural Economics, 1–15*. https://doi.org/10.1111/AGEC.12659.
Visser, M., Jumare, H., & Brick, K. (2020). Risk preferences and poverty traps in the uptake of credit and insurance amongst small-scale farmers in South Africa. *Journal of Economic Behavior and Organization, 180*, 826–836. https://doi.org/10.1016/j.jebo.2019.05.007.
Vlek, C., & Stallen, P. J. (1980). Rational and personal aspects of risk. *Acta Psychologica, 45*(1–3), 273–300. https://doi.org/10.1016/0001-6918(80)90038-4.
Wachinger, G., Renn, O., Begg, C., & Kuhlicke, C. (2013). The Risk Perception Paradox—Implications for Governance and Communication of Natural Hazards. *Risk Analysis, 33*(6), 1049–1065. https://doi.org/10.1111/J.1539-6924.2012.01942.X.
Weber, E. U. (2010). Risk attitude and preference. *Wiley Interdisciplinary Reviews: Cognitive Science* (Vol. 1(1, pp. 79–88). Ltd: John Wiley & Sons. https://doi.org/10.1002/wcs.5.
Weber, E. U., Blais, A.-R., & Betz, N. E. (2002). A domain-specific risk-attitude scale: Measuring risk perceptions and risk behaviors. *Journal of Behavioral Decision Making, 15*(4), 263–290. https://doi.org/10.1002/BDM.414.
Weber, E. U., & Hsee, C. (1998). Cross-cultural differences in risk perception, but cross-cultural similarities in attitudes towards perceived risk. *Management Science, 44*(9), 1205–1217. https://doi.org/10.1287/mnsc.44.9.1205.
Weber, E. U., & Milliman, R. A. (1997). Perceived risk attitudes: Relating risk perception to risky choice. *Management Science, 43*(2), 123–144. https://doi.org/10.1287/mnsc.43.2.123.
West, B. T., & Blom, A. G. (2017). Explaining interviewer effects: A research synthesis. *Journal of Survey Statistics and Methodology, 5*(2), 175–211. https://doi.org/10.1093/jssam/smw024.
Wooldridge, J. (2010). *Econometric analysis of cross section and panel data* ((2nd (ed.)).). The MIT Press.
Zellner, A., & Theil, H. (1992). Three-Stage Least Squares: Simultaneous Estimation of Simultaneous Equations. In B. R. Koerts (Ed.), *Henri Theil's Contributions to Economics and Econometrics* (pp. 147–178). Dordrecht: Springer. https://doi.org/10.1007/978-94-011-2546-8_10.
Zimmerman, F. J., & Carter, M. R. (2003). Asset smoothing, consumption smoothing and the reproduction of inequality under risk and subsistence constraints. *Journal of Development Economics, 71*(2), 233–260. https://doi.org/10.1016/S0304-3878(03)00028-2.