Received: 8 November 2020 | Revised: 27 January 2021 | Accepted: 7 March 2021

DOI: 10.1111/agec.12659

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists
IAAE
WILEY

ORIGINAL ARTICLE

# Linking risk preferences and risk perceptions of climate change: A prospect theory approach

**Alexis H. Villacis**[1] | **Jeffrey R. Alwang**[2] | **Victor Barrera**[3]

[1] Morrison School of Agribusiness, W. P. Carey School of Business, Arizona State University, Mesa, Arizona, USA

[2] Department of Agricultural and Applied Economics, Virginia Tech, Blacksburg, Virginia, USA

[3] National Institute for Agricultural Research of Ecuador INIAP, Quito, Ecuador

**Correspondence**
Alexis Villacis, Morrison School of Agribusiness, W. P. Carey School of Business, Arizona State University, Mesa, AZ, USA.
Email: alexis.villacis@asu.edu

**Abstract**

This article explores how farmer risk preferences are related to their perception of risk of climate change. We measure risk preferences and risk perceptions using a survey and a lab-in-the-field experiment conducted with one of the most vulnerable groups to climate change in Latin America. We find that farmers that behave in accordance with the assumptions of Prospect Theory —a paradigm where risk preferences are characterized by risk aversion, loss aversion, and probability distortion—are more likely to perceive greater risks of climate change. Our results contribute to the understanding of farmer behavior in developing countries. Moreover, since perception of a risk is a necessary prerequisite for deciding on actions to adapt to climate risk, the results have important policy implications for the development and adoption of new technologies aimed at mitigating the effects of climate change (climate-smart agricultural technologies).

KEYWORDS

climate change, prospect theory, risk perceptions, risk preferences

JEL CLASSIFICATION

C93, D81, D83, D91, O13, Q15, Q54

## 1 | INTRODUCTION

Little is known about the relationship between risk preferences[1] and risk perceptions[2]. Nowhere is this discord clearer than in the discourse about climate change (CC). To address these gaps, we use a lab-in-the-field experiment and survey data to (i) elicit and assess risk preferences among smallholder farmers, and (ii) evaluate the link between risk preferences and risk perceptions of climate change.

Understanding CC risk perceptions and risk preferences is of economic interest due to their implications for (i) the development and adoption of new climate-smart agricultural technologies, and (ii) risk management decisions among smallholder farmers. Risk perception has been argued to be a necessary prerequisite for the adoption of adaptation strategies for mitigating the effects of climate and local weather variability (Deressa et al., 2011; Hansen et al., 2004; Maddison, 2007; Mulenga et al., 2017; Silvestri et al., 2012). Likewise, various empirical studies have documented the importance of risk preferences in technology

[1] Risk preferences refer to an individual's choice when faced with probabilistic events. These choices, in combination with an underlying utility function, define risk attitudes, i.e., risk-seeking/risk averse, loss averse, etc. Depending on how an individual evaluates the riskiness of the events, she may base her choice on the variance, the expected value, and/or the type of domain (losses or gains).

[2] Risk perceptions refer to a decision maker's assessment of the risk inherent in a situation. They are important determinants of decision maker behavior as studies have shown they can influence the assessment of uncertainty and distort one's judgments, knowledge, and the ability to perform under risky conditions (Lusk et al., 2014; Lusk & Coble, 2005; Sitkin & Pablo, 1992; Waterfield et al., 2020). They are generally measured by asking about the perceived "seriousness," "concern," and/or "worry" of a situation.

adoption decision-making (Anand et al., 2019; Cárdenas, 2016; Feder, 1980; Feder et al., 1985; Ghadim et al., 2005; Kallas et al., 2010; Liu, 2013; Magnan et al., 2020).

Comprehending the links among these behavioral traits can help to design customized and more effective interventions aiming at mitigating vulnerability to and the effects of climate change. For instance, if farmers perceive the risk associated with climate change as very threatening to their agricultural production, a response of policy makers would be to offer them crop insurance. However, insurance demand can be low if farmers are risk-seeking for losses, since it is rational to not buy insurance and face the risk of a potential high loss, instead of paying for insurance and facing a small but certain loss. Another response of policy makers would be to promote adoption of climate-smart agricultural technologies but adoption of such technologies can be low if farmers are loss averse and suffer from the endowment effect, since they will be less willing to change their behavior.

Climate change, the systematic alteration of average weather patterns, is difficult for people to perceive on a sensory level (Weber, 2010). Therefore, CC risk perceptions are unique because they are influenced by the ability to evaluate changes in long-term conditions, and by related psychological factors (van der Linden, 2017). A substantial amount is known about how perceptions of risk of climate change are influenced by socio-demographic, cognitive, experiential, and socio-cultural factors (Helgeson et al., 2012; van der Linden, 2015; Xie et al., 2019); but little attention has been given to how risk preferences can influence perceptions of risk from CC.

We use Prospect Theory (PT) in combination with the experimental design of Tanaka et al. (2010) and explore if risk preference parameters elicited in an experiment are significantly associated with an individual's stated CC risk perceptions. For this study, PT provides a better conceptualization of risk preferences than the Expected Utility (EU) framework for two reasons. First, PT helps account for loss aversion and its connection to status quo bias that could explain why some might disregard the effects of climate change. Second, PT helps account for probability distortion that is normally connected to events with low probability of occurrence, such as extreme weather events. Neither feature is present in the EU framework, as EU just elicits risk aversion, the only parameter in its value function.

This research is conducted with a vulnerable group to climate change in Latin America—indigenous farmers in the Ecuadorean Andes[3]. Findings show that individuals who behave in accordance with the assumptions of prospect theory are more likely to perceive risks associated with CC as being more threatening at a personal level. Those individuals who distort probability information are more likely to perceive greater risk of CC.

We contribute to the substantive literature on CC risk perceptions and the more general literature on risk preferences[4]. First, this research is one of the first studies examining how elicited risk preferences are related to perceptions of CC risk and weather phenomena[5]. Second, we quantify the contribution of individual risk preference elements (i.e., loss aversion and probability distortion) to the perceived risks of CC.

The remainder of this article is organized as follows. Section 2 describes the conceptual framework and experimental design used to elicit risk parameters. It also discusses the use of Prospect Theory as a concept to explain farmers' CC risk perceptions. Section 3 discusses the survey and data and presents descriptive statistics. Section 4 presents the empirical framework used to model the determinants of risk perceptions and discusses how risk preferences should influence these perceptions. It also discusses how we approached societal vs. personal risk judgments. Section 5 presents a descriptive analysis of the results from the field experiment. It then shows results from the estimation of the empirical model. Section 6 summarizes and discusses implications of the findings.

## 2 | THEORETICAL FRAMEWORK

In the psychology literature, perception refers to the *process* of receiving information and stimuli from one's surroundings and converting them into psychological responses (Garner et al., 1956). The perception of risk is, therefore, a mental construct (Sjöberg, 2000) that distinguishes between the existence of objective real-world threats and the subjective evaluation of those threats (Rosa, 2003; van der Linden, 2017). The subjective evaluation of threats can make climate change risk perceptions vary significantly among individuals. For example, although actual changes in temperatures and rainfall patterns do not exist in some locations, farmers in some studies in these areas report perceiving climatic change (Bryan et al., 2009; Deressa et al., 2009; Uddin et al., 2017).

This subjective psychological component of risk perceptions, combined with social and cultural characteristics, contributes to the observed heterogeneity of climate

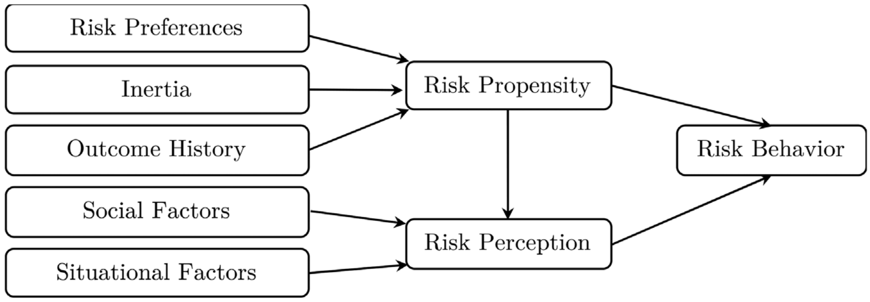
[3] Section 1 in *Supporting Information* provides background on climate change, environmental conditions and agricultural practices in this study area.

[4] We also extend the use of PT to farmers in the Latin American region. To the best knowledge of the authors, Galarza (2009) is the only existing study using PT with farmers in Latin America; its target population was Peruvian farmers.

[5] Section 2 in *Supporting Information* discusses two of the more relevant studies in this research area.

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists


**FIGURE 1** Determinants of risk behavior (Sitkin & Pablo, 1992)




change risk perceptions. Various studies have found differences between and within countries, where the perceived risk associated with CC is greater in most of the low- and middle-income countries when compared to the developed world. Political, cultural, and geographic factors have been identified to shape these differences; because of this, the analysis of CC risk perceptions has usually been conducted separately for each country or population (Lee et al., 2015; Leiserowitz, 2007; Tranter, 2013).

Climate change as an objective real-world threat is learned by people through personal experience (associative processing) and/or statistical description (analytic processing) (Chaiken & Trope, 1999; Epstein, 1994; Sloman, 1996; Weber, 2010). Personal experience refers to the assessment of stimuli from one's surroundings, such as extreme weather events, increases in temperatures, flooding, etc. Statistical information comes via reports of rainfall, news reports, etc. Studies have shown that personal experiences[6] have a stronger influence on CC perceptions compared to statistical description, even though the latter is generally more reliable (Erev & Barron, 2005; Hertwig et al., 2004). Weber (2010) argues that nonscientists and most people rely more on personal experience and in cases where this experience disagrees with statistical information, the personal experience usually prevails because it comes in faster and is more vivid.

Existing models of perceptions of risk of CC generally incorporate four broad determinants: socio-demographic, cognitive, experiential and socio-cultural factors (e.g., Helgeson et al., 2012; van der Linden, 2015). While these studies combine different theoretical views into a comprehensive set of key psychological determinants, little or no attention has been given to the role of risk preferences on risk perceptions. Risk preferences are necessary as existing theory on risk behavior indicates that risk preferences affect risk perceptions through what is called "the decision maker's risk propensity" (Sitkin & Pablo, 1992). In *Model of the Determinants of Risk Behavior*, Sitkin and Pablo (1992) argue that risk preferences alone do not determine specific risk behaviors, but instead they affect what is called the *risk propensity* of a person. Subsequently, *risk propensity* in combination with social and other situational factors determines risk perceptions. Ultimately, *risk propensity* and risk perceptions determine risk behavior (see Figure 1). The causal relationship between risk preferences and risk perceptions, operationalized through *risk propensity* in the context of climate change, is the main focus of this article.

*Risk propensity* is the general likelihood or tendency of a person to take or avoid risks; conceptually, risk propensity is revealed by the shape of an underlying utility function (Weber & Milliman, 1997). Sitkin and Pablo (1992) argue that *risk propensity* is not conceptualized as a stable trait of an individual; it is dynamic and depends on risk preferences and on the inertia of the decision-maker and outcomes of prior risky decisions (history). Use of this conceptualization is motivated by the observation that most studies do not offer a causal mechanism to explain how risk preferences are translated into risk behavior[7].

In the experimental literature, individual risk preferences are derived from people's choices over gambles or lotteries[8]. In the economics literature, the most prominent framework for the conceptualization and analysis of risk preferences (i.e., the way the risk propensity is revealed) is expected utility theory. In the EU, the shape of the utility function reflects individual risk preferences, e.g., a convex utility function reflects a risk-seeking individual. In contrast, a risk-averse individual's utility function is concave. Although EU is widely used in experimental studies, individual choices in conditions of low, imprecise, or multiple probabilities have been shown, empirically and

[6] Personal exposure to temperature increases and extreme weather events plays a crucial role in forming mental constructs. Although the impact of temperature increases on mental constructs is not directly testable, their effect on risk perceptions may vary depending on individual characteristics. For example, gradual temperature increases might be imperceptible to young farmers, due to their relatively short exposure, while older farmers have a longer experience horizon influencing their perceptions.

[7] Studies commonly use risk preferences as a direct determinant of risk behavior (See for instance Liu, 2013).

[8] Early studies elicited risk preferences during standard household surveys (Antle, 1987; Moscardi & de Janvry, 1977), but since the revolutionary work of Binswanger (1980), use of experimental methods—normally employing lotteries with different expected payoffs and variance—has become the standard means of eliciting risk preferences.

experimentally, to be inconsistent with a single probability distribution, as generally assumed by EU (Lange, 2003; Lange & Treich, 2008). Climate change is a particular example that involves imprecise and/or low probabilities, and hence, the applicability of the EU to climate change is suspect.

Prospect theory (PT) (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992) is an alternative paradigm used to describe risk preferences. In PT, individual risk preferences are not only characterized by risk aversion, but also by loss aversion and nonlinear probability weighting. Loss aversion reflects the sensitivity of changes in well-being to loss compared to gain, or the idea that people are more sensitive to losses than to gains of the same magnitude. Loss aversion is produced by making the underlying value function steeper in the region of losses than in the region of gains. Nonlinear probability weighting refers to the individual tendency of overweighting low probabilities and underweighting high probabilities.

PT is preferred to EU as a conceptual basis linking risk preferences to farmers' CC risk perceptions for two reasons. First, in contrast to the EU, PT accounts for loss aversion and its strong implications for the concept of status quo bias[9] (Kahneman et al., 1991; Kahneman & Tversky, 1984; Samuelson & Zeckhauser, 1988; Thaler, 1980). Status quo bias in the context of climate change could offer explanations for disregarding the effects of climate change simply because an individual has a strong tendency to remain at the status quo[10].

Second, while EU weights outcomes by their objective probability, PT offers a theoretical framework allowing for probability distortion. Extreme weather events—signals of climate change—have a low probability of occurrence. Studies have shown that when low-probability events occur, they have a more substantial impact on related decisions than justified by their probability (Yechiam et al., 2005). In other words, even if frosts, flooding, and droughts have a low objective probability of occurrence, if farmers experience any of these, they will likely overweight its future likelihood. These events also lead to crop damages and economic losses, which can have a further behavioral implication. The economic losses will reinforce the negative outcome of the low probability event, increasing the degree of probability distortion. They also impact an individual's sensitivity to losses.

[9] An important implication of loss aversion is that individuals have a strong tendency to remain at the status quo, because the disadvantages of leaving it loom larger than advantages (Kahneman et al., 1991).

[10] Jost and Hunyady (2016), argue that in addition to status quo bias, system justification theory also explains why some people also adopt motivated perceptions to view the current system as stable, fair, and/or legitimate, even when the system may be disadvantageous to others.

## 2.1 | Prospect theory

Formally, prospect theory as proposed by Tversky and Kahneman (1992), is expressed in the context of a gamble:

$$(x_{-m}, p_{-m};\ x_{-m+1}, p_{-m+1}; \cdots;\ x_0, p_0; \cdots;\ x_{n-1}, p_{n-1};\ x_n, p_n), \tag{1}$$

which is evaluated as:

$$\sum_{i=-m}^{n} \pi_i v(x_i). \tag{2}$$

Here $x_i$ is a gain (or loss) that occurs with probability $p_i$; outcomes are arranged in increasing order such that $x_i < x_j$ for $i < j$ and $x_0 = 0$; $v(x)$ is the value function and it is an increasing function with $v(0) = 0$; $\pi_i$ are decision weights. We assume that agents behave in accordance to the assumptions of cumulative prospect theory and the farmer utility is defined as:

$$PT(x,\ p; y,\ 1-p) = \begin{cases} v(y) + w(p)[v(x) - v(y)];\ x > y > 0 \text{ or } x < y < 0 \\ w(p)v(x) + w(1-p)v(y);\ x < 0 < y \end{cases}. \tag{3}$$

$PT(x,\ p; y,\ 1-p)$ is the expected value over binary prospects $(x;\ y)$, with corresponding probabilities $(p;\ 1-p)$. The value function, $v(x)$ is defined as a piecewise power function that assigns different values for gains $(x > 0)$ and losses $(x < 0)$, such that:

$$v(x) = \begin{cases} x^{\sigma};\ x \geq 0 \\ -\lambda(-x)^{\sigma};\ x < 0 \end{cases}. \tag{4}$$

$\sigma$ determines the curvature or concavity of the value function for gains and losses and is the proxy for risk aversion. $\lambda$ describes the curvature below 0 relative to the curvature above 0 and reflects the degree of loss aversion. The usual empirical finding is $\sigma < 1$ along with $\lambda > 1$ —the agent is risk-averse and more sensitive to losses than to gains (Bocquého et al., 2014).

The function $w(p)$ represents probability weighting. We use the axiomatically derived weighting function of Prelec (1998) as follows:

$$w(p) = \frac{1}{[\exp(\ln(1/p))]^{\alpha}}. \tag{5}$$

The usual expected finding is $\alpha < 1$, that is the agent will overweight small probabilities and underweight large probabilities[11] (Bocquého et al., 2014). This model of

[11] Section 3 in *Supporting Information* provides a further discussion of the parameters of the PT function.

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists



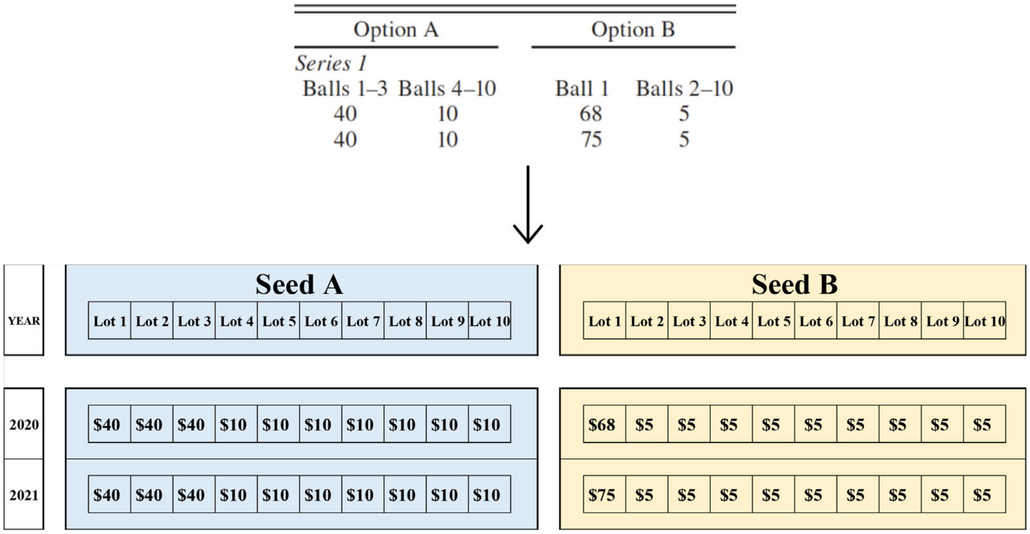



**FIGURE 2** Lottery representation of the risk experiment [Color figure can be viewed at wileyonlinelibrary.com]

Prospect Theory reduces to Expected Utility when $\alpha = 1$ and $\lambda = 1$.

As previously argued, PT probability weighting and loss aversion relate closely to climate change and its behavioral implications. Therefore, PT parameters can help explain farmers' CC risk perceptions better than EU, as EU just elicits risk aversion. While the roles of risk aversion, loss aversion, and probability weighting on farmer perceptions of risk of CC have not been formally tested, many studies have explored the role of these parameters in other agricultural settings (Bocquého et al., 2014; Feng et al., 2020; Franken et al., 2014; Liebenehm & Waibel, 2014; Liu, 2013; Tanaka et al., 2010; Vollmer et al., 2019; Zhao & Yue, 2020).

## 2.2 | Experimental design and procedure

We used the experimental design of Tanaka et al. (2010) to elicit and estimate the structural parameters of the PT utility function[12]. Tanaka et al. (2010) provides a direct bridge between plays in a lottery game and PT, as every combination of the participant's choices in the game determine unique values of PT parameters[13].

To ease the understanding of these lotteries and probabilities for our participants, we adapted the lotteries to an agricultural illustration. The probabilities and payoffs were explained to participants by illustrating a farm composed of 10 lots. All lots are equally sized and a lot's particular payoff from using either Seed A or Seed B accompanies the illustration. Participants were told that due to climatic events, at the end of each year only one random lot out of the ten would survive. To enforce monotonic switching, we asked participants at which year (row) they would "switch" from Seed A to Seed B in each series.

Figure 2 shows how series 1, rows 1 and 2, of Table 2 in Tanaka et al. (2010) were adapted and presented to participants[14]. Our illustration implicitly shows that seed A in the year 2020 offers a 30% chance of receiving 40 USD and a 70% chance of receiving 10 USD, while seed B in the same year offers a 10% chance of receiving 68 USD and a 90% chance of receiving 5 USD. This illustration is used to tackle one of the main disadvantages of eliciting risk parameters using complex methods––failure by participants of understanding the procedures and the concepts of probability (Charness et al., 2013). This disadvantage may be amplified in such field studies where subjects are farmers in a developing country with relatively low levels of education, although literacy is high in Ecuador.

Participants were told that if they decided to choose Seed A for the year 2020, and lot 3 survives at random, they would have earned 40 USD, while those who chose Seed B would have earned 5 USD. In contrast, if lot 1 survives, then those who chose Seed B would have earned 68 USD. Subjects were given printed instructions and separate printed sheets for each game (series), and they were asked to record their answers. The printed instructions contained 3 examples similar to the one above. The instructions were also explained verbally. In addition to specifying the year of the switch from seed A to seed B, participants had the option

[12] This design also allows determination of whether EU fits the data better, as it allows estimation of an empirical specification of EU. This design has been tested with farmers in developing countries, including Vietnam, China, Mali, and Burkina Faso (Bocquého et al., 2014; Liebenehm & Waibel, 2014; Liu, 2013; Tanaka et al., 2010).

[13] Section 4 in *Supporting Information* provides more details of the experimental design of Tanaka et al. (2010)

[14] Figures S1, S2, and S3 in *Supporting Information* show the complete lotteries used in the experiment.

of never switching (always choosing seed A) or changing at year 1 (always choosing seed B).

Illiterate farmers were not allowed to join the experiment. Subjects who had difficulty completing record sheets by themselves were helped by research assistants who cautiously avoided recommending specific choices. Participants received 4 USD for showing up to the experiment. At the end of the experiment and survey, a numbered ball was drawn from a bingo cage to randomize and determine which series, year, and a lot of choices would be played for real money as a bonus. The bonus ranged from [-3, 3] USD, and it was applied based on their actual choices during play. Farmers were told that in the case of gains, participants that chose the option that got the larger value would obtain a bonus of 3 USD, while those who chose the option with the smaller value would obtain a bonus of only 1 USD. Likewise, in the case of losses, participants that chose the option that got the larger value would lose 3 USD, while those who chose the option with the smaller value would lose only 1 USD[15]. The average earning for participating in the games was 6.5 USD, roughly the wage of a one-half working day for agricultural labor. The monetary incentives were used to make the experiment incentive-compatible, as literature shows that in games, auctions, and risky choices, incentives often reduce variance in responses and cause participants to behave more towards realistic choices (Camerer & Hogarth, 1999).

## 3 | DATA AND DESCRIPTIVE STATISTICS

### 3.1 | Study area and survey

During summer 2019, we partnered with the Ecuadorian Institute of Agricultural Research (INIAP), a government research institute, to conduct the study in four indigenous villages in Chimborazo province. In addition to climate change, heavy erosion—caused mainly by intensive tillage—is an increasing threat to agricultural production in this province. The selected villages were Balcashi, Llucud, Puculpala, and Puelazo, where farming is mostly comprised of pasture-potato-corn rotations and dairy production. INIAP is currently undertaking a pilot extension program in these villages to encourage adoption of conservation agriculture practices[16]. To mitigate the effects of climate change while conserving soil and improving soil health and productivity, conservation agriculture practices include reduced or minimum tillage, maintenance of soil cover, and adoption of improved crop rotations[17].

Village populations ranged from 264 to 512 and 52% of the population are women (Gobierno Autónomo Descentralizado Parroquial Rural Quimiag, 2015). On average, two members of each family engage in income-earning activities. Elevation varies from 3,000 to 4,500 meters above sea level, annual precipitation is 500 to 2,000 millimeters, and average temperatures over the year are 12 to 20 Celsius degrees. The lab-in-the-field experiment to elicit the individual risk preferences involved 202 farmers. Following participation in experiment, farmers were questioned about household and individual characteristics.

The study team administered the experiment and survey, while INIAP scientists provided organization and logistics. Experiments started approximately at 6 p.m. and lasted about two and one-half hours. Before running the experiments and surveys, members and leaders of each village were asked for cooperation and help in recruiting subjects. Meeting dates, times, and locations were announced by village leaders. During the announcements, villagers were summoned to attend a regular assembly and asked to be part of a study conducted by INIAP. Farmers were told they would receive monetary compensation for their participation. These announcements were made using the public communications system—village-specific megaphones.

### 3.2 | Data description

Summary statistics are shown in Table 1 for the main variables of interest. The average participant is about 44 years old, has finished elementary school, earns between 0 to 300 USD/month, and owns around 1.82 hectares of farmland. Most have access to irrigation and own dairy cattle (89% and 88%, respectively). Although not tested in this study, one can argue that access to irrigation affects perceived risk of climate change, as irrigation makes rainfall less important for plant growth. All participants indicated having heard of climate change.

[15] The maximum loss was set to 3 USD to avoid the loss of money by the farmers, given they received 4 USD for showing up to the experiment. See Liu (2013) for a detailed discussion on payments using Tanaka's experimental design, and how for ethical reasons, studies avoid the loss of money by the farmers.

[16] The criterion for the selection of these villages was based on the "degree of acceptance" of these communities to INIAP personnel.

[17] Results of a global meta-analysis performed by Pittelkow et al. (2015) show no-till in combination with soil cover and crop rotations significantly increases rainfed crop productivity in dry climates, suggesting conservation agriculture may become an important climate-change adaptation strategy for ever-drier regions of the world.

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists
IAAE



**TABLE 1** Summary statistics: characteristics of participants in risk game

| Variable | Description | Mean | Std. Dev. |
|---|---|---|---|
| Age | Age in years | 43.70 | 16.04 |
| Female | Gender dummy = 1 if Female, 0 otherwise | .55 | .50 |
| Education | Education level. Ordinal: | 2.54 | 1.38 |
| = 0 | if never attended school | .05 | - |
| = 1 | if attended some elementary school | .13 | - |
| = 2 | if finished elementary school | .46 | - |
| = 3 | if attended some high school | .05 | - |
| = 4 | if finished high school | .23 | - |
| = 5 | if attended some college | .05 | - |
| = 6 | if finished college | .03 | - |
| Children | Number of children in the household | 1.12 | 1.23 |
| Household Size | Number of household members | 3.80 | 1.72 |
| Area | Area of total farming land (hectares) | 1.82 | 2.08 |
| Distance | Distance of farm to nearest commercial road (meters) | 291.55 | 631.20 |
| Rent | Dummy = 1 if respondent rents farmland | .12 | .33 |
| Nonfarm Employment | Dummy = 1 if respondent has nonfarm employment | .25 | .44 |
| Income | Income derived from farm and nonfarm activities. Ordinal: | 1.93 | 1.09 |
| = 1 | if 0 - 300 USD/month | .45 | - |
| = 2 | if 301 - 600 USD/month | .30 | - |
| = 3 | if 601 - 900 USD/month | .14 | - |
| = 4 | if 901 - 1,500 USD/month | .08 | - |
| = 5 | if > 1,500 USD/month | .03 | - |
| Irrigation | Dummy = 1 if respondent has access to irrigation system | .89 | .31 |
| Extension | Dummy = 1 if respondent has been visited by extension agent during the last year | .16 | .37 |
| Livestock | Dummy = 1 if respondent has dairy cattle | .88 | .32 |
| Observations | Total number of participants | 202 | |

The high proportion of women among participants (55%) aligns with the demographic characteristics of the area described above[18]. Moreover, high female participation reflects the gender relations in indigenous farming communities in the Andes. Women and men in these communities control the means and earnings of the agricultural production in an egalitarian manner, and there is a balance of power between wife and husband (Hamilton, 1998).

[18] The gender imbalance in the Ecuadorian Andes might be explained by the fact that women are less likely than men to be international migrants (Gray 2009).

## 4 | EMPIRICAL FRAMEWORK

### 4.1 | The risk perceptions model

An ordered probit model was used to examine how risk preferences influence CC risk perceptions. In the model, perceptions of risks of CC depend on risk aversion, loss aversion, and probability distortion. The ordered probit model containing individual-specific controls and the elicited PT risk parameters is given by:

$$y^*_i = \boldsymbol{X}_i'\beta + \boldsymbol{R}_i'\psi + u_i \quad i = 1, \dots, n \quad u_i \sim N(0, 1), \quad (6)$$

$i$ indexes participant $i$, $i = 1, \dots, n$ where $n$ is the study size; $y_i^*(-\infty < y_i^* < +\infty)$ is the underlying latent variable representing respondent $i$'s propensity to agree with a certain risk perception; $\boldsymbol{X}_i$ is a vector containing individual-specific controls relevant in explaining risk perceptions of climate change according to the literature (cognitive, experiential, socio-demographic, and socio-cultural factors); $\boldsymbol{R}_i$ is a vector containing individual-specific PT risk parameters elicited in the experiment; $\beta$ and $\psi$ are vectors of parameters, *not* including an intercept. The relationship between the unobserved (latent) $y_i^*$ and the observed variable $y_i$ (individual $i$'s response to the survey question concerning climate change risk perceptions) is given by:

$$y_i = 1 \; if -\infty < y_i^* < \kappa_1; \; y_i = 2 \; if \, \kappa_1 < y_i^* < \kappa_2;$$
$$y_i = 3 \; if \, \kappa_2 < y_i^* < +\infty, \tag{7}$$

where the parameters $\kappa_1$ and $\kappa_2$ are the threshold parameters, also known as "cut-points".

Individuals can characterize CC as a distant psychological risk, i.e., happening more to "other" people and places (Gifford et al., 2009; Leiserowitz, 2005; Spence et al., 2012). Due to this, recent studies assessing CC risk perceptions (van der Linden, 2015, 2017) have highlighted the importance of the distinction between personal (i.e., self-regarding) levels of risk judgments and societal (i.e., other-regarding) levels of risk judgments[19].

We differentiate and measure CC risk perceptions along these two dimensions of risk judgments. To evaluate CC as personal risk, participants were asked about *Crop Management Practices, Output Prices*, and *Input Prices (Costs)*. To evaluate climate change as a societal risk, participants were asked about their *Village*. Participants were asked if they think that "the effects of CC on their *Crop Management Practices*" will be *not important, slightly important, moderately important, important, or very important*. Risk perceptions take on a value of 1 for individuals who answered not important; a value of 2 for individuals who responded *slightly important, moderately important*, or *important;* and a value of 3 for *very important*. We argue that crop management practices, output prices, and input prices (costs) relate closely to personal levels of risk judgments as farmers deal with them regularly during their farming activities. On the other hand, the idea of the effect of climate change over the village implicitly involves the assessment of risk over other people[20], thus, it relates to judgments about societal risks. Using a scale of 1–3, overall risk perceptions of CC were reasonably high, with $\bar{y} = 2.54$ and $SD = .52$ for the case of crop management practices; $\bar{y} = 2.57$ and $SD = .54$ for case of output prices; $\bar{y} = 2.62$ and $SD = .50$ for case of input prices; and $\bar{y} = 2.39$ and $SD = .52$ for the case of the geographic location (village).

The influence of experiential factors (*personal experience*) in CC risk perceptions is captured by the inclusion of *Age*, as older farmers have more farming experience and have witnessed climatic phenomena for a longer time. Age is expected to be positively related to CC risk perceptions, meaning higher risk perceptions for older farmers. As it can be argued that younger people are more exposed to CC through schooling and social media, this cognitive factor is also controlled for.

The role of cognitive factors (*statistical description*) in perceptions of risk from CC is thought to have two components: general knowledge, measured by inclusion of *education*, and additional agricultural knowledge reflected by *Extension*. *Education* and *Extension* are expected to increase familiarity with climate change, and consequently, be positively related to the dependent variable.

The influence of socio-demographic factors is assumed to be captured by including *Income* as a control. This variable also tests the hypothesis that concerns for the environment increase with *Income*; the expected sign is positive (Tjernström & Tietenberg, 2008). Other individual/household characteristics included as controls are *Gender, Household Size, Area, Off-farm Job, Irrigation, Livestock*, and *Location fixed effects*. Their inclusion is justified on the grounds that socio-demographic and socio-cultural factors (i.e., Gender, Household size, Area, Location), as well as experiential factors (i.e., Off-farm Job, Irrigation, Livestock) influence perceptions of risk of climate change (van der Linden, 2015). They also control for variation in other subject-specific characteristics. This helps when testing for the effect of risk preferences on CC risk perceptions. In addition, various studies have reported interviewer effects, which tend to have stronger effects in subjective questions and among female respondents (Himelein, 2016; West & Blom, 2017). Since CC risk perception is a subjective concept *Interviewer fixed effects*[21] are also included.

The role of risk parameters in CC risk perceptions is hypothesized to emerge through the unique characteristics of PT—loss aversion and probability weighting. Following Liu (2013), to facilitate interpretation of the coefficient on probability distortion, we replace the value of $\alpha$ (probability distortion) with a dummy variable which is set equal to 1 to indicate individuals who overweight low probability outcomes ($\alpha < 1$), and 0 to indicate individuals who do not overweight low

[19] See Tyler and Cook (1984) for a discussion on the difference between self vs. other-regarding risk judgments.

[20] Judging risk over others is closely related to the concept of *optimism bias* and the erroneous belief that others are more likely to be impacted by the same risk one faces (Weinstein, 1989).

[21] We tested for the joint significance of the Interviewer fixed effects using a Likelihood Ratio Test. Results show Interviewer fixed effects are jointly significant at the .001% level in all models (See Section 6 in *Supporting Information*).

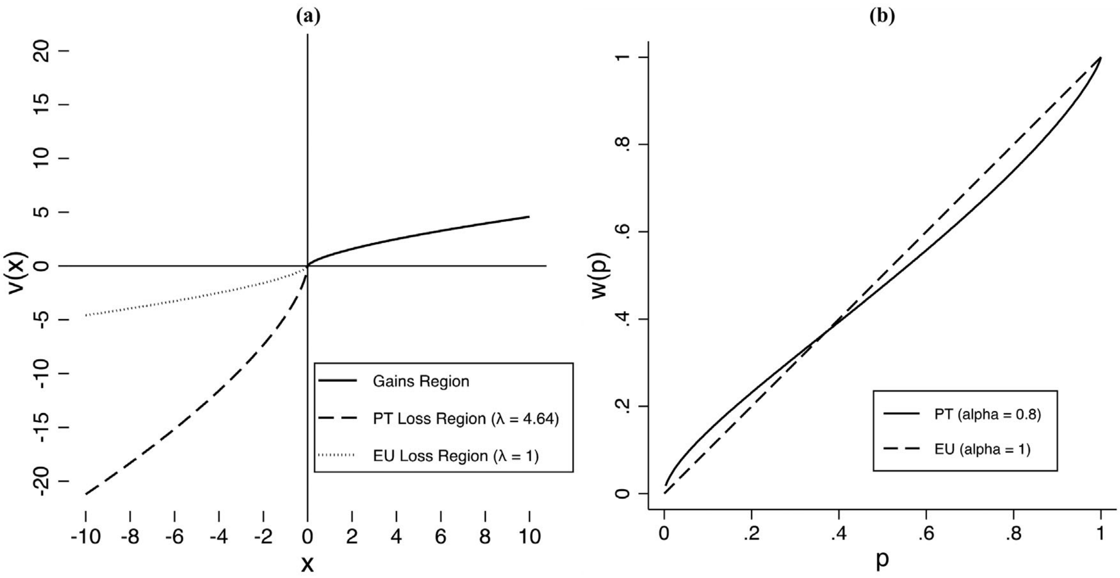



**FIGURE 3** PT value function (a) and PT weighting function (b)

probability outcomes ($\alpha \geq 1$). Likewise, we replace the value of $\lambda$ (loss aversion) with a dummy variable equal to 1 to indicate individuals who are loss averse ($\lambda > 1$), and 0 otherwise ($\lambda \leq 1$).

As previously discussed, loss aversion and its relationship to status quo bias might imply that the respondent neglects the existence of climate change when making decisions. Hence loss aversion ($\lambda$) is expected to be negatively related to a farmer's perception of CC risk. Correspondingly, the behavioral phenomenon of probability distortion can provide an explanation for the impact of extreme (low probability) weather events on CC risk perceptions. Probability distortion ($\alpha$) is expected to be positively related to CC risk perception; respondents who overweight probabilities are more likely to give a higher ranking to the risk associated with CC. The level of risk aversion $\sigma$ (value function curvature) is also included; it is expected to be negatively related to perceptions of CC risk. More risk-seeking farmers are less likely to give high rankings to the risk associated with CC.

## 5 | RESULTS AND DISCUSSION

### 5.1 | Descriptive analysis of PT parameters

Tanaka's et al. (2010) procedure was followed to estimate the structural parameters of the PT utility function. The average of $\sigma$ is .66, indicating that the average participant is risk-averse. The average of $\alpha$ is .80, suggesting that on average, people tend to overweight low probabilities. These results are close to the findings in the Vietnam farmer's subsample of Tanaka et al. (2010). The average of $\lambda$ in our sample is 4.64, indicating that people are more sensitive to losses than to gains, at a magnitude of 4 to 1. This result is close to the finding of Liu (2013) in China.

In Figure 3(a) we present the simulated PT value function $v(x)$ from Equation (4) for gains and losses using the estimates of $\sigma$ and $\lambda$. As expected, the shape of the PT utility in the gain's domain is concave, while it is convex in the loss domain. In addition, over the loss domain, the slope of the PT value function is steeper than in the gain domain; this is consistent with the original findings of Tversky and Kahneman (1992). For reference, we also plot in the loss region the value function using $\lambda = 1$, as this represents the case of an individual that would behave in accordance with the EU. In Figure 3(b) we present the PT weighting function $w(p)$ from Eq.(5) using the average estimate of $\alpha$. It shows individuals overestimate probabilities approximately under .35, and this overestimation increases as probabilities approach zero. Likewise, probabilities above .35 are underestimated, and most of the underestimation happens around .8. For reference, we also plot the objective probability weighting assumed by the EU ($\alpha = 1$).

The distributions of the parameters $\sigma$, $\alpha$, and $\lambda$ are shown in Figure 4. Results show the estimated mean values of $\alpha$ and $\lambda$ are significantly different from one at the .01% significance level, rejecting the EU in favor of PT. This suggests the PT utility function specification, along with the experimental design, describes the choices better than the standard EU function.

In accordance with the egalitarian structure of the society where the experiments took place, we found

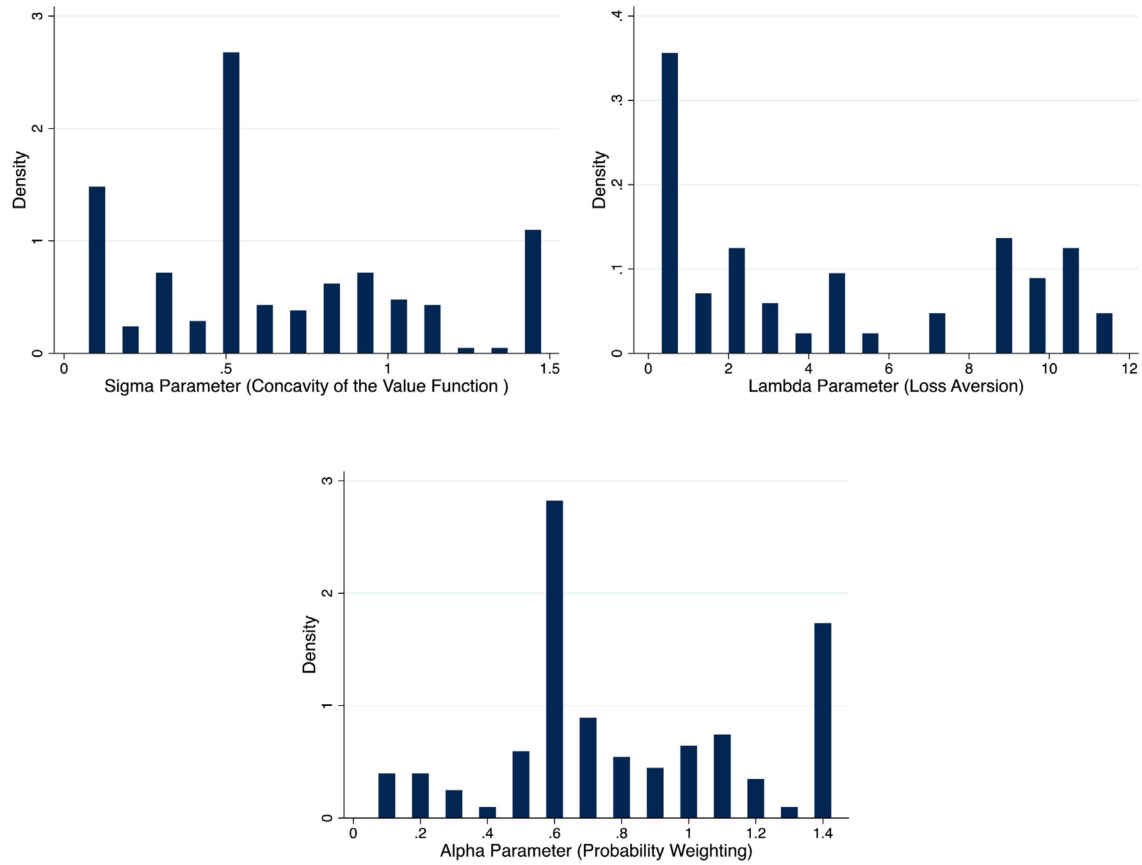



**FIGURE 4** Distribution of risk preference parameters [Color figure can be viewed at wileyonlinelibrary.com]

no statistical difference in the level of risk aversion by gender[22]. However, results showed the next differences across genders: (i) female participants were more loss averse than male participants on average ($\lambda_{female}$ = 4.80 vs. $\lambda_{male}$ = 3.77), and (ii) female participants distorted probability information less than males ($\alpha_{female}$ = .89 vs. $\alpha_{male}$ = .75).

## 5.2 | Empirical model estimates

Table 2 reports the marginal effects for the ordered probit estimates[23]. Individuals who distort probability information stated a higher CC risk perception over all the dependent variables. For example, the phenomenon of distorting probability information is associated with being 23.1% less likely to perceive the risks of climate change on *output prices* as being *important* and 23.5% more likely to perceive them as being *very important*. These results suggest that the incorrect assessment of probability information leads farmers to perceive the risk associated with climatic phenomena as more threatening. This phenomenon of probability distortion has a larger impact on the perceived risks of CC on *crop management practices* (31.4%), and a relatively smaller influence on the perceived risks of CC on the *village* (14.1%).

Individuals with higher values of $\sigma$ (curvature of the value function), that is, those who are less risk−averse[24], stated a lower perception of risk of CC *on crop management practices*. A one-unit increase in the $\sigma$ scale (a decrease in the level of risk aversion), is associated with being 36.7% more likely to perceive the risk of CC on *crop management practices* as *important* and being 36.7% less likely to

[22] It is common in the experimental literature to find that women are more risk averse than men (Croson & Gneezy, 2009; Eckel & Grossman, 2008). Interestingly, this relationship reverses in a matriarchal society (Gneezy et al., 2009). Section 5 in *Supporting Information* provides details of the mean values of the risk preference parameters by gender.

[23] Section 6 in *Supporting Information* provides a further discussion of the ordered probit estimates. Robustness checks included the model estimation using the full sample and interval-censored regressions. Results are qualitatively robust to these alternative model specifications.

[24] Similarly, being less risk averse can be interpreted as being more risk loving. This analysis corresponds to the gain's domain. In the loss domain, higher values of $\sigma$ are interpreted as being more risk averse (less risk loving).

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists
IAAE



**TABLE 2** Marginal effects of the determinants of risk perceptions of climate change

| | Crop Mngt. practices | Output prices | Input prices | Village |
|---|---|---|---|---|
| Marginal effect on Prob. ($y_i = 2$) | | | | |
| $\sigma$ (Value function curvature) | .367*** | .196* | .039 | .102 |
| $\lambda > 1$ (Loss aversion) | −.105 | −.068 | −.016 | −.139* |
| $\alpha < 1$ (Probability distortion) | −.314*** | −.231*** | −.192** | −.141* |
| Education = 3 | −.518** | .114 | .203 | .099 |
| Education = 4 | −.486** | .041 | .112 | −.061 |
| Education = 5 | −.446* | −.121 | −.117 | −.212 |
| Education = 6 | −.651*** | −.102 | −.116 | −.453** |
| Marginal effect on Prob. ($y_i = 3$) | | | | |
| $\sigma$ (Value function curvature) | −.367*** | −.199* | −.039 | −.104 |
| $\lambda > 1$ (Loss aversion) | .105 | .069 | .016 | .142* |
| $\alpha < 1$ (Probability distortion) | .314*** | .235*** | .193** | .144* |
| Education = 3 | .519** | −.115 | −.204 | −.102 |
| Education = 4 | .487** | −.041 | −.113 | .061 |
| Education = 5 | .448* | .121 | .117 | .213 |
| Education = 6 | .653*** | .103 | .116 | .456** |

*Notes*: Marginal effects calculated at mean values of independent variables. Asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Marginal effects on Prob. ($y_i = 1$) not shown as none of the variables was statistically significant for this category.

perceive it as *very important*. This result suggests that risk-seeking farmers perceive CC risk as less threatening to outcomes associated with specific agricultural practices. Literature indicates that less risk-averse farmers are more willing to adopt new agricultural technologies (e.g., Feder, 1980; Feder et al., 1985). A similar but lesser pronounced effect of $\sigma$ is also observed for the case of the perceived risks of CC over *output prices*.

Contrary to the initial hypothesis, loss-averse individuals stated a higher perception of risk of CC to their *village*. Loss-averse individuals are 13.9% less likely to perceive that risks of CC to their village are *important* and 14.2% more likely to perceive it as very *important*. One possible explanation is that people might feel a close affinity for their village, and this is reflected in their measure of loss aversion.

Education is significantly associated with the perceived risks of CC related to outcomes of *crop management practices*. More educated individuals state a higher perception of risk of CC to this outcome. Being older and having a higher income does not translate into a greater perception of the risks associated with CC. Surprisingly, the variable Extension was not statistically significant in the model. This may be because INIAP just began its extension program in the study area at the time of the experiments. In addition, only a small proportion of farmers in the sample (16%) claimed to have been visited by extension agents recently. This may have caused this parameter to be poorly identified.

Behavior elicited from the PT experiment was statistically significant in every model reported in Table 2. In general terms, results indicate that individuals who distort probabilities were more likely to give higher rankings to CC risk perceptions over personal risk judgments. This impact of probability distortion is less pronounced on the perceived risks of CC on judgments of risk to society (the village outcome). A plausible explanation is that the impact of extreme weather events on crops and agricultural prices is more visible or of immediate concern to farmers.

Risk-loving individuals were less likely to give higher rankings to CC risk perceptions on *crop management practices*. Status quo bias, as represented by the variable $\lambda$ (Loss aversion), does not appear to explain risk perceptions of climate change. The findings suggest that farmers who perceive prospective losses greater than equivalent prospective gains are more likely to perceive risks of climate change to their *geographic location (village)*.

Lastly, none of the control variables was consistently significant across the models. This pattern of results deserves further scrutiny, but it presents evidence suggesting PT parameters help with the distinction between societal and personal risk judgments when it comes to the evaluation of CC risk perceptions of farmers. This evidence agrees with the findings of van der Linden (2015).

## 6 | SUMMARY AND CONCLUDING REMARKS

This article explores how elicited farmers' risk preferences correlate with their perceptions of risk from CC. This research varies from previous papers in that it is the first empirical study offering evidence that Prospect Theory can be used as a mediating mechanism to explain the relationship between risk preferences and individual risk perceptions. It also contributes to the existing literature on climate change.

Findings show that farmers who distort probability information are more likely to state higher perception of risks related to climate change. Education is also significantly related to the perceptions of risk from CC, specifically, on crop management practices. The relationship between education and CC risk perceptions highlights the importance of the role of *cognitive* factors and confirm the findings of Maddison (2007), Nyanga et al. (2011), O'Connor et al. (1999), and Shi et al. (2016).

Our findings constitute *prima facie* evidence suggesting risk preferences, as measured in this study, influence perceptions of risk of climate change. As extensively argued in the literature, it may be most effective to change risky choice behavior by enhancing individuals' perception of the riskiness of a situation (Cooper et al., 1988; Sitkin & Weingart, 1995; Weber & Milliman, 1997). Therefore, identifying the extent to which perceptions of risk of CC can be influenced is of importance for designing and executing policies aiming at mitigating effects of climate change. Policy interventions to improve access to information and education would do most to affect CC risk perceptions and stimulate adoption of adaptation strategies. Thus, provision of agricultural extension services containing education material related to CC can facilitate the process of agricultural development. Interventions to promote adaptation practices should consider the parallel facilitation of accurate long-term weather information and other advice related to climate change. Although extension services are limited in Ecuador and throughout Latin America, these can be effective facilitators for nudging farmers' behavior.

An important caveat of this article is that the findings presented here do not challenge the importance of cognitive, experiential, socio-demographic, and socio-cultural factors, and how they influence perceptions of CC risk. Instead, results highlight the role of individual risk preferences in forming risk perceptions, as theorized by Sitkin and Pablo (1992). It is possible that subjects who behave in accordance with EU might structurally differ in their perceptions of risk of climate change when compared to those who behave in accordance with PT. This topic deserves further scrutiny, unfortunately, the risk preferences of the participants of our experiment do not let us test this hypothesis. Alternatively, risk taking behavior could also be assessed using sensation-seeking scales like the Domain-Specific Risk-Taking Scale (DOSPERT). Future research can compare which of these methods and theories better explains the behavior of subjects towards CC risk perceptions. Similarly, plant physiological responses to climate change, production costs and agricultural practices can vary substantially across crops, and could lead farmers to have context-dependent risk preferences and CC risk perceptions. Future research can explore these potential differences and make customized policy recommendations based on context specifics.

Our study did not control for the "recency effect", for example, the recent occurrence of a rare weather event, as it can also influence perceptions of climate change risk (Li et al., 2011; Marx et al., 2007; Weber & Stern, 2011). It also did not explore the role of time preferences and how they might impact risk perceptions. As discussed in the literature, temporal discounting influences how people evaluate future risks against present risks (Trope & Liberman, 2010). Likewise, our study did not investigate the effects of remittances and social safety nets. These could act as informal insurance, allowing farmers take more risky decisions, and hence impacting the perceptions of climate change risk. Future research should examine these avenues as they likely influence perceptions of climate-related phenomena.

Although the external validity of the results needs to be verified, our results show that risk preferences are significantly associated with risk perceptions in the context of climate change. Hence, the findings presented here can also have important implications for empirical studies that use both risk preferences and perceptions to predict certain behaviors, including adoption decisions. Causal inference and identification strategies might need to account for this correlation, as risk preferences might affect both risk perceptions and observed risky behavior.

## DATA APPENDIX AVAILABLE ONLINE

A data appendix to replicate the main results is available in the online version of this article. Please note: Wiley-Blackwell is not responsible for the content or functionality of any supporting information supplied by the authors. Any queries (other than missing material) should be directed to the corresponding author for the article.

### ACKNOWLEDGMENTS

The authors thank personnel from the Ecuadorian Institute of Agricultural Research (INIAP) for help in the data collection. We are very grateful to Ashok Mishra as well as various colleagues at Arizona State University, Virginia

Tech, Texas A&M, and University of Minnesota for useful comments and suggestions. The article also benefitted greatly from the comments of two anonymous journal reviewers. All remaining errors are ours.

## REFERENCES

Anand, M., Miao, R., & Khanna, M. (2019). Adopting bioenergy crops: Does farmers' attitude toward loss matter? *Agricultural Economics*, *50*(4), 435–450. https://doi.org/10.1111/agec.12501

Antle, J. M. (1987). Econometric estimation of producers' risk attitudes. *American Journal of Agricultural Economics*, *69*(3), 509–522. https://doi.org/10.2307/1241687

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

Bocquého, G., Jacquet, F., & Reynaud, A. (2014). Expected utility or prospect theory maximisers? Assessing farmers' risk behaviour from field-experiment data. *European Review of Agricultural Economics*, *41*(1), 135–172. https://doi.org/10.1093/erae/jbt006

Bryan, E., Deressa, T. T., Gbetibouo, G. A., & Ringler, C. (2009). Adaptation to climate change in Ethiopia and South Africa: Options and constraints. *Environmental Science & Policy*, *12*(4), 413–426. https://doi.org/10.1016/j.envsci.2008.11.002

Camerer, C. F., & Hogarth, R. M. (1999). The effects of financial incentives in experiments: A review and capital-labor-production framework. *Journal of Risk and Uncertainty*, *19*(1), 7–42. https://doi.org/10.1023/A:1007850605129

Cárdenas, J. C. (2016). Human behavior and the use of experiments to understand the agricultural, resource, and environmental challenges of the XXI century: J. C. Cárdenas. *Agricultural Economics*, *47*(S1), 61–71. https://doi.org/10.1111/agec.12311

Chaiken, S., & Trope, Y. (1999). *Dual-process Theories in Social Psychology*. Guilford Press.

Charness, G., Gneezy, U., & Imas, A. (2013). Experimental methods: Eliciting risk preferences. *Journal of Economic Behavior & Organization*, *87*, 43–51. https://doi.org/10.1016/j.jebo.2012.12.023

Cooper, A. C., Woo, C. Y., & Dunkelberg, W. C. (1988). Entrepreneurs' perceived chances for success. *Journal of Business Venturing*, *3*(2), 97–108. https://doi.org/10.1016/0883-9026(88)90020-1

Croson, R., & Gneezy, U. (2009). Gender differences in preferences. *Journal of Economic Literature*, *47*(2), 448–474. https://doi.org/10.1257/jel.47.2.448

Deressa, T. T., Hassan, R. M., & Ringler, C. (2011). Perception of and adaptation to climate change by farmers in the Nile basin of Ethiopia. *The Journal of Agricultural Science*, *149*(1), 23–31. https://doi.org/10.1017/S0021859610000687

Deressa, T. T., Hassan, R. M., Ringler, C., Alemu, T., & Yesuf, M. (2009). Determinants of farmers' choice of adaptation methods to climate change in the Nile Basin of Ethiopia. *Global Environmental Change*, *19*(2), 248–255. https://doi.org/10.1016/j.gloenvcha.2009.01.002

Eckel, C. C., & Grossman, P. J. (2008). Chapter 113 men, women and risk aversion: Experimental evidence. In C. R. Plott & V. L. Smith (Eds.), *Handbook of Experimental Economics Results* (Vol., 1, pp. 1061–1073). Elsevier. https://doi.org/10.1016/S1574-0722(07)00113-8

Epstein, S. (1994). Integration of the cognitive and the psychodynamic unconscious. *American Psychologist*, *49*(8), 709–724. https://doi.org/10.1037/0003-066X.49.8.709

Erev, I., & Barron, G. (2005). On adaptation, maximization, and reinforcement learning among cognitive strategies. *Psychological Review*, *112*(4), 912–931. https://doi.org/10.1037/0033-295X.112.4.912

Feder, G. (1980). Farm size, risk aversion and the adoption of new technology under uncertainty. *Oxford Economic Papers*, *32*(2), 263–283. JSTOR.

Feder, G., Just, R. E., & Zilberman, D. (1985). Adoption of agricultural innovations in developing countries: A Survey. *Economic Development and Cultural Change*, *33*(2), 255–298. https://doi.org/10.1086/451461

Feng, H., Du, X., & Hennessy, D. A. (2020). Depressed demand for crop insurance contracts, and a rationale based on third generation Prospect Theory. *Agricultural Economics*, *51*(1), 59–73. https://doi.org/10.1111/agec.12541

Franken, J. R. V., Pennings, J. M. E., & Garcia, P. (2014). Measuring the effect of risk attitude on marketing behavior. *Agricultural Economics*, *45*(5), 525–535. https://doi.org/10.1111/agec.12104

Galarza, F. (2009). Choices under risk in rural Peru. *Staff Paper - Agricultural and Applied Economics*, University of Wisconsin-Madison, No.542. https://www.cabdirect.org/cabdirect/abstract/20103205264

Garner, W. R., Hake, H. W., & Eriksen, C. W. (1956). Operationism and the concept of perception. *Psychological Review*, *63*(3), 149–159. https://doi.org/10.1037/h0042992

Ghadim, A. K. A., Pannell, D. J., & Burton, M. P. (2005). Risk, uncertainty, and learning in adoption of a crop innovation. *Agricultural Economics*, *33*(1), 1–9. https://doi.org/10.1111/j.1574-0862.2005.00433.x

Gifford, R., Scannell, L., Kormos, C., Smolova, L., Biel, A., Boncu, S., Corral, V., Güntherf, H., Hanyu, K., Hine, D., Kaiser, F. G., Korpela, K., Lima, L. M., Mertig, A. G., Mira, R. G., Moser, G., Passafaro, P., Pinheiro, J. Q., Saini, S., … Uzzell, D. (2009). Temporal pessimism and spatial optimism in environmental assessments: An 18-nation study. *Journal of Environmental Psychology*, *29*(1), 1–12. https://doi.org/10.1016/j.jenvp.2008.06.001

Gneezy, U., Leonard, K., & List, J. (2009). Gender differences in competition: Evidence from a matrilineal and a patriarchal society. *Econometrica*, *77*(5), 1637–1664. https://doi.org/10.3982/ECTA6690

Gobierno Autónomo Descentralizado Parroquial Rural Quimiag. (2015). *Plan de Desarrollo y Ordenamiento Territorial Diagnóstico 2015*. Retrieved March 30, 2020, from http://app.sni.gob.ec/sni-link/sni/PORTAL_SNI/data_sigad_plus/sigadplusdiagnostico/0660821990001_Diagnostico_24-06-2015_22-18-04.pdf

Hamilton, S. (1998). *The two-headed household: Gender and rural development in the Ecuadorean Andes*. University of Pittsburgh Press.

Hansen, J. W., Marx, S. M., & Weber, E. U. (2004). *The Role of Climate Perceptions, Expectations, and Forecasts in Farmer Decision Making: The Argentine Pampas and South Florida: Final Report of an IRI Seed Grant Project*. Retrieved March 01, 2020, from https://academiccommons.columbia.edu/doi/10.7916/D8N01DC6

Helgeson J., van der Linden, S., & Chabay, I. A. Wals & P. Corcoran (Eds). (2012). The role of knowledge, learning and mental models in public perceptions of climate change related risks. *Learning for sustainability in times of accelerating* *change* (pp. 329–346). The Netherlands: Wageningen Academic Publishers.

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

Himelein, K. (2016). Interviewer effects in subjective survey questions: Evidence from Timor-Leste. *International Journal of Public Opinion Research*, *28*(4), 511–533. https://doi.org/10.1093/ijpor/edv031

Jost John T., Hunyady Orsolya (2005). Antecedents and Consequences of System-Justifying Ideologies. *Current Directions in Psychological Science*, *14*, (5), 260–265. https://doi.org/10.1111/j.0963-7214.2005.00377.x.

Kahneman, D., Knetsch, J. L., & Thaler, R. H. (1991). Anomalies: The endowment effect, loss aversion, and status quo bias. *Journal of Economic Perspectives*, *5*(1), 193–206. https://doi.org/10.1257/jep.5.1.193

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*(1), 263–291.

Kahneman, D., & Tversky, A. (1984). Choices, values, and frames. *American Psychologist*, *39*(4), 341–350. https://doi.org/10.1037/0003-066X.39.4.341

Kallas, Z., Serra, T., & Gil, J. M. (2010). Farmers' objectives as determinants of organic farming adoption: The case of Catalonian vineyard production. *Agricultural Economics*, *41*(5), 409–423. https://doi.org/10.1111/j.1574-0862.2010.00454.x

Lange, A. (2003). Climate change and the irreversibility effect – combining expected utility and maximin. *Environmental and Resource Economics*, *25*(4), 417–434. https://doi.org/10.1023/A:1025054716419

Lange, A., & Treich, N. (2008). Uncertainty, learning and ambiguity in economic models on climate policy: Some classical results and new directions. *Climatic Change*, *89*(1), 7–21. https://doi.org/10.1007/s10584-008-9401-5

Lee, T. M., Markowitz, E. M., Howe, P. D., Ko, C.-Y., & Leiserowitz, A. (2015). Predictors of public climate change awareness and risk perception around the world. *Nature Climate Change*, *5*(11), 1014–1020. https://doi.org/10.1038/nclimate2728

Leiserowitz, A. (2005). American risk perceptions: Is climate change dangerous? *Risk Analysis*, *25*(6), 1433–1442. https://doi.org/10.1111/j.1540-6261.2005.00690.x

Leiserowitz, A. (2007). *International Public Opinion, Perception, and Understanding of Global Climate Change* (Human Development Report 2008, pp. 1–40). https://core.ac.uk/download/pdf/6248846.pdf

Li, Y., Johnson, E. J., & Zaval, L. (2011). Local warming: daily temperature change influences belief in global warming. *Psychological Science*, *22*(4), 454–459. https://doi.org/10.1177/0956797611400913

Liebenehm, S., & Waibel, H. (2014). Simultaneous estimation of risk and time preferences among small-scale cattle farmers in West Africa. *American Journal of Agricultural Economics*, *96*(5), 1420–1438. https://doi.org/10.1093/ajae/aau056

Liu, E. M. (2013). Time to change what to sow: Risk preferences and technology adoption decisions of cotton farmers in China. *The Review of Economics and Statistics*, *95*(4), 1386–1403. https://doi.org/10.1162/REST_a_00295

Lusk, J., & Coble, K. (2005). Risk perceptions, risk preference, and acceptance of risky food. *American Journal of Agricultural Economics*, *87*(2), 393–405. https://doi.org/10.1111/j.1467-8276.2005.00730.x

Lusk, J., Schroeder, T. C., & Tonsor, G. T. (2014). Distinguishing beliefs from preferences in food choice. *European Review of Agricultural Economics*, *41*(4), 627–655. https://doi.org/10.1093/erae/jbt035

Maddison, D. (2007). *The Perception Of And Adaptation To Climate Change In Africa*. The World Bank. https://doi.org/10.1596/1813-9450-4308

Magnan, N., Love, A. M., Mishili, F. J., & Sheremenko, G. (2020). Husbands' and wives' risk preferences and improved maize adoption in Tanzania. *Agricultural Economics*, *51*(5), 743–758. https://doi.org/10.1111/agec.12589

Marx, S. M., Weber, E. U., Orlove, B. S., Leiserowitz, A., Krantz, D. H., Roncoli, C., & Phillips, J. (2007). Communication and mental processes: Experiential and analytic processing of uncertain climate information. *Global Environmental Change*, *17*(1), 47–58. https://doi.org/10.1016/j.gloenvcha.2006.10.004

Moscardi, E., & Janvry, A. de. (1977). Attitudes toward risk among peasants: An econometric approach. *American Journal of Agricultural Economics*, *59*(4), 710–716. https://doi.org/10.2307/1239398

Mulenga, B. P., Wineman, A., & Sitko, N. J. (2017). Climate trends and farmers' perceptions of climate change in Zambia. *Environmental Management*, *59*(2), 291–306. https://doi.org/10.1007/s00267-016-0780-5

Nyanga Progress H, Johnsen Fred H, Aune Jens B, Kalinda Thomson H (2011). Smallholder Farmers' Perceptions of Climate Change and Conservation Agriculture: Evidence from Zambia. *Journal of Sustainable Development*, *4*(4), https://doi.org/10.5539/jsd.v4n4p73.

O'Connor, R. E., Bard, R. J., & Fisher, A. (1999). Risk perceptions, general environmental beliefs, and willingness to address climate change. *Risk Analysis*, *19*(3), 461–471. https://doi.org/10.1111/j.1539-6924.1999.tb00421.x

Pittelkow, C. M., Liang, X., Linquist, B. A., van Groenigen, K. J., Lee, J., Lundy, M. E., van Gestel, N., Six, J., Venterea, R. T., & van Kessel, C. (2015). Productivity limits and potentials of the principles of conservation agriculture. *Nature*, *517*(7534), 365–368. https://doi.org/10.1038/nature13809

Prelec, D. (1998). The probability weighting function. *Econometrica*, *66*(3), 497–527. JSTOR. https://doi.org/10.2307/2998573

Rosa, E. (2003). The logical structure of the social amplification of risk framework (SARF): Meta-theoretical foundations and policy implications. In N. Pidgeon, R. E. Kasperson, & P. Slovic (Eds.), *The social amplification of risk* (pp. 47–49). Cambridge University Press. HHUhttps://doi.org/10.1017/CBO9780511550461.003U

Samuelson, W., & Zeckhauser, R. (1988). Status quo bias in decision making. *Journal of Risk and Uncertainty*, *1*(1), 7–59. https://doi.org/10.1007/BF00055564

Shi, J., Visschers, V. H. M., Siegrist, M., & Arvai, J. (2016). Knowledge as a driver of public perceptions about climate change reassessed. *Nature Climate Change*, *6*(8), 759–762. https://doi.org/10.1038/nclimate2997

Silvestri, S., Bryan, E., Ringler, C., Herrero, M., & Okoba, B. (2012). Climate change perception and adaptation of agro-pastoral communities in Kenya. *Regional Environmental Change*, *12*(4), 791–802. https://doi.org/10.1007/s10113-012-0293-6

Sitkin, S. B., & Pablo, A. L. (1992). Reconceptualizing the determinants of risk behavior. *The Academy of Management Review*, *17*(1), 9–38. JSTOR. https://doi.org/10.2307/258646

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). The methodology of risk perception research. *Quality and Quantity*, *34*(4), 407–418. https://doi.org/10.1023/A:1004838806793

Sloman, S. A. (1996). The empirical case for two systems of reasoning. *Psychological Bulletin*, *119*(1), 3–22. https://doi.org/10.1037/0033-2909.119.1.3

Spence, A., Poortinga, W., & Pidgeon, N. (2012). The Psychological Distance of Climate Change. *Risk Analysis*, *32*(6), 957–972. https://doi.org/10.1111/j.1539-6924.2011.01695.x

Tanaka, T., Camerer, C. F., & Nguyen, Q. (2010). Risk and time preferences: Linking experimental and household survey data from Vietnam. *American Economic Review*, *100*(1), 557–571. https://doi.org/10.1257/aer.100.1.557

Thaler, R. (1980). Toward a positive theory of consumer choice. *Journal of Economic Behavior & Organization*, *1*(1), 39–60. https://doi.org/10.1016/0167-2681(80)90051-7

Tjernström, E., & Tietenberg, T. (2008). Do differences in attitudes explain differences in national climate change policies? *Ecological Economics*, *65*(2), 315–324. https://doi.org/10.1016/j.ecolecon.2007.06.019

Tranter, B. (2013). The great divide: Political candidate and voter polarisation over global warming in Australia. *Australian Journal of Politics & History*, *59*(3), 397–413. https://doi.org/10.1111/ajph.12023

Trope, Y., & Liberman, N. (2010). Construal-level theory of psychological distance. *Psychological Review*, *117*(2), 440–463. https://doi.org/10.1037/a0018963

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

Tyler, T. R., & Cook, F. L. (1984). The mass media and judgments of risk: Distinguishing impact on personal and societal level judgments. *Journal of Personality and Social Psychology*, *47*(4), 693–708. https://doi.org/10.1037/0022-3514.47.4.693

Uddin, M. N., Bokelmann, W., & Dunn, E. S. (2017). Determinants of farmers' perception of climate change: A case study from the coastal region of Bangladesh. *American Journal of Climate Change*, *6*(1), 151–165. https://doi.org/10.4236/ajcc.2017.61009

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 der Linden, S. (2017). *Determinants and Measurement of Climate Change Risk Perception, Worry, and Concern* (SSRN Scholarly Paper ID 2953631). Social Science Research Network. https://doi.org/10.2139/ssrn.2953631

Vollmer, E., Hermann, D., & Musshoff, O. (2019). The disposition effect in farmers' selling behavior: An experimental investigation. *Agricultural Economics*, *50*(2), 177–189. https://doi.org/10.1111/agec.12475

Waterfield, G., Kaplan, S., & Zilberman, D. (2020). Willingness to pay versus willingness to vote: Consumer and voter avoidance of genetically modified foods. *American Journal of Agricultural Economics*, *102*(2), 505–524. https://doi.org/10.1002/ajae.12001

Weber, E. U. (2010). What shapes perceptions of climate change? *WIREs Climate Change*, *1*(3), 332–342. https://doi.org/10.1002/wcc.41

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

Weber, E. U., & Stern, P. C. (2011). Public understanding of climate change in the United States. *American Psychologist*, *66*(4), 315–328. https://doi.org/10.1037/a0023253

Weinstein, N. D. (1989). Optimistic biases about personal risks. *Science (New York, N.Y.)*, *246*(4935), 1232–1233. https://doi.org/10.1126/science.2686031

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

Xie, B., Brewer, M. B., Hayes, B. K., McDonald, R. I., & Newell, B. R. (2019). Predicting climate change risk perception and willingness to act. *Journal of Environmental Psychology*, *65*, 101331. https://doi.org/10.1016/j.jenvp.2019.101331

Yechiam, E., Barron, G., & Erev, I. (2005). The role of personal experience in contributing to different patterns of response to rare terrorist attacks. *Journal of Conflict Resolution*, *49*(3), 430–439. https://doi.org/10.1177/0022002704270847

Zhao, S., & Yue, C. (2020). Risk preferences of commodity crop producers and specialty crop producers: An application of prospect theory. *Agricultural Economics*, *51*(3), 359–372. https://doi.org/10.1111/agec.12559

## SUPPORTING INFORMATION

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

**How to cite this article:** Villacis, A. H., Alwang, J. R., & Barrera, V. Linking risk preferences and risk perceptions of climate change: A prospect theory approach. *Agricultural Economics*. 2021*52:*; 863–877. https://doi.org/10.1111/agec.12659