Environment for Development

Discussion Paper Series

October 2019 ■ EfD DP 19-21

Alternatives for Risk Elicitation in the Field

Evidence from Coffee Farmers in Costa Rica

Maria A. Naranjo, Francisco Alpízar, and Peter Martinsson

The Environment for Development (EfD) initiative is an environmental economics program focused on international research collaboration, policy advice, and academic training. Financial support is provided by the Swedish International Development Cooperation Agency (Sida). Learn more at www.efdinitiative.org or contact info@efdinitiative.org.

Central America
Research Program in Economics and Environment for Development in Central America Tropical Agricultural Research and Higher Education Center (CATIE)

Chile
Research Nucleus on Environmental and Natural Resource Economics (NENRE)
Universidad de Concepción

China
Environmental Economics Program in China (EEPC)
Peking University

Colombia
The Research Group on Environmental, Natural Resource and Applied Economics Studies (REES-CEDE), Universidad de los Andes, Colombia

Ethiopia
Environment and Climate Research Center (ECRC)

Ghana
The Environment and Natural Resource Research Unit, Institute of Statistical, Social and Economic Research, University of Ghana, Accra

India
Centre for Research on the Economics of Climate, Food, Energy, and Environment, (CECFEE), at Indian Statistical Institute, New Delhi, India

Kenya
School of Economics
University of Nairobi

Nigeria
Resource and Environmental Policy Research Centre, University of Nigeria, Nsukka

South Africa
Environmental Economics Policy Research Unit (EPRU)
University of Cape Town

Sweden
Environmental Economics Unit
University of Gothenburg

Tanzania
Environment for Development Tanzania
University of Dar es Salaam

Uganda
EfD-Makera, School of Economics and Department of Agribusiness and Natural Resource Economics, Makerere University, Kampala

USA (Washington, DC)
Resources for the Future (RFF)

Vietnam
University of Economics
Ho Chi Minh City, Vietnam

Contents

Discussion papers are research materials circulated by their authors for purposes of information and discussion. They have not necessarily undergone formal peer review.

Alternatives for Risk Elicitation in the Field: Evidence from Coffee Farmers in Costa Rica

Maria A. Naranjo, Francisco Alpízar, and Peter Martinsson*

Abstract:

Although field experimental methods are the workhorse of researchers interested in risk preferences, practitioners find surveys easier to implement. This paper compares results from experimental versus survey-based methods to elicit farmers' risk attitudes, in context-free and context-specific decision settings. We then explore how the different survey estimates of risk preferences relate to real-life farming choices in a population of coffee farmers in Costa Rica. Our results indicate that one should be careful when extrapolating risk attitudes across contexts. Contextualized, survey-based estimates of risk preferences do not correlate with general context-free survey estimates, yet context-free survey estimates do predict risk-taking behavior in a context-free risk experiment. Importantly, context-specific survey estimates are associated with risk-taking in the same agricultural real-life context, while context-free survey estimates are not. Practitioners interested primarily in using risk preferences as inputs into policy design should make sure that preferences are elicited in the specific context targeted by the potential policy instrument.

Key Words: risk attitudes, risk elicitation methods, stated preference method, agriculture

JEL Codes: Q1; C9; C91; D81

---

*Maria A. Naranjo (corresponding author: maria.naranjo@wur.nl) and Francisco Alpízar, Wageningen University & Research, the Netherlands and Environment for Development Initiative (EfD) - CATIE, Costa Rica. Peter Martinsson, University of Gothenburg, Sweden.

1. Introduction

In an agricultural setting there is nothing like certainty. On a daily basis, farmers have to make decisions involving risk, from the choice of crops, use of inputs and timing of harvest, to the purchase of crop insurance and other strategies to cope with weather variation and price fluctuations. A good understanding of farmer's risk attitudes is needed in the context of development and agricultural programs, because the adoption or success of a given policy, which could include uptake of new crops, change in technology or purchase of crop insurance, varies with the target population's risk preferences (Barseghyan et al. 2018 and Viceisza 2016). Policy-makers and researchers need to collect information about risk attitudes to draw correct conclusions, which raises the question of how to best measure risk preferences for practical purposes.

The standard in the economics literature is the use of incentivized low-stakes experiments, where individual's choices have direct consequences for their earnings.[1] However, conducting similar risk experiments in the field as in a lab, for example with farmers, is costly, as well as cognitively and logistically complicated (Jacobson and Petrie 2009; Friedman et al. 2014) and with different general results (He at al., 2018). An alternative is to use stated preference data on risk attitudes collected via survey questionnaires, which are less expensive and easier to comprehend and apply to a more extensive population. However, based on the logic of induced value theory, stated preference can be criticized for not having direct consequences for respondents. Falk and Heckman (2009) summarize this discussion and argue that experiments and surveys are complements, and both have their pros and cons.

Risk experiments typically are conducted in a context-free environment, where individuals make decisions between different lotteries that have direct consequences for them. Experiments can vary regarding the elicitation method or choice task, whether they are framed in the loss or gain domain, probabilities, and stakes.[2] By contrast, survey methods often use Likert scales to elicit risk attitudes. Survey-based methods are typically more elaborative about the framing of the question, with context-specific questions regarding risk-taking in, for example, driving or health-related choices, often complemented by a general context-free assessment of willingness to take risk in general, as in Dohmen et al. (2011).

In this paper, we explore the performance of survey-based methods for eliciting risk attitudes in the field, as a relevant tool that can be easily implemented by practitioners and policy-makers in developing countries. We use a population of farmers in rural Costa Rica to first asses the correlations between a context-free survey estimate and context-specific survey estimates. We then test whether stated risk preferences are correlated with risk preferences obtained in an incentivized experiment. Finally, we test how the results from survey-based and

[1] See discussion on induced value theory in, e.g., Smith (1976).
[2] See Jamison et al. (2012) and Harrison and Rutström (2008) for a complete review on risk elicitation methods.

incentivized experiments on risk attitudes relate to real-life farming choices. This paper makes two major contributions to the literature. First, it contributes to the under-researched issue of the extent to which survey risk preferences are stable across contexts (Barseghyan et al. 2018). We combine survey and experimental settings to gain insight into whether differences in context affect whether and how risk estimates can be directly applied to make real-life predictions. Second, our paper contributes to the literature on the role that lab in the field experiments play in informing policymaking, and the nature of different empirical methods to estimate parameters associated with key characteristics such as risk preferences (Viceisza 2016).

Our findings can be summarized as follows. First, we find that risk preferences obtained in context-free versus contextualized survey estimates are not consistent. Second, survey-based risk-taking attitudes estimated without a context are good predictors of behavior in the context-free setting of a risk experiment. We dig deeper and explore how the survey-based estimate of willingness to take risk relates to the utility function parameters obtained experimentally. Higher *stated* willingness to take risk is associated with less pessimism, less sensitivity to changes in probabilities that increase the likelihood of a loss, and more loss aversion. Third, we explore how stated, i.e., survey-based risk preferences relate to real life decisions involving risk, and find that context matters: context-free survey estimates of risk-taking are not associated with actual risk-taking behavior in the agricultural setting, but when risk attitudes are elicited in a specific context, we do find a relationship with real-life farming choices. Higher willingness to take risk is associated with the implementation of agricultural practices that require more farm investment. In contrast, farmers who report less willingness to take risks are more likely to have higher expenditures in fertilizer use. This last result is consistent with studies showing that applying fertilizer reduces the risk of pests and low yields in coffee farming in Central America (Avelino et al. 2015), but we recognize the effect can be crop and input specific.

Researchers and practitioners should be careful when extrapolating risk attitudes across contexts and should try to estimate risk preferences in the specific context in which they are interested. For general financial decisions, the estimation of risk preferences without a context might be sufficient, but if the analysis focuses on evaluating policies targeting a specific technology or input (e.g., fertilizer use or implementation of improved seed varieties), risk preferences should be elicited in that particular context.

The rest of this paper is organized as follows. The next section describes our conceptual framework and hypotheses. The third section describes the study area, the sample selection, and the fieldwork implementation. Section four explains the methods, including the experimental design and modeling approach. Section five presents the results, and the last section concludes the paper.

2. Conceptual Framework and Hypotheses

We divide our analysis into three sets of research questions. First, we investigate whether risk attitudes are consistent in context-free versus context-specific survey elicitation formats. Second, we test whether the context-free survey estimate predicts risk-taking behavior in an incentivized experiment. Third, we investigate how different survey-based estimates of risk attitudes relate to real-life farming choices. In this section, we describe our theoretical considerations and develop our hypotheses, supported by a review of previous studies.

2.1 Consistency of Risk Attitudes Across Context

We begin by investigating whether we can use one general survey-based measure of risk preferences to characterize risk-taking in different contexts, and in agriculture in particular. If that is the case, adding a simple question to a questionnaire can help practitioners characterize risk attitudes.

Some studies have found that risk attitudes or preferences are stable across different contexts (Dohmen et al. 2011; Vieider et al. 2015; Einav et al. 2012). On the other hand, Lönnqvist et al. (2014) and Barseghyan et al. (2011) do not find a link between context-free and context-specific risk preferences. Hence, evidence is still mixed. More importantly, studies have used subjects from developed countries or student samples in a controlled lab setting, neither of which can be considered a standard population (Henrich, Heine and Norenzayan 2010), particularly if the purpose is to extrapolate those results to the developing world.[3]

In this study, we present an extension to Dohmen et al. (2011) by applying their survey structure to income-generating decisions,[4] using a population of developing country farmers. Questions are framed as willingness to take risk in a setting (i) with no context, (ii) with a financial context, (iii) with a general agricultural context, and (iv) with three agriculture-specific contexts: changing or diversifying crops, changing coffee varieties, and applying farm inputs such as fertilizer and pest control.

If survey-based estimates for willingness to take risk in different contexts are correlated with the general survey-based estimate of risk, then we can conclude that stated risk preferences are transferable or consistent across specific contexts. Otherwise, a principal component analysis can be applied to identify whether we can group risk preferences into different groups depending on the context used to elicit them. In other words, we test the following hypothesis:

---

[3] Dohmen et al. (2011) used the German Socio-Economic Panel to compare stated risk attitudes in the survey to responses in real-stakes lotteries. Lönnqvist et al. (2014) conducted the experiment at the Laboratory for Experimental Economics in Bonn. Barseghyan et al. (2011) and Einav et al. (2012) used data from the United States and Vieider et al. (2015) applied controlled lab experiments with students in 30 countries who also responded to a series of survey stated preference questions.

[4] Dohmen et al. (2011) studied the stability of risk attitudes across six contexts: general, car driving, financial matters, sports and leisure, career, and health. These contexts do not relate to specific decisions in the main income activity of a household.

H1: there is a correlation between survey-based, i.e., stated willingness to take risks in general, and stated willingness to take risks in specific contexts. Note that rejecting the hypothesis might be the result of two potential situations. One is a methodological problem, whereby one could argue that stated risk preferences are inadequate measures of true preferences. Alternately, one could argue that risk preferences differ between contexts.

2.2 Experimental Validation of Survey Estimates

Irrespective of the model of risk preferences assumed by the researcher,[5] risk experiments are typically designed without a context: individuals make decisions between simple lotteries. Experimental designs vary on type of elicitation format (choices between two lotteries or between a lottery and a safe alternative, payoffs framed in the loss or gain domain, size of the payoff, and probabilities. For example, some experiments offer options over gambles that increase in expected value (Binswanger 1980; Cardenas and Carpenter 2013). Others elicit certainty equivalents of fixed bets (Henrich and McElreath 2002) or offer a series of paired lotteries to obtain prospect theory parameters (e.g., Tanaka, Camerer, and Nguyen 2010), investigating gain-ranked events (gain domain) and loss-ranked events (loss domain) (e.g., Sutter et al. 2013; Vieider et al. 2015).

We want to explore whether stated, survey-based estimates of willingness to take risks in general are correlated with risk preference estimates resulting from an incentivized lab-style experiment. We use the survey-based general willingness to take risks (with no context) because the experiment is context-free as well. Previous studies have found that a general estimate of risk predicts risk-taking in an experiment (Vieider et al. 2015; Dohmen et al. 2011). However, a recent study by Charness and Viceisza (2016) finds different results in a developing country context. They test subjects' comprehension of three methods in rural Senegal: two experimental tasks (the Holt–Laury task and the Gneezy–Potters mechanism) and a non-incentivized willingness-to-risk scale following Dohmen et al., 2011). They find that only the experimental estimates from Gneezy–Potters are correlated with the willingness to risk question in general.[6]

Our second objective aims to test whether general survey estimates predict risk preferences in an incentivized experiment. In other words, we ask whether those who report

---

[5] For the application of Expected Utility theory to non-expected utility models, including rank-dependent expected utility theory and cumulative prospect theory (CPT), see Barseghyan et al. (2018) for a complete review on the risk preferences models.

[6] Similar comparisons have been done between experimental elicitation techniques. For example, Deck et al. (2013), Crosetto and Filippin (2016) and Dulleck et al. (2015) find significant variation between different methods to elicit risk preferences. Deck et al. (2013) compare strategies developed by Holt and Laury (2002), Eckel and Grossman (2008), Deck et al. (2008) and Lejuez et al. (2002). Crosetto and Filippin (2016) compare Holt and Laury (2002), Eckel and Grossman (2008) and Gneezy and Potters (1997) with Crosetto and Filippin (2013), while Dulleck et al. (2015) compare Holt and Laury (2002) to Andreoni and Harbaugh (2009). This work shows there are clear concerns regarding what the different estimation methods actually tell us about risk preferences, and call for increase scrutiny of the external validity of lab experiments (Levitt and List 2007).

higher willingness to take risks are less risk averse in the experiment. Accordingly, hypothesis 2 is: *H2: Survey-based willingness to take risk (without context) is correlated with risk preferences obtained in a context-free experiment.*

2.3 Risk Attitudes and Real-Life Farming Choices

Our final research question aims to analyze how different estimates of risk preferences relate to real-life farming choices in our sample of Costa Rican coffee farmers. We analyze decisions that require significant financial investment: changing to other coffee varieties, changing to other crops, or diversifying coffee farming with other crops. We also analyze fertilizer and pest control applications, which are more day-to-day management practices.

The effect of risk on investment decisions in a farm depends on the specific agricultural activity and biophysical environment (Hanus and Schoop 1989). Previous literature shows that risk aversion delays the adoption of new technologies because uncertainty regarding a new technology discourages individuals who are more reluctant to take a risk (Feder 1980; Liu 2013; Holden and Quiggin 2017). Investment in agricultural technologies is costly, and farmers have to balance the advantages regarding reduced exposure to uncertainty in agriculture (for example, by replacing their plantation with improved coffee varieties that are more resistant to pests and drought) with the increased exposure to financial risk resulting from the acquisition of loans to pay the new technology.[7]

Therefore, we expect risk-averse farmers to implement fewer costly technological changes (like diversifying their farm or investing in expensive coffee varieties), as these come with higher exposure to financial risk. For instance, Brick and Visser (2015) find risk-averse farmers are more likely to maintain the use of traditional seeds and less likely to use modern farming inputs that require costly financing. Lusk and Coble (2005) find risk aversion is associated with less consumption of genetically-modified food. Holden and Quiggin (2017) find that more risk-averse households were less likely to adopt improved maize varieties and less likely to dis-adopt traditional local maize. Guiso and Paiella (2008) find that individuals with higher income uncertainty or liquidity constraints exhibit a higher degree of absolute risk aversion.

In contrast, the effect of risk on farm inputs can be ambiguous. Farm inputs can increase not only the level of output but also the variability of profit. In other words, although fertilizer can increase the average farm yield and profits, there is still a chance that production fails, leaving the farmer with a small yield and high input costs (Hanus and Schoop 1989; Vablauwe et al. 2016). As a result, farmers can manage risk through input use, but they can also be discouraged from adopting an input because the input is associated with output variability (Vablauwe et al. 2016). Furthermore, farmers' risk perceptions do not necessarily correspond

[7] For a comprehensive discussion see e.g., Feder et al. (1985) and Just and Zilberman (1983).

with the biophysical effect of fertilizer on yield variability. For example, a typical farmer in the U.S. applies more fertilizer than the utility maximizing level (Babcock 1992), as producers consider fertilizer to be risk-reducing (Sriramaratnam et al. 1987).

As a result, in some contexts risk aversion encourages expenditures on practices that reduce exposure to agricultural risk (Barham et al. 2014; Alpízar et al. 2011), especially if practices do not involve large investments. For example, applying fertilizer and actively controlling for pests reduces the risk of pests and low yields (Avelino et al. 2015) and risk aversion increases pesticide use in China (Liu and Huang 2013). On the other hand, Roosen and Hennessy (2003) and Khor et al. (2015) show theoretically and empirically that an increase in risk aversion reduces fertilizer use intensity, but recognize that it might not be the same for farmers of different wealth levels; and Verschoor et al. (2016) find that purchase of fertilizer correlates with risky choices in the lab.[8] Hence, we contribute to the debate by analyzing how different estimates of survey risk attitudes relate to real-life farming choices. According to the theory, we hypothesized that farmers who are more willing to take risks are also more likely to implement investments and changes in their farms, as follows, hence: *H3: Survey-based willingness to take a risk in general and in different contexts is positively correlated with the implementation of risky real-life farming choices.*

3. Description of the Study Area, Sample, and Implementation

Our study took place in the year 2014 in two coffee regions of Costa Rica: Tarrazú and Brunca. Households were sampled through stratified random sampling based on the density of coffee plots within six districts of the two coffee regions (three districts from each region and a total of 33 villages surveyed).[9] Only household head farmers took part in the survey and experiment.

The experiment was part of a larger survey and was conducted with each randomly selected farmer at his or her house. First, a survey questionnaire collected detailed household characteristics and farming practices. After completing the survey, the farmer was presented with the incentivized risk experiment, followed by a set of hypothetical willingness to take risks questions, as in Vieider et al. 2015. In our final sample, we have 293 coffee farmers. Their household socioeconomic characteristics and coffee farm characteristics are presented in Table

[8] Regarding non-agricultural contexts, Sutter et al. (2013) study the effects of adolescents' risk aversion on their BMI, smoking, drinking, and savings. Falk et al. (2018) look at smoking and employment; Fairley and Weitzel (2017) look at student borrowing behavior; and Galizzi et al. (2016) look at smoking, savings and food consumption, finding no relationship between different measures and real-life behavior. Finally, in a developing country context, Hardeweg et al. (2013) find risk aversion as the willingness to take risks if related to being self-employed and purchasing of lottery tickets.

[9] Costa Rica's national public administration divides the country into provinces, cantons, and districts. Districts were chosen to capture the spread and variation of intensity of the coffee rust epidemic in 2012-13. A total of 33 villages were surveyed.

1. In our sample, coffee farmers have on average only primary education, have life experience in coffee farming, and on average 57% of their income is earned through selling coffee.[10]

Table 1. Variables and Sample Means from Survey Sample

Variable	N	Mean	min	max	sd
Household characteristics					
Household head female	293	0.10	0	1	0.30
Age (years)	293	51.77	19	86	13.64
Education (years)	293	5.795	0	15	2.61
Household size	293	3.33	1	10	1.38
Household head labor in another farm	293	0.13	0	1	0.33
Total farm area (ha)	293	5.49	0.04	109	9.96
Number of bedrooms in house	293	3.11	1	7	0.90
Coffee farm characteristics					
Farm experience (years)	293	25.50	1	71	14.49
% of income coming from coffee	278	56.78	0	100	36.20
Total area planted with coffee (ha)	293	3.48	0.09	41.77	4.62
Brings coffee to a cooperative	293	0.78	0	1	0.42
Farm affected by coffee leaf rust	293	0.81	0	1	0.39
Real-life farming risky choices					
Changed coffee variety	293	0.36	0	3	0.66
Changed or diversified with other crops	293	0.08	0	1	0.27
Number of fertilizer applications (2013)	293	2.58	0	6	0.74
Number of pest control applications (2013)	293	3.40	0	8	1.49

We gathered extensive information on all farmers' management practices.[11] We focus on four sets of activities that are standard practices for conventional coffee farming and not dependent on specific characteristics of topography: i. changing crops or diversifying the farm by adding other crops in recent years; ii. changing coffee variety in recent years, iii. the number of fertilizer applications and iv. the number of pest control applications in the year before the survey. From these practices, we can observe that diversification with other crops is very rare among coffee farmers. In addition, only 13% of the farmers have changed the coffee variety in the last 10 years before the survey. Regarding fertilizer, agronomists recommend a minimum

[10] Only 278 farmers out of 293 answered the question related to the percentage of income from coffee activities.
[11] We collect information about the following farming practices: contour planting, use of deviation ditches, natural barriers, shadow management, windbreakers, terraces, live coverage, pruning, application of pesticides and herbicides, fertilizer application, change or diversification with other crops, and change of coffee varieties.

of three applications per year and preventive use of pesticide (de Melo 2014). In our sample, the average number of fertilizer applications is below that recommendation.

4. Methods

In this section, we provide details of the survey questions used to elicit risk preferences, describe the design and implementation of the risk experiment, and explain our analytical approach to test our three hypothesis.

4.1 Survey Questions

We asked a set of hypothetical willingness to take risks questions based on Dohmen et al. (2011)**.** The general survey-based question to elicit risk attitudes is stated as follows: "*On a scale where the value 0 means "not at all willing to take risks" and the value 10 means "very willing to take risks; how do you see yourself, are you a person who is fully prepared to take risks or do you try to avoid taking risks?"* (Dohmen et al., 2011, p.525).

When asking farmers about their willingness to take risks in specific contexts, we focus both on non-agriculture and agriculture-relevant contexts and decisions. In the non-agricultural context, we followed Dohmen et al. (2011) in asking about specific contexts of financial matters, driving a car, sport and leisure, working (outside of the farm) and health-related decisions. In the agricultural context, we asked about their willingness to take risks in financial matters, farming (in general), and then in specific farming contexts: when changing or diversifying with other crops, when changing to different coffee varieties, and regarding the use of pesticides and fertilizer. All questions follow the same structure as Dohmen et al. (2011). For example: "*On a scale where the value 0 means "not at all willing to take risks" and the value 10 means "very willing to take risks; how do you see yourself* ***regarding your decisions on changing to other coffee varieties****, are you a person who is fully prepared to take risks or do you try to avoid taking risks?"*

4.2 Experimental Design and Modeling Approach

In the risk experiment, we elicited individuals' risk attitudes with real payoffs, following a design by Vieider et al. (2019). Their design elicits certainty equivalents (CEs), which are easy to explain to subjects with low education. Three tasks were offered in the gain domain, three in the loss domain and one in a mixed domain involving both gain and loss. In the experiments in the gain and loss domains, probabilities changed between 50/50, 10/90 and 90/10 of winning or losing the fixed amount (see Table 2). Choices are expressed by simple prospects in the format (p, x; y), where p is the probability of outcome x and (1-p) the corresponding probability of outcome y. In the gain domain, a subject was asked to make a choice between a certain amount and a lottery to win either 5000 Costa Rican Colones (CRC) or nothing.[12] In each task the winning probability was the same but the certain amount was gradually increased in value. Risk attitude was elicited based on when a subject switched from choosing a lottery to the certain amount. In the loss domain, the farmer had an initial endowment of 5000 CRC and the choice between gradually increasing payments to avoid a lottery where the total endowment could potentially be lost, where risk attitude was elicited in same manner as in the gain domain. Lastly, we included a task necessary to estimate loss aversion (i.e., mixed prospect), which offered the possibility of winning 5000 CRC extra or losing part of the endowment.

Table 2. Choice List for Risk Tasks in the Experiment

Gains	***Losses***	***Mixed***
(0.5, 5000; 0)	(0.5, -5000; 0)	0~(0.5, 5000; z*)
(0.1, 5000; 0)	(0.1, -5000; 0)	
(0.9, 5000; 0)	(0.9, -5000; 0)	

Note: z* varied in a choice list from 5000 to 200 Colones.

At the end of the experiment, one of the seven choice tasks was randomly selected by taking a chip out of a bag. A second random draw was used to decide which alternative from that choice task was to be played out for real. If a farmer chose the certain amount in that specific choice task, that was the amount paid out. In case the lottery was preferred by the farmer, we used another bag containing precisely ten chips numbered from 1-10 to represent probabilities, and this distribution was known and shown to the farmer. We explained this to the farmers graphically using a transparent urn (see Table A5 in Appendix), making sure the farmer understood the odds.

This method of experimental elicitation allows us to determine the certainty equivalent (CE) for each prospect directly. The certainty equivalent is defined as the midpoint between two levels of sure payoffs where the farmer switches from the lottery to the sure payoff in the gain domain, or from the certain payoff to a lottery in the loss domain (Sutter et al. 2013). In other words, in the gain domain, we determine the willingness to accept increasing certain amounts over a lottery to win a prize; for the loss domain, we determine the certain amount farmers are willing to give up to avoid a lottery where they risk losing their endowment. Consequently, the higher the certainty equivalent, the more willing the farmer is to take a risk in the gain domain. The higher the certainty equivalent, the less willing the farmer is to take risks in the loss domain. For the analysis, we specify the certainty equivalent in the loss domain

[12] 5000 Colones equals about USD 8.62.

lotteries with negative values to show the same direction: the higher the value of the certainty equivalent, the more willingness to take risks.

4.3 Modeling Risk Preferences Parameters

A common approach in the experimental literature is to characterize risk preferences through a single parameter that reflects the curvature of the utility function using expected utility theory (Holt and Laury 2002). However, several studies have highlighted the predictive power of prospect theory by Tversky and Kahneman (1992) (e.g., Liu 2013; Camerer 2001). The experimental set-up allows us to investigate the choices using the prospect theory. The prospect theory builds on the idea that people evaluate outcomes relative to a reference point (Kahneman and Tversky, 1979). This is why we have three tasks in the gain domain, three tasks in the loss domain, and one task in the gain-loss domain. We varied the probabilities in both the gain and loss domains to allow us to test for the general finding that individuals tend to underweight high probability events and overweight low probability events (Babcock 2015; Tversky and Kahneman 1992).

We model individual preferences following L'Haridon and Vieider (2019). They use a cumulative prospect theory model (CPT) in the format (p, x; y), where p is the probability of obtaining the outcome x and y is achieved with the corresponding probability (1-p), $|x| > |y|$. We assume preferences are reference-dependent and, in the experiment, are framed with a reference point equal to zero (Tversky and Kahneman 1992; Abdellaoui et al. 2011; L'Haridon and Vieider 2019).[13] The utility of a prospect (PU) for outcomes that fit in one domain (gain or loss) can be represented as follows:

$$PU = w^j(p)v(x) + \left[1 - w^j(p)\right]v(y) \;, \tag{1}$$

where $w^j(p_i)$ is the probability weighting function that combines probabilities into decision weights[14]. The decision domains are specified by j, which takes the values for gains and for losses. For mixed prospects, where $x > 0 > y$, the utility is represented as:

$$PU(x,p) = w^+(p)v(x) + w^-(1-p)v(y) \tag{2}$$

We follow the functional forms indicated by L'Haridon and Vieider (2019) and assume a piecewise linear utility function as follows:

$$v(x) = \begin{cases} x & if \quad x > 0 \\ -\lambda(-x) & if \quad x \le 0 \end{cases}, \tag{3}$$

where λ is the *loss aversion* parameter that defines the curvature below zero relative to the curvature above zero, and values $\lambda > 1$ indicate loss aversion, where higher values of λ indicate the farmer is more loss averse (Vieider et al., 2019). In this framework, risk preferences are

[13] Reference-dependence is an important principle in prospect theory. Individuals evaluate outcomes relative to a reference point to evaluate gains and losses.

[14] The function is strictly increasing and satisfies $w(0) = 0$ and $w(1) = 1$

captured by probability weighting and loss aversion. Similarly to Vieider et al. (2019) and L'Haridon and Vieider (2019), we adopt a two-parameter weighting function by Prelec, (1998)[15]:

$$w^j(p) = \exp\left[-\beta^j\big(-ln(p)\big)^{\alpha^j}\right] \tag{4}$$

The parameters of the Prelec function provide a detailed behavioral interpretation. The parameter α governs the slope of the probability weighting function, with values $\alpha < 1$ indicating *probabilistic insensitivity* for gain and losses. Values $\alpha < 1$ also indicate the weighting function has an inverted S-shape, which shows an overweighting of low probabilities of the largest gains or biggest losses and an underweighting of high probabilities (Liu 2013; L'Haridon and Vieider 2019).[16] The parameter β governs the elevation of the weighting function, indicating the weight assigned to the best outcome for gains and the worst outcome for losses. Therefore, the higher values for β indicate increased *probabilistic pessimism* for gains and increased *probabilistic optimism* for losses. Consequently, we refer to the parameter β as *pessimism* for gains and *optimism* for losses (Vieider et al., 2019).

4.4 Analytical Strategy to Test Hypotheses

Armed with the estimates resulting from our survey-based risk preference elicitation method and from our risk preference experiment, we turn to our analytical strategy to test our hypotheses.

To test hypothesis 1, namely that there is a correlation between general and specific survey-based risk attitudes, we will use the Spearman's rank-order correlation coefficient measuring the strength and direction of a correlation between two variables measured on an ordinal scale and, complement this with a principal component analysis.

To test hypothesis 2, namely that survey-based willingness to take risk (without context) is negatively correlated with risk preferences obtained in a context-free experiment, we regress the normalized risk aversion estimate across probabilities and experimental domains, and the utility function parameters on the respondent's answer to the general risk question.

To test hypothesis 3, namely that survey-based willingness to take a risk in general and in different contexts is positively correlated with the implementation of risky real-life farming choices, we analyze our data by regressing the real-life farm practices on survey-based risk preferences.

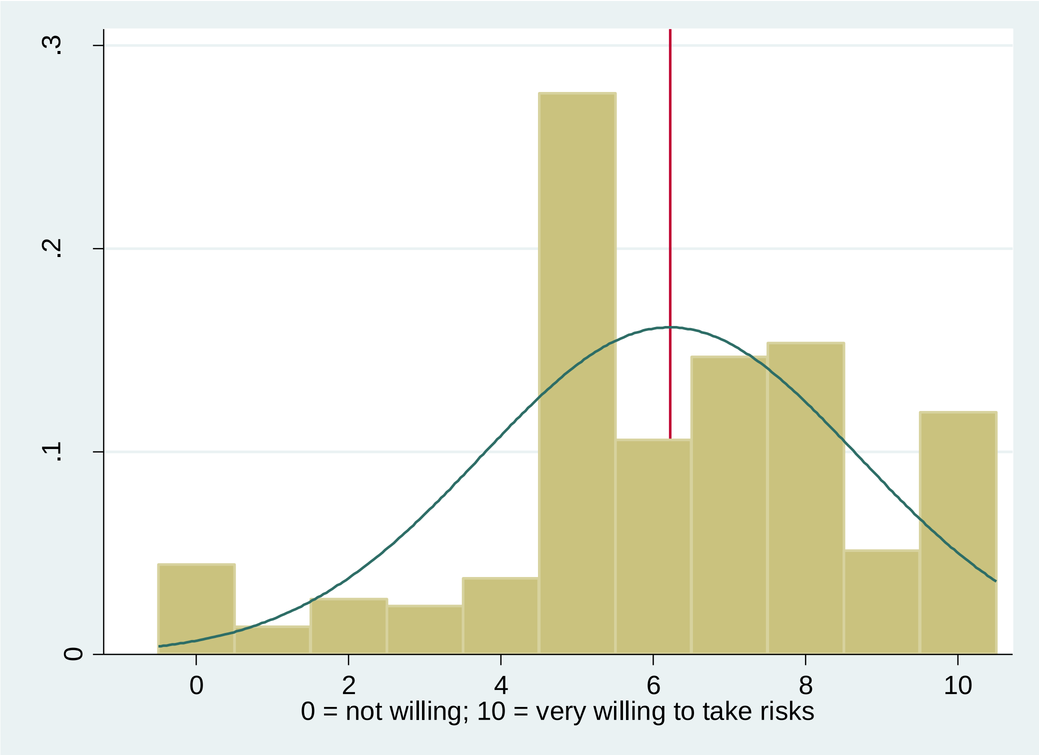
[15] The model and functional forms for the certainty equivalent adopted follow L'Haridon and Vieder (2019). To the deterministic certainty equivalents we add an error term to allow for stochastic elements in the decision process (L'Haridon and Vieider, 2019). All parameters are estimated using the log-likelihood function, programmed in STATA.

[16] We could assume the value of α to be equal to one ($\alpha = 1$). This assumption will indicate linearity of the weighting function (the expected utility case), and then the parameter β can be considered as the standard estimate of risk aversion.

5. Results

We start by presenting the descriptive statistics of the data collected via the survey and the experiments. Figure 1 shows the distribution of responses to the general survey-based risk question. Our data shows that a relatively small fraction of respondents choose low values, indicating that most farmers are willing to take risks in a context-free situation. This result is very different from Dohmen et al. (2011), where only a small fraction of respondents choose high values and subjects are on average less willing to take risks.

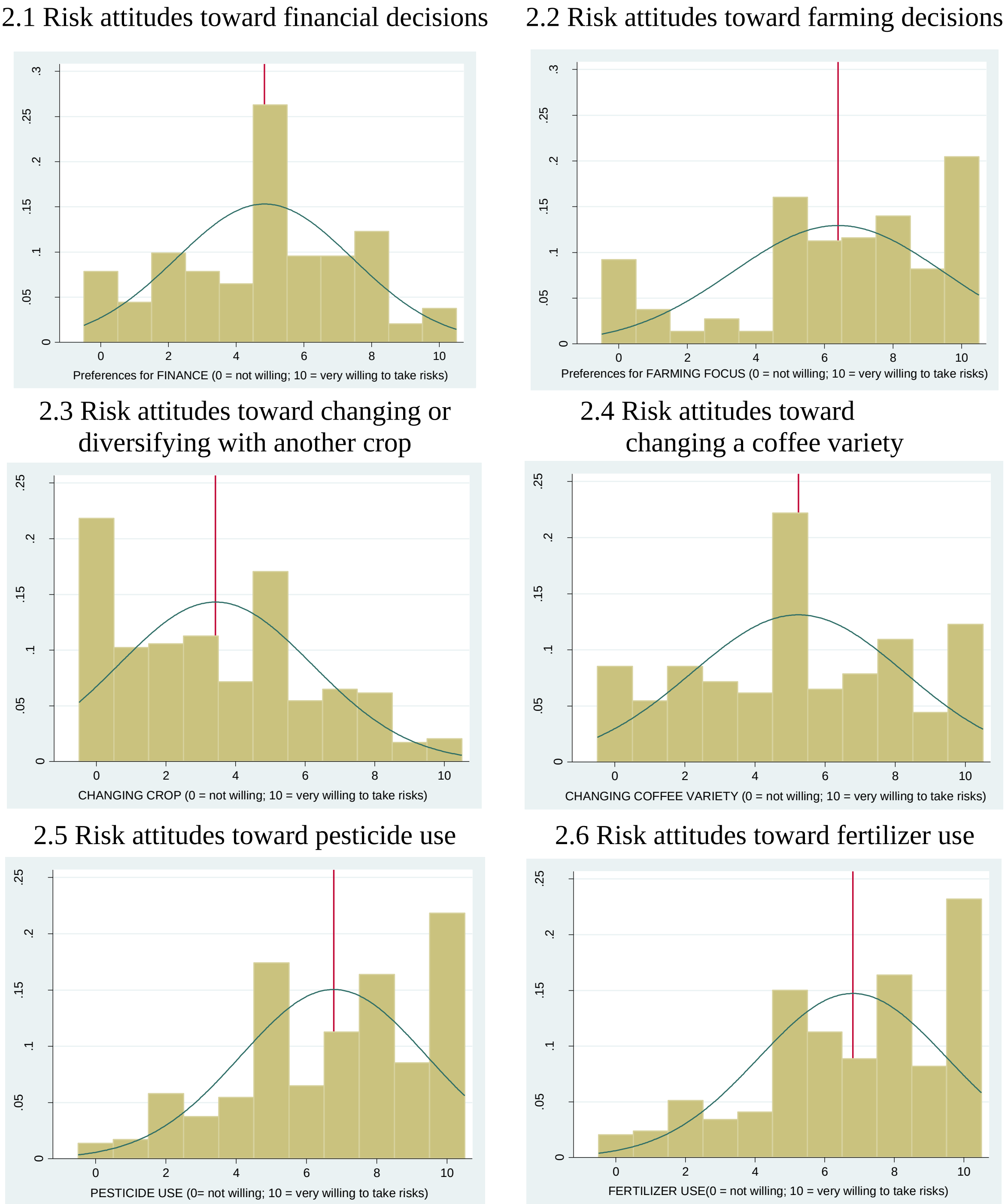
Figure 1. Farmer's Response to General Survey-Based Risk Preference Question



Note: Red line indicates mean response to general survey-based risk question and blue line shows the adjusted frequency distribution.

We compare our responses to the context-specific attributes used in Dohmen et al. (2011) with their results (see Table A1 and Table A2. in Appendix). Overall, our sample is less risk averse. Moreover, there is weaker correlation between the different specific risk attributes, but the tendency of positive and significant correlation between the attributes is the same. In Figure 2, we present the distribution of responses to the context-specific risk questions related to agriculture. We see variation in the different agriculture-specific attitudes. Farmers are relatively more risk averse with regards to changing crop and coffee variety compared to the use of pest control and fertilizer.

Figure 2. Farmer's Response to Context-Specific Risk Preferences Questions



Note: Red line indicates the average response to risk question and blue line show the adjusted probability distribution.

We present the nonparametric representation of the experimental data in the top panel of Table 3. Following Bouchouicha and Vieider (2017), we estimate a relative risk premium (r_{ik}) for each individual *i* and lottery *k*, by normalizing their certainty equivalents (ce_{ik}) with the outcomes of each of the lotteries (x_k and y_k), and subtracting this from the probability (p_k), i.e., the probability of obtaining the outcome x_k, with $|x| > |y|$, hence: $r_{ik} = p_k - \frac{ce_{ik} - y_k}{x_k - y_k}$. This relative risk premium is comparable across outcome levels and across probabilities, with r_{ik} > 0 implying individual *i* is risk averse, r_{ik} < 0 is risk seeking, and r_{ik} = 0 is risk neutral.

Table 3. Summary of Experimentally Elicited Risk Preferences. Non-Parametric Results Presented in Panel 1, Parametric Estimates in Panel 2.

Variables		**Mean**	**min**	**max**	**sd**
	(p, x; y)				
Risk preference (r_{ik}) by lottery	(0.1, 5000; 0)	-0.304	-0.850	0.050	0.317
	(0.5, 5000; 0)	-0.152	-0.450	0.450	0.251
	(0.9, 5000; 0)	0.035	-0.050	0.850	0.208
	(0.1, -5000; 0)	0.211	0.150	1.050	0.176
	(0.5, -5000; 0)	0.844	0.550	1.450	0.235
	(0.9, -5000; 0)	1.467	0.950	1.850	0.308
	0~(0.5, 5000; z*)	3.992	2.717	5.308	1.015
Utility function parameters	$\boldsymbol{\alpha}^{+}$ *(probabilistic sensitivity to gains)*	0.604	0.598	0.607	0.002
	$\boldsymbol{\beta}^{+}$*(probabilistic pessimism)*	0.544	0.541	0.548	0.002
	$\boldsymbol{\alpha}^{-}$ *(probabilistic sensitivity to losses)*	0.419	0.414	0.421	0.001
	$\boldsymbol{\beta}^{-}$ *(probabilistic optimism)*	1.380	1.371	1.383	0.002
	λ *(loss aversion)*	3.892	3.849	3.914	0.012

Consistent with the cumulative prospect theory (CPT) pattern (see Tversky and Kahneman (1992) and more recently Harbaugh et al. (2014)), individuals are risk-seeking over low-probability gains and risk-averse over high-probability gains. In the loss domain, we do see that individuals are risk-averse over low-probability losses, but remain risk averse over high-probability losses as well.

The second panel of Table 3 shows the parameters of the utility function estimated following L'Haridon and Vieder (2019). Our results show in general that farmers are loss averse (λ >1), with overweighting of low probabilities of the largest gains or biggest losses, and underweighting of high probabilities ($\alpha < 1$), indicating an inverted S-shape of the weighting function. Farmers are more optimistic regarding losses than pessimistic about their gains, as shown by $\boldsymbol{\beta}^{-} > \boldsymbol{\beta}^{+}$. Levels of loss aversion and probability weighting are similar to previous studies[17].

Results showing on average risk seeking behavior in the gain domain are similar to Charness and Viceisza (2016) and Vieider et al. (2016, 2014), who find farmers are willing to take risks in Senegal, Vietnam, and Ethiopia, respectively. On the other hand, results differ from Verschoor et al. (2016), who find higher levels of risk aversion hypothetically and in their

[17] Liu and Huang (2013) report a coefficient of loss aversion of 3.47 (3.92) and probability weighting equal to 0.69 (0.23).

risk experiment. In this regard, our study shows supporting evidence that farmers in developing countries are not necessarily more risk-averse than subjects from developed countries.

5.1 Correlations between General and Context-Specific Survey Risk Attitudes

We begin to investigate whether risk preferences estimated using the stated "willingness-to-take risk-in-general" question (i.e. context free) are correlated with risk preferences estimated using stated "willingness-to-take risk" in a specific agricultural context. To do this, we use the Spearman's rank-order correlation coefficient measuring the strength and direction of a correlation between two variables measured on an ordinal scale. We test the hypothesis that the Spearman's correlation coefficient (ρ) is equal to zero. Furthermore, given that we are testing multiple hypotheses, we report the adjusted p-values according to the Bonferroni correction method. The Bonferroni correction method uses a lower critical value according to the number of hypotheses tested. As a result, the probability of observing at least one significant result remains below the specific significance level applied when conducting one test only (Dunn 1961).

The context-free survey estimate is significantly correlated at the 5% significance level only with the context-specific preferences related to finances (first column of Table 4). The latter also significantly correlates with changing or diversifying with other crops (second column). We find no correlation between the general (no context) or finance risk-taking estimates and the estimates in the context of pest control and fertilizer at the 5% level. On the other hand, when asking farmers about their willingness to take risks framed in the farming context (third column), this correlates significantly with risk preferences estimates regarding pest control and fertilizer applications.

Similar to Dohmen et al. (2011), we find that stated risk preferences with no context, or contextualized in a setting of personal finance, do correlate with each other, but not with risk preferences elicited in specific agricultural settings (with the exception of changing crops). Interestingly, we do see significant correlations between stated willingness to take risk estimates elicited for different agricultural context, like pest control and fertilizer application. We do not know of previous studies showing how context-specific risk preferences could be. Take for example the preferences elicited in the context of changing coffee variety, pest control and fertilizer use. All of these activities relate to being a coffee producer, and all of them are significantly correlated.

Table 4. Correlations between Survey-Based Estimates to take Risks in General and Agricultural Specific Contexts

	General	Finances	Farming	Changing crop	Changing variety	Pest control	Fertilizer used
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
General (no context)	1						
Finances	0.4314***	1					
Farming	0.1585	0.1497	1				
Changing crop	0.1374	0.2763***	0.1488	1			
Changing variety	0.1444	0.1603	0.0746	0.2656***	1		
Pest control used	0.1646*	0.1140	0.2473***	0.0176	0.3248***	1	
Fertilizer used	0.1078	0.0965	0.2538***	-0.0450	0.2888***	0.8146***	1

Note: Coefficients refer to Spearman's ρ and are calculated using all non-missing observations between a pair of variables; *** p<0.01, ** p<0.05, * p<0.1.using Bonferroni correction method for adjusted p-values.

To complement our analysis, we performed a principal component analysis to identify the factors or components that express the maximum information out of the survey estimates (see Table A4 in Appendix for details). The principal component analysis confirms that farmers use two different decision heuristics to confront risk, depending on (i) whether the risk is associated with financial decisions, changes in crops or uncontextualized risk, or (ii) whether the risk is associated with management decisions like buying inputs (e.g. agrochemicals), or changing coffee varieties.

The results tell a coherent story in which those practices that require more financial investment, such as changing to other crops, relate more to the financial and to the context-free estimate of risk. Risk preferences regarding on-farm management practices, such as changing varieties or expenditures on fertilizer or pest control, correlate with each other. Thus, it is essential to elicit risk attitudes for the specific context of interest, and one should be careful when extrapolating risk attitudes across contexts.

5.2 Comparison between Survey Estimates and Experimentally Elicited Risk Preferences

To better evaluate the performance of our survey-based estimates of risk preferences, we test whether survey data predict risk-taking behavior in an incentivized risk experiment. We focus the analysis on the survey-based willingness to take risks in general (i.e., our context free estimate), as it comes closer to the context free description of decision making in the experiment. Our experimental data allows us to perform this validation in two ways: using the certainty equivalents directly and using utility function parameters.

First, to test the predictive power of the survey question, we regress the risk premium (r_{ik}) for all individuals and lotteries in the gain and loss domains, using the respondent's answer to the general risk question as the explanatory variable (Table 5). To ensure robustness, we cluster the standard errors at the village level (33 clusters) using the Wild bootstrap method (Cameron et al. 2008). We also control for different socio-economic and agricultural related variables (see note below Table 5).

The coefficient for the willingness to take risks can be interpreted both in sign and size. For example, the coefficient in column 1 (-0.032; p-value < 0.01) means that a higher willingness to take risk is correlated with having a lower risk premium, i.e., a subject that is more risk seeking or less risk averse. The fact that the estimated coefficient in column 1 is larger in absolute terms than the coefficient in column 2 (-0.014; p-value < 0.10) means that a higher willingness to take risk has a bigger effect for low probabilities. We find no such effect for high probability gains.

In the loss domain, we find that the higher the willingness to take risk, the lower the risk premium, i.e., there is more risk seeking or less risk averse behavior only for the higher probabilities. In both the gain and loss domain, we find that for all lotteries (except column (5)) a higher willingness to take risk in general is associated with more risk seeking or less risk averse behavior.

Table 5. Predicting Experimental Choices with Context Free Survey-Based Risk Attitudes

Dependent variable: risk premium for all lotteries and in gain/loss domains
A lower risk premium means the subject is more risk seeking or less risk averse

	Gain domain			Loss domain			Mixed
	10%	50%	90%	10%	50%	90%	50%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Willingness to take risks in general (context free) *(0 "not at all willing to take risks" 10 "very willing to take risks")*	-0.032***	-0.014*	-0.008	0.002	-0.013*	-0.024***	0.005
	[0.011]	[0.008]	[0.008]	[0.005]	[0.008]	[0.008]	[0.027]
Constant	-0.004	-0.006	0.293***	0.237**	0.811***	1.569***	3.684***
	[0.061]	[0.134]	[0.000]	[0.109]	[0.000]	[0.000]	[0.000]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Village fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	278	278	278	278	278	278	278
R-squared	0.095	0.057	0.064	0.081	0.075	0.086	0.074

Note. Each coefficient estimate is based on a separate OLS regression of the respective dependent variable on this particular risk estimate and a set of controls. Control variables included: gender, age, education (years), household size, household head labor in another farm, total farm area (ha), number of bedrooms in the house, farm experience (years), percentage of income coming from coffee, total area planted with coffee (ha), whether farmers bring coffee to a cooperative, and whether farm was affected by the coffee leaf rust. Fixed effects at the district level (6 districts). Cluster standard error at the village level (33 villages). Wild bootstrap with 1000 replications following Cameron et al. (2008). Robust standard errors in brackets, *** p<0.01, ** p<0.05, * p<0.1.

For our second test, we use the utility function parameters estimated from the experimental data to assess the predictive power of the survey-based willingness to take risks estimate. We regress each of the expected utility function parameters on the general willingness to take risk question (Table 6). Farmers reporting more willingness to take risks in the survey question are relatively less pessimistic, less sensitive to changes in probabilities that increase the likelihood of a loss in the experiment, and more loss averse. We associate this last result with the endowment effect, where people are willing to take risks to avoid losses (Kahneman and Tversky 1979). We also note that the willingness to take risk survey was not designed to test loss aversion specifically.

Our results show the context-free survey-based estimates predict risk-taking behavior in the context-free, incentivized experiment, confirming our hypothesis.

Table 6. Willingness to take Risks in General and Utility Function Parameters

	Dependent variable: utility function parameters				
	α^+ *(sensitivity gains)*	β^+ *(pessimism)*	α^- *(sensitivity losses)*	β^- *(optimism)*	λ *(loss aversion)*
	(1)	(2)	(3)	(4)	(5)
Willingness to take risks in general (0-10)	0.00003 [0.00004]	-0.00014*** [0.00005]	-0.00009** [0.00004]	0.00013 [0.00008]	0.00104*** [0.00038]
Constant	0.60227*** [0.00000]	0.54578*** [0.00000]	0.41866*** [0.00000]	1.37900*** [0.00000]	3.88161*** [0.00000]
Control variables	Yes	Yes	Yes	Yes	Yes
Village fixed effects	Yes	Yes	Yes	Yes	Yes
Mean dependent variable	0.604	0.544	0.419	1.380	3.892
Observations	278	278	278	278	278
R-squared	0.088	0.123	0.096	0.060	0.097

Each coefficient estimate is based on a separate OLS regression of the respective dependent variable on this particular risk estimate and a set of controls. Control variables included: gender, age, education (years), household size, household head labor on another farm, total farm area (ha), number of bedrooms in the house, farm experience (years), percentage of income coming from coffee, total area planted with coffee (ha), whether farmers bring coffee to a cooperative, and whether farm was affected by the coffee leaf rust. Fixed effects at district level (6 districts). Cluster standard error at the village level (33 villages). Wild bootstrap with 1000 replications following Cameron et al. (2008). Robust standard errors in brackets, *** p<0.01, ** p<0.05, * p<0.1.

5.3 Risk Attitudes and Real-Life Farming Choices

Finally, we study how the different survey estimates relate to real-life choices. Thus, our dependent variables are a series of real-life farming choices: i. whether the farm had any sort of crop diversification in the last decade; ii. did the farmer change coffee variety in the last decade (yes/no); iii. number of fertilizer applications; and iv. number of pest control applications in the last year prior to the survey (2013).

We analyze our data by regressing the four real-life farm practices on each one of our survey-based risk preferences estimates (i. with no context, ii. in a financial context, iii. in a farming context, iv. in a context of crop diversification, v. in a context of changing coffee variety, vi. in a context of deciding how much fertilizer to use, and vii. in a context of deciding how much pesticide to use). Results are shown in Table 7.

Each cell of the table explains whether a higher willingness to take risk in each specific context is correlated to a given real life behavior; a positive coefficient is interpreted as meaning that those who are more willing to take risk are more likely to have increased the practice in the past. All regressions include a set of control variables including district fixed effects. Further, we control for correlation at village level by clustering the standard errors (33 clusters) and applying the wild bootstrap following Cameron et al. (2008).

We start by looking at the estimates for *crop diversification* (Column 1). None of the coefficients are significant except for the coefficient for willingness to take risk in diversifying the farm (p-value < 0.05), i.e., those more willing to take risks in that context are also those who diversified in the past.

When looking at the results for those who reported having changed their *coffee variety* in real life (Column 2), we find again that the coefficient estimates for the general survey-based risk question (with no context), the financial context and the farming context are not significantly correlated with real life past behavior. However, when explicitly contextualized as a willingness to take risks in the context of changing coffee variety, the coefficient is positive and significant (p-value < 0.05). The willingness to take risk in the use of fertilizer and pest control is also positively correlated with past changes in coffee variety (p-value < 0.05 and p-value < 0.01, respectively). A change in coffee variety is an ambitious farming decision for a coffee farmer, so it is expected that it is correlated with higher willingness to take risk in the use of farm inputs. Previous studies using context-free estimates found risk aversion is associated with less implementation of agricultural practices that required more farm investment (Brick and Visser 2015; Verschoor et al. 2016; Holden and Quiggin 2017). Our results show that we can only confirm the hypothesis that the context-specific willingness to take risk is positively associated with changing coffee varieties and we cannot confirm the same for the context-free survey estimate.

The application of fertilizer and pest control inputs is part of a farmer's day to day in Costa Rica, where coffee farms have one of the highest productivities per hectare in the world (Samper 2010). Our last two columns of Table 7 show no correlation (except for one coefficient) between our willingness to take risk estimates and the decision to use these inputs in increasing quantities. This is to be expected, because most farmers apply large amounts of fertilizers and inputs, irrespective of whether they are more or less risk averse. Moreover, the role of pest control and fertilizer in a farmer production strategy is unclear. In some cases, risk aversion is associated with less fertilizer purchase (Roosen and Hennessy 2003; Khor et al. 2015; Verschoor et al. 2016), as fertilizer can increase not only output but also its variability (Vablauwe et al. 2016). In other cases, the application of fertilizer reduces the risk of pests and low yields (Avelino et al. 2015) and can be perceived as a risk-reducing strategy. Similar results regarding pesticide have been found in China (Liu and Huang 2013), with high availability and input use.

Table 7. Risk Survey-Based Estimates on Real-Life Farming Practices

	(1)	(2)	(3)	(4)
	Diversified	*Changed variety*	*Fertilizer*	*Pesticide*
a) General (no context)	0.007 [0.006]	0.002 [0.007]	0.017 [0.020]	0.003 [0.039]
	Diversified	*Changed variety*	*Fertilizer*	*Pesticide*
b) Finances context	0.009 [0.005]	-0.000 [0.007]	-0.014 [0.014]	-0.013 [0.025]
	Diversified	*Changed variety*	*Fertilizer*	*Pesticide*
c) Farming context	0.008 [0.005]	0.008 [0.006]	0.007 [0.014]	-0.033 [0.024]
	Diversified	*Changed variety*	*Fertilizer*	*Pesticide*
d) Crop change/diversify context	0.013** [0.006]	-0.002 [0.008]	-0.011 [0.013]	0.019 [0.023]
	Diversified	*Changed variety*	*Fertilizer*	*Pesticide*
e) Variety change context	-0.001 [0.005]	0.015** [0.006]	-0.003 [0.016]	-0.027 [0.037]
	Diversified	*Changed variety*	*Fertilizer*	*Pesticide*
f) Fertilizer context	0.009 [0.006]	0.014** [0.007]	-0.017 [0.013]	0.008 [0.017]
	Diversified	*Changed variety*	*Fertilizer*	*Pesticide*
g) Pest control context	0.002 [0.008]	0.018*** [0.006]	-0.033** [0.016]	0.039 [0.036]
Constant	*Yes*	*Yes*	*Yes*	*Yes*
Control variables	*Yes*	*Yes*	*Yes*	*Yes*
Village fixed effects	*Yes*	*Yes*	*Yes*	*Yes*
Mean dependent variable	0.075	0.115	2.604	3.451
Observations	278	278	278	278

Each coefficient estimate is based on a separate OLS regression of the respective dependent variable on this particular risk estimate and a set of controls. Dependent variables: *diversified* (whether the farm had any sort of crop diversification in the last decade (yes/no)), *changed variety* (Changed coffee variety (yes/no)), *fertilizer* (Number of applications of fertilizer) and *pesticide* (Number of applications of pesticide). Control variables included: gender, age, education (years), household size, household head labor in another farm, total farm area (ha), number of bedrooms in the house, farm experience (years), percentage of income coming from coffee, total area planted with coffee (ha), whether farmers bring coffee to a cooperative, and whether farm was affected by the coffee leaf rust. Fixed effects at the district level (6 districts). Cluster standard error at the village level (33 villages). Wild bootstrap with 1000 replications following Cameron et al. (2008). Robust standard errors in brackets, *** p<0.01, ** p<0.05, * p<0.1.

The previous results are based on simple correlations and shall not be interpreted as showing causality. We acknowledge that reverse causality might be a concern: prior experience with a particular farm practice – for example, crop diversification – might make a farmer report more willingness to take the risk of diversifying her farm. We choose, however, to present the results for two reasons. First the farmers' real decisions and our survey took place at totally different moments in time. Secondly, and most important for our case, the argument that having good prior experience with a practice could make the farmer more willing to take risks can also be true for the opposite claim (i.e., when a farmer has bad prior experience with crop diversification, she should be less willing to take a risk at the time of the survey). Most importantly, we believe that our argument in favor of using highly targeted risk preferences estimates still holds even if endogeneity could be a potential confounding factor.

6. Conclusions and Discussion

In this paper, we evaluate a survey-based method for estimating risk attitudes that can be easily implemented by practitioners in developing countries. We first assess the correlations between stated willingness to take risk in a context free setting and in context-specific settings, all elicited using surveys. We then test whether these survey-based risk preferences predict risk-taking behavior in an incentivized experiment. Finally, we show how the different survey-based estimates of risk attitudes relate to real-life agricultural choices in a population of coffee farmers in Costa Rica.

Our findings can be summarized in three main results. First, we find that stated risk preferences with no context or set in the very similar context of personal finance (i.e. changes in income), do correlate with each other, but not with risk preferences elicited in specific agricultural settings (with the exception of changing crops, a highly costly practice). Interestingly, we do see significant correlations between stated willingness to take risk estimates elicited for different agricultural contexts, like overall farming, pest control and fertilizer application. The principal component analysis confirms that farmers use two different decision heuristics to confront risk. One depends on whether the risk is associated with financial decisions, changes in crops or uncontextualized risk, and the other depends on whether the risk is associated with management decisions like buying inputs or changing coffee varieties.

Second, the survey-based estimates of risk preferences (with no context) significantly predict risk-taking behavior in the uncontextualized experiment, which is in line with previous studies (Vieider et al. 2015; Dohmen et al. 2011; Hardeweg et al. 2013). Regarding the utility function parameters, we find that higher willingness to take risk is associated with less pessimism, less sensitivity to changes in probabilities that increase the likelihood of a loss, and more loss aversion, suggesting farmers are willing to take risk in order to avoid losses. We do not know of other studies relating survey risk estimates to risk preferences parameters.

Third, we find a clear pattern of correlation between contextualized willingness to take risk and actual, real-life behavior. Our willingness to take risk in a specific agricultural context is correlated with real-life farming choices in the context of crop diversification and changed coffee variety. On the contrary, context-free survey-based estimates of risk preferences are not associated with farming behavior.

In the face of costly investments and management decisions, farmers balance the advantages of reducing exposure to the intrinsic uncertainty from agricultural production with increased exposure to financial risk, for example acquiring loans to replace their plantation with improved coffee varieties that are resistant to pests. A common assumption in economics is the stability of risk preferences across decision contexts (Barseghyan et al. 2018). Our study shows that we cannot assume one general trait across different specific contexts within agriculture. Similar results have been found in other contexts, for example, insurance choices (Einav et al. 2012; Barseghyan et al. 2013) and social preferences (de Oliveira, Eckel and Croson 2012). Understanding how preferences are affected by context and the type of decision is key to using actions from one context to predict actions in another context (de Oliveira, Eckel, and Croson 2012).

A key conclusion of this paper is the need to use highly targeted, contextualized risk preferences estimates. Projects or programs interested in using risk preferences as inputs into the design of policy instruments should make sure that preferences are elicited in the specific context targeted by the prospective policy instrument. If the policy instrument aims at influencing general financial decisions, the estimation of risk preferences without a context might suffice. However, if the policy instrument targets a specific adoption, say fertilizer use or implementation of improved seeds varieties, risk preferences should be elicited in that particular context.

References

Abdellaoui, M., Baillon, A., Placido, L., and Wakker, P. P. (2011). "The rich domain of uncertainty: Source functions and their experimental implementation." *American Economic Review* 101(April):695–723.

Akay, A., Martinsson, P. Medhin, H., and Trautmann, S. T. (2012). "Attitudes toward uncertainty among the poor: an experiment in rural Ethiopia." *Theory and Decision* 73:453–464.

Alpízar, F., Carlsson, F., and Naranjo, M. A. (2011). "The effect of ambiguous risk, and coordination on farmers' adaptation to climate change — A framed field experiment." *Ecological Economics* 70(12):2317–2326.

Andreoni, J., and Harbaugh, W. (2009). "Unexpected Utility: Experimental Tests of Five Key Questions about Preferences over Risk."

Avelino, J., Cristancho, M., Georgiou, S., Imbach, P., Aguilar, L., Bornemann, G., Läderach, P., Anzueto, F., Hruska, A. J., and Morales, C. (2015). "The coffee rust crises in Colombia and Central America (2008–2013): impacts, plausible causes and proposed solutions." *Food Security* 7(303). 9.

Babcock, B. A. (1992). "The Effects of Uncertainty on Optimal Nitrogen Applications." *Review of Agricultural Economics* 14(2):271–280.

Babcock, B. A. (2015). "Using Cumulative Prospect Theory to Explain Anomalous Crop Insurance Coverage Choice." *American Journal of Agricultural Economics* 97(5):1371–1384.

Barham, B. L., Chavas, J. P., Fitz, D., Salas, V. R., and Schechter, L. (2014). "The roles of risk and ambiguity in technology adoption." *Journal of Economic Behavior and Organization* 97:204–218.

Barseghyan, L., Molinari, F., O'Donoghue, T., and Teitelbaum., J. C. (2013). "The nature of risk preferences: Evidence from insurance choices." *American Economic Review* 103(6):2499–2529.

Barseghyan, L., Prince, J., and Teitelbaum, J. C. (2011). "Are risk preferences stable across contexts? Evidence from insurance data." *American Economic Review* 101(2):591–631.

Barseghyan, L., Ted, O., Molinari, F., and Teitelbaum, J. C. (2018). "Estimating Risk Preferences in the Field." *Journal of Economic Literature* 56(2):501–564.

Binswanger, H. P. (1980). "Attitudes toward risk: Experimental measurement in rural India." *American Journal of Agricultural Economics* 62(3):395–407.

Bouchouicha, R., and Vieider, F. M. (2017). "Accommodating stake effects under prospect theory." *Journal of Risk and Uncertainty* 55(1):1–28.

Brick, K., and Visser, M. (2015). "Risk Preferences, Technology Adoption and Insurance Uptake: a Framed Experiment." *Journal of Economic Behavior & Organization* 118:383–396.

Camerer, C. F. (2001). "Prospect Theory in the Wild: Evidence from the Field." In D. Kahneman and A. Tversky, eds. *Choices, Values, and Frames*. Cambridge University Press., pp. 288–300.

Cameron, A. C., Gelbach, J. B., and Miller, D. L. (2008). "Bootstrap-based improvements for inference with clustered errors." *The Review of Economics and Statistics* 90(3):414–427.

Cardenas, J. C., and Carpenter, J. (2013). "Risk attitudes and economic well-being in Latin America." *Journal of Development Economics* 103(1):52–61.

Charness, G., and Viceisza, A. (2016). "Three Risk-elicitation Methods in the Field: Evidence from Rural Senegal." *Review of Behavioral Economics* 3(2):145–171.

Crosetto, P., and Filippin, A.. (2016). "A theoretical and experimental appraisal of four risk elicitation methods." *Experimental Economics* 19(3):613–641.

Crosetto, P., and Filippin, A. (2013). "The 'bomb' risk elicitation task." *Journal of Risk and Uncertainty* 47(1):31–65.

Deck, C., Lee, J., and Reyes, J. (2008). "Risk attitudes in large stake gambles: evidence from a game show." *Applied Economics* 40(1):41–52.

Deck, C., Lee, J., Reyes, J. A., and Rosen, C. C. (2013). "A failed attempt to explain within subject variation in risk taking behavior using domain specific risk attitudes." *Journal of Economic Behavior & Organization* 87:1–24.

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., and Wagner, G. G. (2011). "Individual Risk Attitudes: Measurement, Determinants, and Behavioral Consequences." *Journal of the European Economic Association* 9(3):522–550.

Dulleck, U., Fooken, J., and Fell, J. (2015). "Within-Subject Intra- and Inter-Method Consistency of Two Experimental Risk Attitude Elicitation Methods." *German Economic Review* 16(1):104–121.

Dunn, O. J. (1961). "Multiple Comparisons among Means." *Journal of the American Statistical Association* 56(293):52–64.

Eckel, C .C., and Grossman, P. J. (2008). "Forecasting risk attitudes: An experimental study using actual and forecast gamble choices." *Journal of Economic Behavior & Organization* 68(1):1–17.

Einav, B. L., Finkelstein, A., Pascu, I., and Cullen, M. R. (2012). "How General Are Risk

Preferences? Choices under Uncertainty in Different Domains Author(s):" *The American Economic Review* 102(6):2606–2638.

Fairley, K., and Weitzel., U. (2017). "Ambiguity and risk measures in the lab and students' real-life borrowing behavior." *Journal of Behavioral and Experimental Economics* 67:85–98.

Falk, A., Becker, A., Dohmen, t., Enke, B., Huffman, D., and Sunde, U. (2018). "Global Evidence on Economic Preferences." *The Quarterly Journal of Economics* 133(4):1645–1692.

Falk, A., and Heckman, j. j.. (2009). "Lab experiments are a major source of knowledge in the social sciences." *Science* 326(5952):535–538.

Feder, G. (1980). "Farm Size , Risk Aversion and the Adoption of New Technology under Uncertainty." *Oxford Economic Papers* 32(2):263–283.

Feder, G., Just, R. E., and Zilberman, D. (1985). "Adoption of Agricultural Innovations in Developing Countries: A Survey." *Economic Development and Cultural Change* 33(2):255.

Friedman, D., Isaac, R. M., James, d., and Sunder, S. (2014). "Risky Curves: On the Empirical Failure of Expected Utility." *Santa Cruz Department of Economics, Working Paper Series*.

Galizzi, M. M., Machado, S. R., and Miniaci, R. (2016). "Temporal stability, cross-validity, and external validity of risk preferences measures: experimental evidence from a UK representative sample." *LSE Research Online Documents on Economics*.

Gneezy, U., and Potters, J. (1997). "An Experiment on Risk Taking and Evaluation Periods." *The Quarterly Journal of Economics* 112(2):631–645.

Guiso, L., and Paiella, M. (2008). "Risk Aversion, Wealth, and Background Risk." *Journal of the European Economic Association* 6:1109–1150.

Hanus, H., and Schoop, P. (1989). "Influence of Nitrogen Fertilizer and Fungicide on Yield and Yield Variability in Wheat and Barley." In J. R. Anderson and P. B. R. Hazell, eds. *Variability in Grain Yeilds: Implications for Agricultural Research and Policy in Developing Countries*. Baltimore and London: Johns Hopkins University Press for the International Food Policy Research Institute, pp. 265–269.

Harbaugh, W. T., Krause, K., and Vesterlung, L. (2010). "The fourfold pattern of risk attitudes in choice and pricing tasks." *The Economic Journal* 120(545):595–611.

Hardeweg, B., Menkhoff, L., and Waibel, H. (2013). "Experimentally Validated Survey Evidence on Individual Risk Attitudes in Rural Thailand." *Economic Development and*

Cultural Change 61(4):859–888.

Harrison, G. W., and Rutström, E.E. (2008). “Risk Aversion in the Laboratory.” *Research in experimental Economics* 12(08):41–196.

He, P., M. Veronesi, and Engel, S. (2018). “Consistency of Risk Preference Measures: An Artefactual Field Experiment from Rural China.” *Journal of Development Studies* 54(11):1955–1973.

Henrich, J., Heine, S. J., and Norenzayan, A. (2010). “Most people are not WEIRD.” *Nature* 466:29.

Henrich, J., and McElreath, R. (2002). “Are Peasants Risk-Averse Decision Makers?” *Current Anthropology* 43(1):172–181.

Holden, S. T., and Quiggin, J. (2017). “Climate risk and state-contingent technology adoption: Shocks, drought tolerance and preferences.” *European Review of Agricultural Economics* 44(2):285–308.

Holt, C., and Laury, S. (2002). “Risk aversion and incentive effects.” *The American Economic Review* 92(5):1644–1655.

Holt, C. A., and Laury, S. K. (2002). “Risk aversion and incentive effects.” *The American Economic Review* 92(5):1644–1655.

Jacobson, S., andPetrie, R. (2009). “Learning from mistakes: What do inconsistent choices over risk tell us?” *Journal of Risk and Uncertainty* 38(2):143–158.

Jamison, J., Karlan, D., and Zinman, J. (2012). “Measuring Risk and Time Preferences and Their Connections with Behavior.” (Working Paper).

Just, R.E., and Zilberman, D. (1983). “Stochastic Structure, Farm Size and Technology Adoption in Developing Agriculture.” *Oxford Economic Papers* 35(2):307–328.

Kahneman, D., and Tversky, A. (1979). “Prospect Theory: An Analysis of Decision under Risk.” *Econometrica* 47(2):263–292.

Kaiser, H. F. (1960). “The Application of Electronic Computers to Factor Analysis.” *Educational and Psychological Measurement* 20(1):141–151.

Khor, L. Y., Ufer, S., Nielsen, T., and Zeller, M. (2015). “The Influence of Individual Risk Behavior on Fertilizer Use Decision in Vietnam.” In *HarvestPlus / International Food Policy Research Institute (IFPRI), USA.*

L’Haridon, O., and Vieider, F. M. (2017). “All Over The Map: A Worldwide Comparison of Risk Preferences.” (Working Paper)

Lejuez, C. W., Read, J. P., Kahler, C. W., Richards, J. B., Ramsey, S. E., Stuart, G. L., Strong, D. R., and Brown, R. A. (2002). “Evaluation of a behavioral measure of risk taking: The Balloon Analogue Risk Task (BART).” *Journal of Experimental Psychology: Applied* 8(2):75–84.

Levitt, S. D., and List, J. A. (2007). “What Do Laboratory Experiments Measuring Social Preferences Reveal About the Real World?” *Journal of Economic Perspectives* 21(2):153–174.

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.

Liu, E. M., and Huang, J. K. (2013). “Risk preferences and pesticide use by cotton farmers in China.” *Journal of Development Economics* 103(1):202–215.

Lönnqvist, J.-E., Verkasalo, M., Walkowitz, G., and Wichardt, P.C. (2014). “Measuring Individual Risk Attitudes in the Lab : Task or Ask ? An Empirical Comparison.” Kiel Working Paper No. No. 1905,

Lusk, J. L., and Coble, K. H. (2005). “Risk Perceptions, Risk Preference, and Acceptance of Risky Food.” *American Journal of Agricultural Economics* 87(2):393–405.

de Melo, E. (2014). “Personal communication of fertilizer applications on coffee production (CATIE).”

de Oliveira, A. C .M., Eckel, C., and Croson, R. T. A. (2012). “The Stability of Social Preferences in a Low-Income Neighborhood.” *Southern Economic Journal* 79(1):15–45.

Prelec, D. 1998. “The probability weighting function.” *Econometrica* 66(3):497–527.

Roosen, J., and Hennessy, D. A. (2003). “Tests for the Role of Risk Aversion on Input Use.” *American Journal of Agricultural Economics* 85(February):30–43.

Samper, M. (2010). “Costa Rica’s response to the coffee crisis.” *Latin American Perspectives* 37(2):72–92.

Smith, V. L. (1976.) “Experimental Economics : Induced Value Theory.” *The American Economic Review* 66(2):274–279.

Sriramaratnam, A. S., Bessler, D. A., Rister, M. E., Matocha, J. E., and Novak, J. (1987). “Fertilization under Uncertainty : An Analysis Based on Producer Yield Expectations.” *American Journal of Agricultural Economics* 69(2):349–357.

Sutter, M., Kocher, M. G., Daniela, G. R., and Trautmann, S. T. (2013). “Impatience and uncertainty: Experimental decisions predict adolescents’ field behavior.” *American Economic Review* 103(1):510–531.

Tanaka, T., Camerer, C. F., and Nguyen, Q. (2010). “Risk and Time Preferences: Linking

Experimental and Household Survey Data from Vietnam." *American Economic Review* 100(1):557–571.

Tversky, A., and Kahneman, D. (1992). "Advances in prospect theory: Cumulative representation of uncertainty." *Journal of Risk and Uncertainty* 5(4):297–323.

Vablauwe, B., Coe, R., and Giller, K. E. (2016). "Beyond Averages: New Approaches To Understand Heterogeneity and Risk of Technology Success or Failure in Smallholder Farming." *Experimental Agriculture*:1–23.

Verschoor, A., D'Exelle, B., and Perez-Viana, B. (2016). "Lab and life: Does risky choice behaviour observed in experiments reflect that in the real world?" *Journal of Economic Behavior and Organization* 128:134–148.

Viceisza, A. C. G. (2016). "Creating a Lab in the Field: Economics Experiments for Policymaking." *Journal of Economic Surveys* 30(5):835–854.

Vieider, F. M., Beyene, A. Bluffstone, R., Dissanayake, S., Gebreegziabher, Z., Mekonnen, A., and Martinsson, p. (2018). "Measuring risk preferences in Ethiopia." *Economic Development and Cultural Change* 66(3):417–446.

Vieider, F. M., Lefebvre, M., Bouchouicha, R., Chmura, T. Hakimov, R., Krawczyk, M., and Martinsson, P. (2015). "Common components of risk and uncertainty attitudes across contexts and domains: Evidence from 30 countries." *Journal of the European Economic Association* 12(3):421–452.

Vieider, F. M., Truong, N., Martinsson, P., and Nam, P. K. (2014). "Risk Preferences and Development Revisited." No. (Working paper),

Appendix

Table A1. Risk Attitudes in Different Contexts.

Context	Our study	Dohmen et al (2011)
General	6.234	4.420
Car driving	4.148	2.927
Financial matters	4.888	2.406
Sport/leisure	5.436	3.486
Career/work	6.669	3.605
Health	4.730	2.934

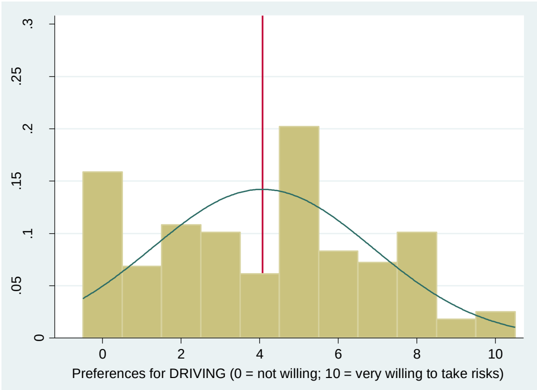
Table A2. Correlation between Risk Attitudes in Different Contexts (Dohmen et al. (2011) in Brackets.

	General	Car driving	Financial matters	Sport/leisure	Career	Health
General	1 (1)					
Car driving	0.2666*** (0.4891)	1 (1)				
Financial matters	0.4205*** (0.5036)	0.4516*** (0.5190)	1 (1)			
Sport/leisure	0.3603*** (0.5595)	0.2864*** (0.5426)	0.3490*** (0.4992)	1 (1)		
Career	0.3423*** (0.6088)	0.1757* (0.5070)	0.3430*** (0.4978)	0.3678*** (0.6033)	1 (1)	
Health	0.0958 (0.4768)	0.3737*** (0.5041)	0.3328*** (0.4564)	0.1380 (0.5205)	0.2162*** (0.5311)	1 (1)

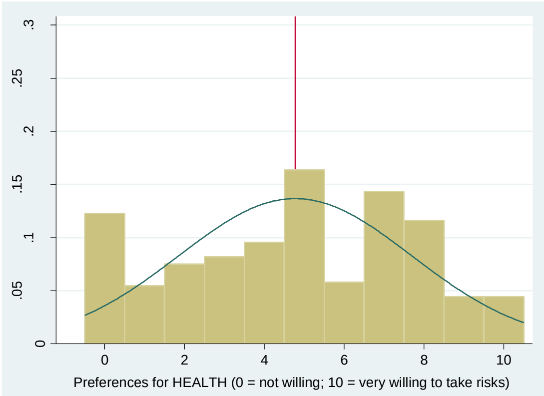
Note: Coefficients refer to Spearman’s ρ and are calculated using all non-missing observations between a pair of variables; *** p<0.01, ** p<0.05, * p<0.1.using Bonferroni correction method for adjusted p-values.

Table A3. Farmer's Responses to other Survey Context-Specific Risk Preferences Estimates

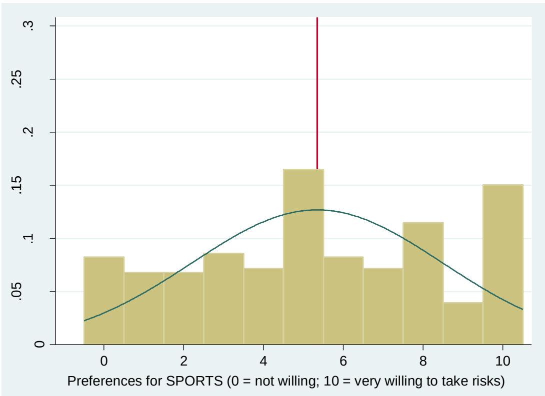
A3.1 Farmer's preferences for driving



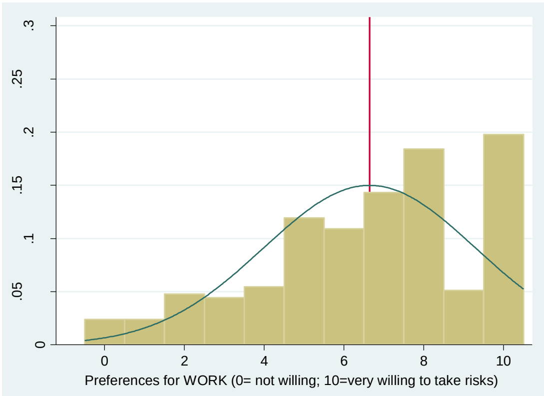
A3.2 Farmer's preferences regarding health



A3.3 Farmer's preferences for sports



A3.4 Farmer's preferences regarding work



Note: Red line indicates mean response to risk question and blue line shows the adjusted probability distribution.

Table A4. Principal Component Analysis Results

A4.1. Principal components and correlations

Component	Eigenvalue	Difference	Proportion	Cumulative
1	**2.35027**	**0.866991**	**0.3358**	**0.3358**
2	**1.48328**	**0.532159**	**0.2119**	**0.5477**
3	0.951121	0.020768	0.1359	0.6835
4	0.930353	0.324798	0.1329	0.8164
5	0.605556	0.093846	0.0865	0.9029
6	0.51171	0.344001	0.0731	0.976
7	0.167708		0.024	1

Following the *Kaiser rule*, we should retain the components with an eigenvalue larger than one (Kaiser 1960). The analysis shows that there are two components with an eigenvalue above one, together explaining 55% of the variation in the data.

A4.2. Principal Components (eigenvectors) and Rotated Components

Variable	Component 1	Component 2	Unexplained
General (no context)		0.549	0.4717
Finances		0.5889	0.3895
Farming			0.7863
Changing crop		0.4834	0.5716
Changing coffee variety	0.3183		0.6841
Pest control used	0.6587		0.1297
Fertilizer used	0.6649		0.1335

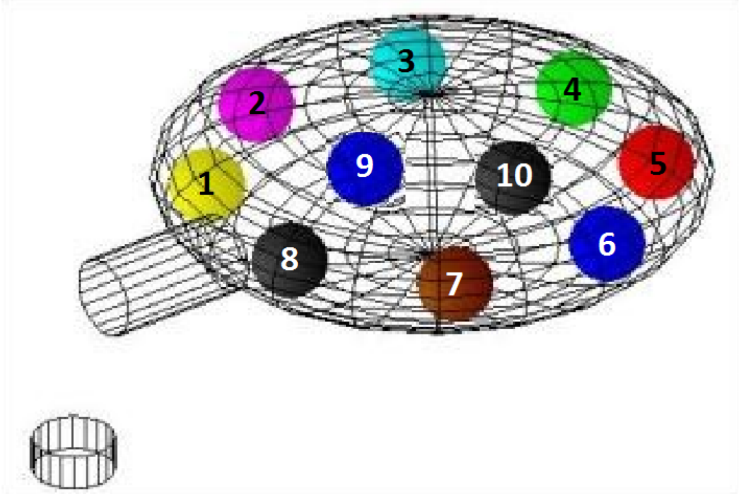
The general estimate (no context), the financial and the changing crop estimates of risk-taking are grouped under one component, while the other farm practices, input used and changing coffee variety, are gathered under the second component. The farming context remained highly unexplained (79%) and not grouped in either of the two components.

A4.3. Kaiser-Meyer-Olkin Measure of Sampling Adequacy

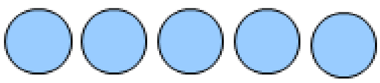
Variable	kmo*
General (no context)	0.608
Finances	0.6167
Farming	0.7484
Changing crop	0.6224
Changing coffee variety	0.7599
Pest control used	0.5619
Fertilizer used	0.5478
Overall	0.5975

*kmo statistic indicates the proportion of variance in these variables that might be caused by underlying factors. High values indicate that a factor analysis is useful with this data. Values less than 0.50 would indicate that the factor analysis is not useful to explain the variation in the data.

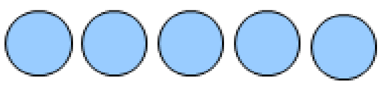
Table A5. Example of Decision Task in the Gain Domain



You win ¢ **5000** if one of the following balls is drawn from the urn:



You win ¢ **0** if one of the following balls is drawn from the urn:



	Lottery		Sure amount
1	O	O	250 ¢ for sure
2	O	O	500 ¢ for sure
3	O	O	750 ¢ for sure
4	O	O	1000 ¢ for sure
5	O	O	1250 ¢ for sure
6	O	O	1500 ¢ for sure
7	O	O	1750 ¢ for sure
8	O	O	2000 ¢ for sure
9	O	O	2250 ¢ for sure
10	O	O	2500 ¢ for sure
11	O	O	2750 ¢ for sure
12	O	O	3000 ¢ for sure
13	O	O	3250 ¢ for sure
14	O	O	3500 ¢ for sure
15	O	O	3750 ¢ for sure
16	O	O	4000 ¢ for sure
17	O	O	4250 ¢ for sure
18	O	O	4500 ¢ for sure
19	O	O	4750 ¢ for sure