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Inconsistent choices over prospect theory lottery games: Evidence from field experiments☆

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ABSTRACT

Expected utility theory and classroom experiments have been commonly used to test the consistency and/or stability of elicited risk preferences among individuals. Usually conducted in developed countries, these studies have shown that risk preferences are inconsistent or unstable. However, the literature falls short when assessing the consistency of risk preferences under the Prospect Theory (PT) paradigm. This study reports the results of lottery games, played during two consecutive experimental sessions, to test the consistency of PT risk preferences among smallholder farmers in Ecuador, a developing country. I find evidence of consistency in the farmers' risk preferences at the sample level. Nonetheless, I find inconsistency in risk preferences (risk aversion, probability distortion, and loss-aversion) at the individual level. I assess whether there is heterogeneity in the results across farmers' demographic and socioeconomic attributes. Evidence suggests that relative consistency in the degree of loss aversion is higher among farmers who are female, own larger farms, and are more educated.

1. Introduction

Agricultural production processes require farmers to undertake risky decisions in a dynamic environment influenced by weather, economic, and social phenomena. During the production process, farmers may revise their initial choices and reevaluate their farming practices over time. For example, a farmer observing a newly adopted pesticide's performance can choose to keep applying the same amount, apply more, or disadopt it. Additionally, when acquiring inputs, farmers may select a "high-risk input" (i.e., a new liquid fertilizer) and, after that, select a "low-risk input" (i.e., a well-known pesticide that the farmer is familiar with). Thus, farmers may change the use of inputs based on their perceived risk or risk preference. These changes in risk preferences may be due to several reasons, including changing circumstances on the field, emotions, income, family and farm dynamics. Indeed, different farmers' behavior in choosing inputs is often described as differences in risk preferences. Consequently, it is assumed that by understanding individual risk preferences, we can predict certain economic behaviors.

The theory assumes that risk preferences are constant (Loewenstein, Read, & Baumeister, 2003). The experimental literature based on the Expected Utility (EU) framework shows that risk preferences are relatively consistent over time,[1] with no systematic differences when the games are similar (Choi, Fisman, Gale, & Kariv, 2007) or between shorter versus more extended periods between games. However, there is a growing number of studies showing that risk preferences are inconsistent or unstable. Specifically, across different settings or different games played on the same day, evidence show risk preferences are not consistent (Binswanger, 1980; Dulleck, Fooken, & Fell, 2015). Most of this work normally uses samples from developed countries – usually well-educated university students – and is based on the Expected Utility (EU) framework. Thus, the studies assume a single parameter is sufficient to characterize an individual's risk preference. Nonetheless, their external validity may not be appropriate for samples other than students found in university labs (Chuang & Schechter, 2015).

By now we know a considerable amount about the consistency of risk preferences, specially with respect to risk aversion — the only parameter in the EU value function. However, very little attention has been given to investigating the consistency of farmers' risk preferences using the Prospect Theory (PT) paradigm — an alternative theory of decision-making under risk or uncertainty that accounts for loss aversion and probability weighting (Kahneman & Tversky, 1979; Tversky &

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[1] Chuang and Schechter (2015) conduct a review of the literature on the stability of (i) risk and time preferences, as measured by experiments, and of (ii) social preferences as measured by both survey questions and experiments.

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Kahneman, 1992). Motivated by this gap in the literature, the objectives of this paper are twofold. First, I evaluate and test the consistency of farmers' PT risk preferences at the individual and the sample level. Second, I examine how inconsistencies in farmers' PT risk preferences correlate with their demographic and socioeconomic characteristics. To achieve these objectives, I conduct a within-subject experiment on a sample of Ecuadorian farmers. Participants played lottery games in two consecutive experimental sessions. These games allow for the elicitation of PT structural risk preference parameters.

I focus on whether farmers' answers to lottery games – and therefore their elicited risk preferences – are meaningful and/or consistent, because they influence the validity of empirical studies that (i) assume PT behavior in a given sample, and (ii) use them to evaluate certain economic behaviors that occurred ex-ante or ex-post.[2] The analysis presented here is closely related to the existing literature investigating the consistency of risk preferences among populations of farmers (Chuang & Schechter, 2015; Reynaud & Couture, 2012). However, it differs from these previous studies and contribute to our understanding of inconsistent choices and risk preferences in two particular ways. First, I study the consistency of risk preferences using PT, which has yet to be tested among farmers and in a developing country context. Second, although not directly testable, by showing how inconsistencies in farmers' PT risk preferences correlate with their demographic and socioeconomic characteristics, I also contribute to our understanding on cognitive function and decision-making.

Results from both experimental sessions confirm the findings of previous empirical studies and show that, on average, participants are risk-averse, overweight low probabilities, and are more sensitive to losses than gains. Using the results from the within-subject experiments, I find evidence of consistency in the farmer's prospect theory risk preferences at the sample level. However, I find inconsistency in risk aversion, probability distortion, and loss-aversion at the individual level. The inconsistency observed at the individual level supports previous studies suggesting that individual choice behavior is more reasonably modeled as a stochastic process rather than a deterministic process (Harrison & Rutström, 2008; Hey & Orme, 1994; Wilcox, 2008). Interestingly, results also show that relative consistency in the degree of loss aversion is more likely to occur with female farmers, those who own larger farms, own livestock, and are more educated.[3] Nonetheless, relative consistency in risk aversion and probability distortion are hardly correlated with farmers' characteristics.

The remainder of this paper is organized as follows. The next section briefly summarizes the literature on the consistency of risk preferences using PT. It also discusses the PT conceptual framework. Section 3 presents the study setting and data, and describes the experimental design used to elicit risk preferences for this study; it also summarizes some descriptive statistics from the survey data. Section 4 presents a descriptive analysis of the results from the lottery experiments and examines the consistency of farmers' risk preferences at the individual and sample levels. Subsequently, I present the empirical framework and results of the correlations between inconsistencies in farmers' risk preferences and their demographic and socioeconomic characteristics. This is followed by a discussion on the implications of the main findings. In Section 5, I summarize the main results, conclude and discuss the limitations of my approach, and provide directions for future research.

[2] For example, Liu (2013) uses PT risk preferences parameters to evaluate the adoption decisions of agricultural technology.

[3] Factors such as scarcity, education, and income have been shown to alter attentional resources and interfere with cognitive functions, which could lead to errors and biases in decision-making (Benjamin, Brown, & Shapiro, 2013; Burks, Carpenter, Goette, & Rustichini, 2009; Choi et al., 2007; Shah, Mullainathan, & Shafir, 2012).

2. Theoretical framework

Consistency of risk preferences is generally defined at the individual level. It implies that one should observe the same willingness to take risks when measuring an individual's risk preferences repeatedly. This approach assumes measurement error does not exist (Schildberg-Hörisch, 2018). Studies of the consistency of risk preferences at the individual level typically report correlations of an individual's risk preferences across experiments (Drichoutis & Vassilopoulos, 2021). As previously mentioned, the majority of this literature is based on the classical EU framework. To my best knowledge, only a few papers have examined consistency using the PT paradigm. These studies rely only on student samples and estimate the individual's risk preference parameters using the maximum likelihood (ML) estimator or the maximum a posteriori (MAP) estimator (Lau, Yoo, & Zhao, 2019). Results from the studies provide mixed conclusions with respect to the consistency at the individual level. Some studies reported correlation coefficients that are larger, signaling consistency (Lau et al., 2019), however, others have found correlation coefficients that are smaller, signaling inconsistency (Glöckner & Pachur, 2012).

Consistency at the sample level refers to whether the distribution of risk preferences across the sample of subjects remains consistent when measured repeatedly (Harrison, Lau, & Yoo, 2020). Lau et al. (2019) is the only study that tests the above hypothesis under the PT framework by analyzing data from longitudinal laboratory experiments conducted by Glöckner and Pachur (2012) and Murphy and ten Brincke (2018). Lau et al. (2019) find inconsistency for the entire population distribution of PT risk preferences.

2.1. Prospect theory

The Prospect theory (PT) analysis is based on Kahneman and Tversky (1979), and Tversky and Kahneman (1992). Formally, the prospect theory utility is defined as[4]:

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

$PT(x,p;y,1-p)$ is the expected value over binary prospects $(x;y)$, with corresponding probabilities $(p;1-p)$; $v(x)$ represents an increasing piecewise power function that assigns different values for gains $(x > 0)$ and losses $(x < 0)$ with $v(0) = 0$ such that:

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

The concavity of the value function for gains and losses is determined by $\sigma \in (0,1.5)$ which represents risk aversion, while λ describes the curvature below 0 relative to the curvature above 0 and describes the degree of loss aversion. In Eq. (1), $w(p)$ represents the axiomatically derived probability weighting function of Prelec (1998):

$$w(p) = \frac{1}{[\exp(\ln(1/p))]^{\alpha}} \tag{3}$$

In Eq. (3), $\alpha \in (0,1.5)$ is the parameter that determines the curvature of the probability weighting function. This model of Prospect Theory reduces to Expected Utility when $\alpha = 1$ and $\lambda = 1$.

[4] Eq. (1) is what a more general preference functional form in Tversky and Kahneman (1992) simplifies to when the lottery in question is a probability distribution over two prizes.

3. Study setting and data

Six experimental sessions, in partnership the Ecuadorian Institute of Agricultural Research (INIAP), were conducted during summer 2019 with a total of 202 participants. These sessions were conducted at four different indigenous farming villages located in the Andes region of the country, namely Balcashi, Llucud, Puculpala, and Puelazo. These villages are on average 45 min away from the city of Riobamba, the closest city and capital of Chimborazo Province. They were selected based on a current agricultural extension program lead by INIAP that facilitated the logistics and access to these locations. Participants – smallholder farmers from the villages – were recruited via announcements made by the community leaders using megaphones, the public communications system of the villages. The announcements communicated meeting dates, times, and locations; they also mentioned farmers will receive a monetary compensation for their participation in the study.

The experiments took place in the village community centers, lasted about two hours, and were conducted during the night, as farmers spent most of the day working on their farms. Upon arrival in the community center, participants were seated randomly and illiterate subjects were excluded from participating in the experiment. Participants were told they will participate in two experimental sessions, where they would play lottery games. The instructions for the lottery games and payment procedures were clearly explained to the participants verbally at the beginning of each experimental session. Printed instructions with examples as well as record sheets were also provided. Following Tanaka, Camerer, and Nguyen (2010), the verbal and instructions contained 3 examples of the lottery games.

Participants played the prospect theory risk elicitation games during two consecutive experimental sessions, and at the end they filled out a questionnaire on household and individual characteristics. Monetary incentives were used to make the experiment incentive-compatible and to motivate participants to behave more towards realistic choices. Participants obtained 4 USD for showing up to the study. After the experiments and survey, a numbered ball from a bingo cage was drawn to randomize and determine which experimental session, game, series, row, and choice would be played for real money as a bonus. This random draw was done for every village where the experiments were conducted. The additional monetary compensation was applied based on their choices in the games and ranged from [−3, 3] USD.[5] The average earning for the participants was 6.5 USD total, including the show-up fee and bonus. This earning compares to the wage of one-half working day on agricultural activities in the region.

3.1. Elicitation method

To elicit and estimate the structural parameters of the PT utility function, I use the experimental design of Tanaka et al. (2010) along with their "mid-point" approximation method for the estimation of the PT structural parameters. This design helps determine unique values of PT structural parameters from plays in an incentivized multiple price list (lottery game).[6]

Tanaka's lottery games were presented in an agricultural illustration to facilitate the understanding of the experiment for the participants (Alekseev, Charness, & Gneezy, 2017; Hill & Viceisza, 2012; Viceisza, 2016; Villacis, Alwang, & Barrera, 2021). To mimic the price lists, participants were showed an illustration of a farm composed of 10 equally sized lots, each of them with a particular payoff from using either Seed A or Seed B across various years. Participants were told that at the end of the crop season only one lot would survive but this would be determined at random. Participants were asked at which year (row) they would "switch" from Seed A to Seed B. By doing this, monotonicity and transitivity requirements are imposed to the subjects, however, this gives up the opportunity to check whether this is actually the case (Holzmeister & Stefan, 2021). Table 1 replicates Series 1 of Tanaka's experimental design and Fig. 1 shows how this series was adapted and presented to participants. This illustration implicitly shows that seed A in the year 2021 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 75 USD and a 90% chance of receiving 5 USD.

Tanaka's design consists of three series or price lists, thus, participants reported their answers in each of the series. Every combination of the participant's choices in the three price lists (lottery games) determine unique values of PT parameters. In the supplemental appendix I provide all the illustrations of the lotteries used with participants (See Supplemental Appendix tables A1 and A2 and figures A1 through A6). The combination of switching points from series 1 and series 2 form a set of two inequalities each. These four inequalities allows the estimation of the parameters for risk aversion (σ) and probability weighting (α). For example, when a participant switches from lottery A to lottery B at row 7 for both series 1 and series 2, the following system of inequalities should be satisfied[7]:

$$\begin{aligned}
&10^{\sigma}+\exp\left[-(-\ln 0.3)^{\alpha}\right](40^{\sigma}-10^{\sigma})>5^{\sigma}+\exp\left[-(-\ln 0.1)^{\alpha}\right](125^{\sigma}-5^{\sigma})\\
&10^{\sigma}+\exp\left[-(-\ln 0.3)^{\alpha}\right](40^{\sigma}-10^{\sigma})<5^{\sigma}+\exp\left[-(-\ln 0.1)^{\alpha}\right](150^{\sigma}-5^{\sigma})\\
&30^{\sigma}+\exp\left[-(-\ln 0.9)^{\alpha}\right](40^{\sigma}-30^{\sigma})>5^{\sigma}+\exp\left[-(-\ln 0.7)^{\alpha}\right](65^{\sigma}-5^{\sigma})\\
&30^{\sigma}+\exp\left[-(-\ln 0.9)^{\alpha}\right](40^{\sigma}-30^{\sigma})<5^{\sigma}+\exp\left[-(-\ln 0.7)^{\alpha}\right](68^{\sigma}-5^{\sigma}).
\end{aligned} \tag{4}$$

Parameters that satisfy these inequalities are $0.65 < \sigma < 0.74$ and $0.66 < \alpha < 0.74$. Following Tanaka's midpoint approximation to one decimal place in the above inequalities, the estimate for σ is 0.7 and for α is 0.7. Tanaka et al. (2010) provides the values for parameters σ and α for all possible combinations resulting from a participant's choices in series 1 and 2 of the lottery games.[8]

After obtaining the estimates of σ and α, we can estimate λ by using the switching point from series 3 and applying the midpoint approximation of each interval as the point estimate. For example, when a participant switches from lottery A to lottery B at row 4 in series 3, the following system of inequalities should be satisfied:

$$\begin{aligned}
&\exp\left[-(-\ln 0.5)^{\alpha}\right](1^{\sigma})+\exp\left[-(-\ln 0.5)^{\alpha}\right]\left[-\lambda(4^{\sigma})\right]>\\
&\quad\exp\left[-(-\ln 0.5)^{\alpha}\right](30^{\sigma})+\exp\left[-(-\ln 0.5)^{\alpha}\right]\left[-\lambda(21^{\sigma})\right].
\end{aligned} \tag{5}$$

$$\begin{aligned}
&\exp\left[-(-\ln 0.5)^{\alpha}\right](1^{\sigma})+\exp\left[-(-\ln 0.5)^{\alpha}\right]\left[-\lambda(4^{\sigma})\right]<\\
&\quad\exp\left[-(-\ln 0.5)^{\alpha}\right](30^{\sigma})+\exp\left[-(-\ln 0.5)^{\alpha}\right]\left[-\lambda(16^{\sigma})\right].
\end{aligned} \tag{6}$$

Following from the example above, if we assume $\sigma = 0.7$ and $\alpha = 0.7$, then the λ values that satisfy inequalities (5) and (6) are $1.70 < \lambda < 2.27$. The midpoint approximation lead to an estimate of λ of 1.98.

To test the consistency of PT risk preferences, participants played the lottery games during two consecutive experimental sessions. Thus, I obtained two sets of PT parameters for each participant. Both experimental sessions were conducted in the same day, one after the

[5] For ethical reasons, I avoided the loss of money by the farmers, thus, losses were managed in accordance to the procedure proposed by Liu (2013).

[6] Recent evidence suggest that when all decisions are shown together in a single list, the mechanism might not be incentive compatible; but when the rows of the list are randomized and shown on separate screens, incentive compatibility is restored (Brown & Healy, 2018).

[7] In Liu (2013), the value function $v(x)$ has the form $v(x) = x^{1-\sigma}$ for $x > 0$; $v(x) = -\lambda(-x)^{1-\sigma}$ for $x < 0$. For consistency, I follow Tanaka's value function presented in Eq. (2) of this paper.

[8] The choice of "never switching" or "switching at row 1", generates only one inequality in each series. The solution to these inequalities are used as lower/upper bounds of the parameters (Liu, 2013; Tanaka et al., 2010).

Table 1
Example of how series 1 of the pairwise lottery choices in Tanaka et al. (2010) was adapted for the second experimental sessions.

Row	First experimental session — Lottery 1 (original order)	
	Lottery A	Lottery B
1	30% winning $40 and 70% winning $10	10% winning $68 and 90% winning $5
2	30% winning $40 and 70% winning $10	10% winning $75 and 90% winning $5
3	30% winning $40 and 70% winning $10	10% winning $83 and 90% winning $5
4	30% winning $40 and 70% winning $10	10% winning $93 and 90% winning $5
5	30% winning $40 and 70% winning $10	10% winning $106 and 90% winning $5
6	30% winning $40 and 70% winning $10	10% winning $125 and 90% winning $5
7	30% winning $40 and 70% winning $10	10% winning $150 and 90% winning $5
8	30% winning $40 and 70% winning $10	10% winning $185 and 90% winning $5
9	30% winning $40 and 70% winning $10	10% winning $220 and 90% winning $5
10	30% winning $40 and 70% winning $10	10% winning $300 and 90% winning $5
11	30% winning $40 and 70% winning $10	10% winning $400 and 90% winning $5
12	30% winning $40 and 70% winning $10	10% winning $600 and 90% winning $5
13	30% winning $40 and 70% winning $10	10% winning $1000 and 90% winning $5
14	30% winning $40 and 70% winning $10	10% winning $1700 and 90% winning $5
	Second experimental session — Lottery 1 (reversed order)	
	Lottery A	Lottery B
1	90% winning $5 and 10% winning $1700	70% winning $10 and 30% winning $40
2	90% winning $5 and 10% winning $1000	70% winning $10 and 30% winning $40
3	90% winning $5 and 10% winning $600	70% winning $10 and 30% winning $40
4	90% winning $5 and 10% winning $400	70% winning $10 and 30% winning $40
5	90% winning $5 and 10% winning $300	70% winning $10 and 30% winning $40
6	90% winning $5 and 10% winning $220	70% winning $10 and 30% winning $40
7	90% winning $5 and 10% winning $185	70% winning $10 and 30% winning $40
8	90% winning $5 and 10% winning $150	70% winning $10 and 30% winning $40
9	90% winning $5 and 10% winning $125	70% winning $10 and 30% winning $40
10	90% winning $5 and 10% winning $106	70% winning $10 and 30% winning $40
11	90% winning $5 and 10% winning $93	70% winning $10 and 30% winning $40
12	90% winning $5 and 10% winning $83	70% winning $10 and 30% winning $40
13	90% winning $5 and 10% winning $75	70% winning $10 and 30% winning $40
14	90% winning $5 and 10% winning $68	70% winning $10 and 30% winning $40

other, with a ten-minute break between experimental sessions. To avoid learning effects (Carlsson, Mørkbak, & Olsen, 2012), for the second experimental session the order of Tanaka's paired lotteries within each series was doubly reversed (horizontally and vertically). This was done to make participants look carefully at their choices again, as it "appeared" to be a different game even though they were the exact same lotteries. Table 1 shows how the order of Series 1 in Tanaka et al. (2010) was adapted for the second experimental session. The same procedure was applied for Series 2 and 3 for the second experimental session (See Supplemental Appendix tables A1 and A2). Finally, the order of the paired lotteries that were shown to participants first (original vs. reversed) was randomized.

3.2. Survey

To establish correlations between the observed behavior and the subject's characteristics, a survey was conducted after the experimental rounds. It included questions related to demographic, socioeconomic, and farm characteristics. As discussed in Liu (2013), participants choosing option A or B all of the time might not have understood or lost interest in the experiment. There were 11 participants who exhibited this behavior during both experimental sessions, 14 did it for the first session only, and 18 did it for the second session only. This added up to 43 participants in total that signaled they might not have understood the experiments. These were excluded from the primary analysis, thereby reducing the final sample to 159 participants. The average age of the participants is about 43 years, and most have finished elementary school only, earning up to 300 USD/month, and cultivating about 1.84 hectares of farmland. Summary statistics and variable descriptions are presented in Table 2.

4. Results

To estimate the structural parameters of the PT utility function, I used the mid-point procedure proposed by Tanaka et al. (2010) and further explained in Liu (2013). A descriptive analysis of the results from the PT experiments is presented in Table 3. In both experimental sessions, average values of σ and α suggest that participants are risk-averse and that they overweight low probabilities respectively.[9] The average values of λ indicate they are more sensitive to losses than gains at an approximate magnitude of 4 to 1.[10]

I am interested in exploring and testing the following three hypotheses. First, to test if the PT risk preferences obtained from the lottery games are consistent at the sample level over the two experimental sessions. Second, to test if the PT risk preferences are consistent at the individual level. Third, test if there are significant correlations between the consistency of farmers' risk preferences and their demographic and socioeconomic attributes.

4.1. Testing consistency at the sample level

Looking at the results from Table 3, the estimated parameter σ (the proxy for risk aversion) has a sample mean of 0.68 in experimental session 1 and 0.60 in experimental session 2. The estimated difference between these sample-level parameters is significantly different from 0 only at the 10% significance level. This suggests that farmers may be sensitive to responding to lottery-type queries eliciting risk preferences across experimental rounds. Perhaps farmers are getting more comfortable in responding to the lottery questions or revealing their

[9] These findings are in accordance with results obtained by Bocquého, Jacquet, and Reynaud (2014), Liebenehm and Waibel (2014), Liu (2013), Luckstead and Devadoss (2019), Sagemüller and Mußhoff (2020), Tanaka et al. (2010) and Ward and Singh (2015).

[10] When $\alpha = 1$ and $\lambda = 1$, Tanaka's PT functional form reduces to a particular EU functional form (Liu, 2013). Out of the 225 possible choices people can select when playing Tanaka's series 1 and 2 (that determine α), only 9 of them lead to $\alpha = 1$. The estimated mean values of α and λ are significantly different from 1 at the 0.01 percent significance level by t-test.

FIRST EXPERIMENTAL SESSION - SERIES 1

YEAR	Seed A Lot 1	Lot 2	Lot 3	Lot 4	Lot 5	Lot 6	Lot 7	Lot 8	Lot 9	Lot 10	Seed B Lot 1	Lot 2	Lot 3	Lot 4	Lot 5	Lot 6	Lot 7	Lot 8	Lot 9	Lot 10
2019	$40	$40	$40	$10	$10	$10	$10	$10	$10	$10	----------									
2020	$40	$40	$40	$10	$10	$10	$10	$10	$10	$10	$68	$5	$5	$5	$5	$5	$5	$5	$5	$5
2021	$40	$40	$40	$10	$10	$10	$10	$10	$10	$10	$75	$5	$5	$5	$5	$5	$5	$5	$5	$5
2022	$40	$40	$40	$10	$10	$10	$10	$10	$10	$10	$83	$5	$5	$5	$5	$5	$5	$5	$5	$5
2023	$40	$40	$40	$10	$10	$10	$10	$10	$10	$10	$93	$5	$5	$5	$5	$5	$5	$5	$5	$5
2024	$40	$40	$40	$10	$10	$10	$10	$10	$10	$10	$106	$5	$5	$5	$5	$5	$5	$5	$5	$5
2025	$40	$40	$40	$10	$10	$10	$10	$10	$10	$10	$125	$5	$5	$5	$5	$5	$5	$5	$5	$5
2026	$40	$40	$40	$10	$10	$10	$10	$10	$10	$10	$150	$5	$5	$5	$5	$5	$5	$5	$5	$5
2027	$40	$40	$40	$10	$10	$10	$10	$10	$10	$10	$185	$5	$5	$5	$5	$5	$5	$5	$5	$5
2028	$40	$40	$40	$10	$10	$10	$10	$10	$10	$10	$220	$5	$5	$5	$5	$5	$5	$5	$5	$5
2029	$40	$40	$40	$10	$10	$10	$10	$10	$10	$10	$300	$5	$5	$5	$5	$5	$5	$5	$5	$5
2030	$40	$40	$40	$10	$10	$10	$10	$10	$10	$10	$400	$5	$5	$5	$5	$5	$5	$5	$5	$5
2031	$40	$40	$40	$10	$10	$10	$10	$10	$10	$10	$600	$5	$5	$5	$5	$5	$5	$5	$5	$5
2032	$40	$40	$40	$10	$10	$10	$10	$10	$10	$10	$1,000	$5	$5	$5	$5	$5	$5	$5	$5	$5
2033	$40	$40	$40	$10	$10	$10	$10	$10	$10	$10	$1,700	$5	$5	$5	$5	$5	$5	$5	$5	$5

☐ I choose seed A for all the years

☐ I choose seed B for all the years

☐ I choose seed A from year 2020 until year ______ ; and seed B from year ______ until year 2033

Fig. 1. Lottery 1 shown in experimental session 1 (original order).

true risk preferences. The above argument is supported by a reduction in the estimated sample standard deviation (SD). The SD of σ between the two experimental sessions decreased slightly from 0.37 to 0.34, thus, possibly signaling a reduction in errors and/or biases in decision-making. However, overall, I find evidence of consistency because the estimated difference between the SD in the two experiments is not significantly different from 0 (p-value = 0.29).

Further, Table 3 shows consistency in the PT parameters α (the proxy for probability distortion) and λ (the proxy for loss aversion). The estimated difference in sample means and standard deviations of α and λ across the experimental sessions is not significantly different from 0 at the traditional significance levels. Fig. 2 provides a graphical illustration of the estimated sample distributions of the PT risk preference parameters across the two experimental rounds. The graphical approach also suggests consistency because there are no apparent shifts in the risk parameters obtained in the second experimental session compared to those obtained in the first session.

As a robustness check, I also conduct a two-sample Kolmogorov–Smirnov (K–S) tests of the equality of distributions. The K–S test is a nonparametric test that allows us to test if the distribution of each of the PT risk preference parameters is statistically similar between the two experimental sessions. Results are presented in Table 4. Column 1 of Table 4 reports the approximate asymptotic p-value associated with the null hypothesis, while column 2 reports the exact p-value for the combined test. I report the “exact p-value” as “approximate

Table 2
Summary statistics: Characteristics of participants.

Variable	Description	Mean	Std. dev.
Age	Age in years	42.94	16.09
Female	Gender dummy = 1 if Female, 0 otherwise	0.55	0.50
Education	Education level. Ordinal:	2.66	1.41
= 0	if never attended school	0.04	–
= 1	if attended some elementary school	0.11	–
= 2	if finished elementary school	0.45	–
= 3	if attended some high school	0.06	–
= 4	if finished high school	0.24	–
= 5	if attended some college	0.06	–
= 6	if finished college	0.04	–
Household Size	Number of household members	3.74	1.66
Area	Area of total farming land (hectares)	1.84	2.04
Distance	Distance of farm to nearest commercial road (meters)	298.83	587.93
Rent	Dummy = 1 if respondent rents farming land	0.11	0.32
Nonfarm Employment	Dummy = 1 if respondent has nonfarm employment	0.28	0.45
Income	Income derived from farm and nonfarm activities. Ordinal.	1.98	1.08
= 1	if 0–300 USD/month	0.43	–
= 2	if 301–600 USD/month	0.30	–
= 3	if 601–900 USD/month	0.16	–
= 4	if 901–1,500 USD/month	0.09	–
= 5	if > 1,500 USD/month	0.03	–
Irrigation	Dummy = 1 if respondent has access to irrigation system	0.88	0.33
Extension	Dummy = 1 if respondent has been visited by extension agent	0.16	0.37
Livestock	Dummy = 1 if respondent has dairy cattle	0.88	0.33

Table 3
Summary statistics of risk preference parameters.

Parameter	(1)	(2)	(3)	(4)	(5)	(6)
	Mean			Standard deviation		
	1st exp.	2nd exp.	P-value	1st exp.	2nd exp.	P-value
Risk aversion (σ)	0.68	0.60	0.09	0.37	0.34	0.29
Probability distortion (α)	0.83	0.82	0.75	0.40	0.44	0.29
Loss aversion (λ)	4.14	4.07	0.85	3.82	4.08	0.41

Notes: The *p*-value in columns 3 and 6 refers to the test of equality of outcomes among the 1st and 2nd experiment.

Table 4
Two-sample Kolmogorov–Smirnov test for equality of distributions.

	(1) *P*-value	(2) *P*-value
Panel A: σ (Risk Aversion)		
Ho: Experiment 1 contains smaller values than Experiment 2	1.000	
Ho: Experiment 1 contains larger values than Experiment 2	0.130	
Ho: Distribution is the same between the 1st and 2nd experiment (Combined K–S)	0.260	0.261
Panel B: α (Probability Distortion)		
Ho: Experiment 1 contains smaller values than Experiment 2	0.601	
Ho: Experiment 1 contains larger values than Experiment 2	0.404	
Ho: Distribution is the same between the 1st and 2nd experiment (Combined K–S)	0.756	0.757
Panel C: λ (Loss Aversion)		
Ho: Experiment 1 contains smaller values than Experiment 2	0.601	
Ho: Experiment 1 contains larger values than Experiment 2	0.243	
Ho: Distribution is the same between the 1st and 2nd experiment (Combined K–S)	0.479	0.48

p-values" are not good for small samples (n < 50), they are too conservative (Gibbons & Chakraborti, 2014).

I am interested in the last line in each panel of Table 4: the *p*-value of the combined K–S test. The combined K–S test null hypothesis posits that the distribution of each of the PT risk preference parameters is the same between the first and second experimental sessions. Here, the p-values indicate that we fail to reject the null, providing further evidence of consistency at the sample level.

4.2. Testing consistency at the individual level

Table 5 reports the within-individual correlation of the PT risk preference parameters. Across the two experimental sessions, I find statistically significant but weak positive correlation in probability distortion (α_1 vs. α_2) and loss-aversion (λ_1 vs. λ_2). I also find a weak negative correlation in risk aversion (σ_1 vs. σ_2) across the two experimental sessions, which is not statistically significant.

These results suggest inconsistency in risk aversion, probability distortion, and loss-aversion at the individual level. In other words, someone with an above-average λ parameter in experimental session 1 does not necessarily have an above-average λ parameter in experimental session 2. This is better observed in Fig. 3 where I provide details of the inconsistencies in risk preferences by showing the magnitude of the participants' values of σ, α and λ across the two experimental sessions. Fig. 3 shows that across the experimental sessions, participants

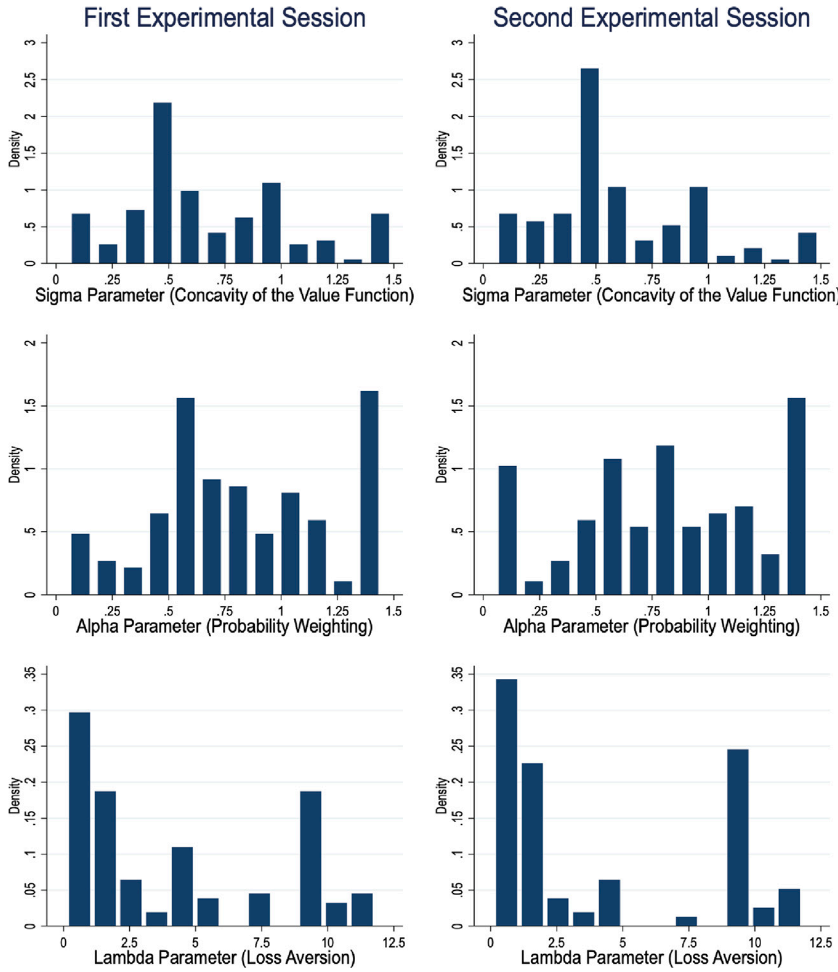

Fig. 2. Distribution of risk preference parameters.
Note: This figure illustrates the distribution of risk preference parameters across the two experimental sessions.

Table 5
Correlation coefficients among PT risk preference parameters.

	σ_1	α_1	λ_1	σ_2	α_2	λ_2
σ_1	1	–	–	–	–	–
α_1	−0.1767**	1	–	–	–	–
λ_1	0.1499*	0.0169	1	–	–	–
σ_2	−0.0852	−0.0014	0.0708	1	–	–
α_2	0.0053	0.1938**	−0.1273	−0.008	1	
λ_2	−0.0208	−0.099	0.1634**	0.2509***	−0.0019	1

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

(i) increased, (ii) decreased, or (iii) had *relative consistency* on the estimated parameters of interest.

I define *relative consistency* as when the estimated parameter of interest obtained during the second experiment is relatively close to the estimates obtained during the first experiment. Given the magnitude of the risk aversion (σ) and probability weighting (α) parameters vary between [0, 1.50] in Tanaka's experimental design, I use ±0.15 intervals to describe *relative consistency* for these specific parameters. For example, suppose a participant's estimated parameter σ is equal to 0.65 for the first experimental session. In that case, the participant is said to have relative consistency in σ if the participant's estimated parameter for the second experimental session falls within the range [0.50, 0.80]. Likewise, for the case of loss-aversion (λ), I use ±1.3 intervals to describe *relative consistency*, as this parameter varies between [0, 13] in Tanaka's experimental design.[11]

Although arbitrary, I use this definition of *relative consistency* to help us establish a conservative approach to consistency. This is because – in the lottery games – switching in a slightly different row (year) can have rather strong effects on the approximated parameters at the individual level when using Tanaka's mid-point method. Thus, we need to be very cautious about the interpretation of changes in the value of the PT parameters. For example, if a participant switches from option A to option B at row 6 in series 1 and 2 of the first experimental session, the estimate of σ will be 0.80 while for α will be 0.70. If in the second experimental session the same participant switches again at row 6 for series 1, but decides to switch at row 10 in series 2, the estimate of σ will be 0.60 while for α will be 0.50, violating *relative consistency*. In general, if we fix the same switching point for series 1 in both experimental sessions, then, one needs to move the switching point in series 2 of the second experimental session by 4 rows or more from the original switching point – played in first experimental session – to violate *relative consistency*.

[11] The risk aversion (σ) and probability weighting (α) parameters takes 30 distinct values in the interval [0.05, 1.50]; the difference between two adjacent values in this parameter is of 0.05. The loss-aversion (λ) parameter takes 203 distinct values in the interval [0, 13]; the difference between two adjacent values in this parameter ranges from 0.01 to 1.65 and is equal to 0.06 on average.

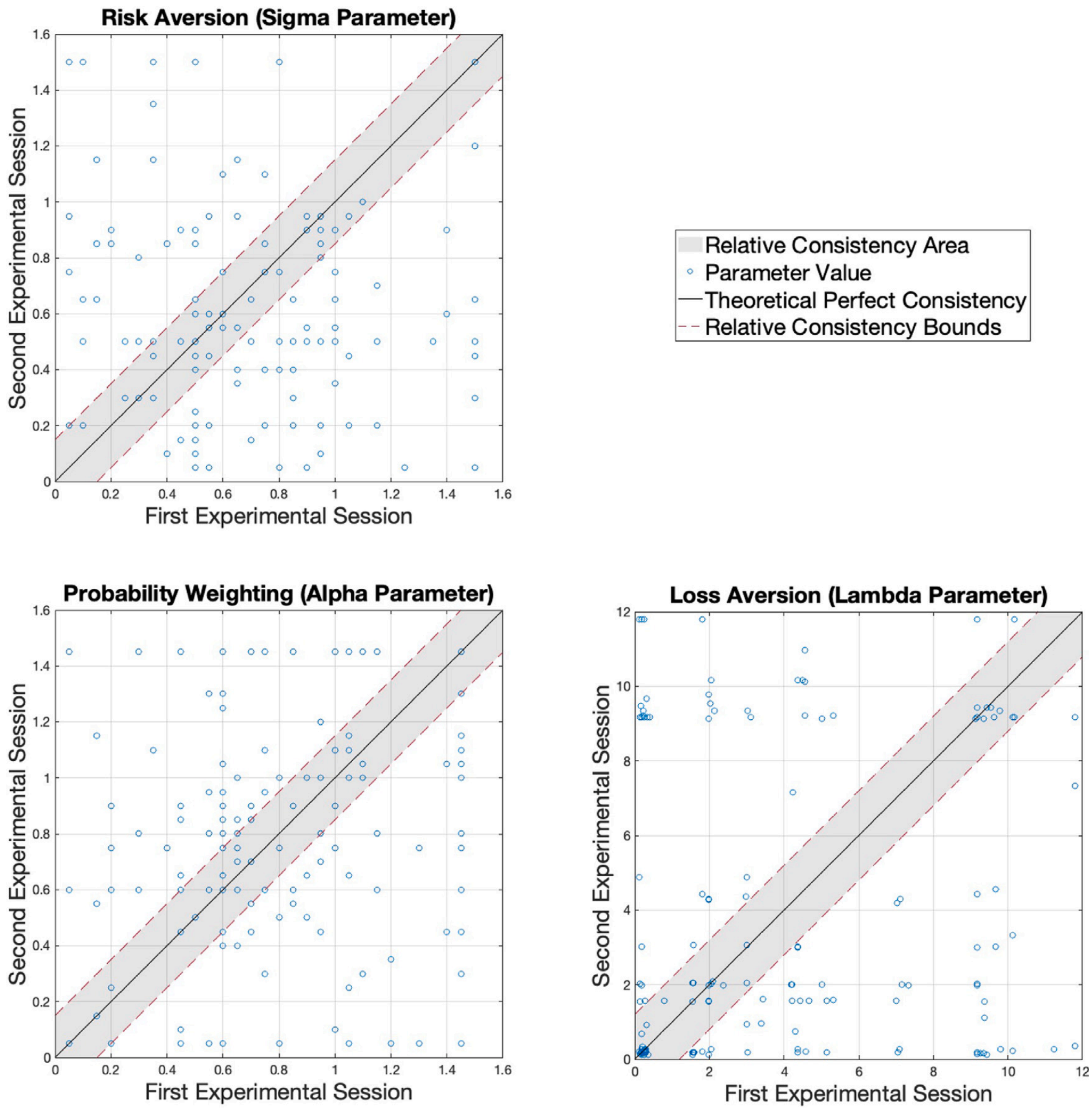

Fig. 3. Estimates of risk preference parameters across the experimental sessions.
Note: This figure illustrates the distribution of risk preference parameters across the two experimental sessions.

Table 6
Frequency of participants by type of inconsistency in risk preferences.

Parameter	Inconsistency in risk preferences			Total
	Increase	Decrease	Relative consistency	
σ (Risk Aversion)	60	38	61	159
α (Probability Distortion)	52	53	54	159
λ (Loss Aversion)	59	47	53	159

A visual assessment of Fig. 3 shows that only around 35% of the farmers in the sample exhibit *relative consistency*. In other words, findings show that most subjects give different answers when the same task is repeated twice within a very short time span. Table 6 shows that an increase in the level of risk aversion (decrease in the value of σ) was found to be the least common type of change among the participants.

4.3. Empirical correlates of relative consistent farmers' risk preferences

To provide further insights into the inconsistency of farmers' risk preferences, I examine how changes in farmers' risk preferences correlate with their demographic and socioeconomic characteristics. To accomplish this, I estimate probit models, where the dependent variable is a binary indicator on whether, across the experimental sessions, a participant (i) increased, (ii) decreased, or (iii) had *relative consistency* in each of the parameters of interest. I estimate these probit models for each of the PT parameters (σ, α and λ), thus, in total, nine models were estimated. Controls included age, gender, education, household size, rent, income, area, distance to nearest road, nonfarm employment, irrigation, extension, and livestock. I also included location fixed effects, interviewer fixed effects and controlled for the order of the paired lotteries that were shown to participants first (original vs. reversed).[12] In Fig. 4, I report only the statistically significant marginal effects of the three probit models related to *relative consistency* for ease of interpretation. In this figure, I plot their point estimates and 95% confidence intervals.

From Fig. 4 there is one relationship that is worth noting. Associations between relative consistency in farmers' risk preferences and

[12] Results are not indicative of any systematic effects attributable to the ordering. See Appendix for the full set of results of the probit model estimates and marginal effects.

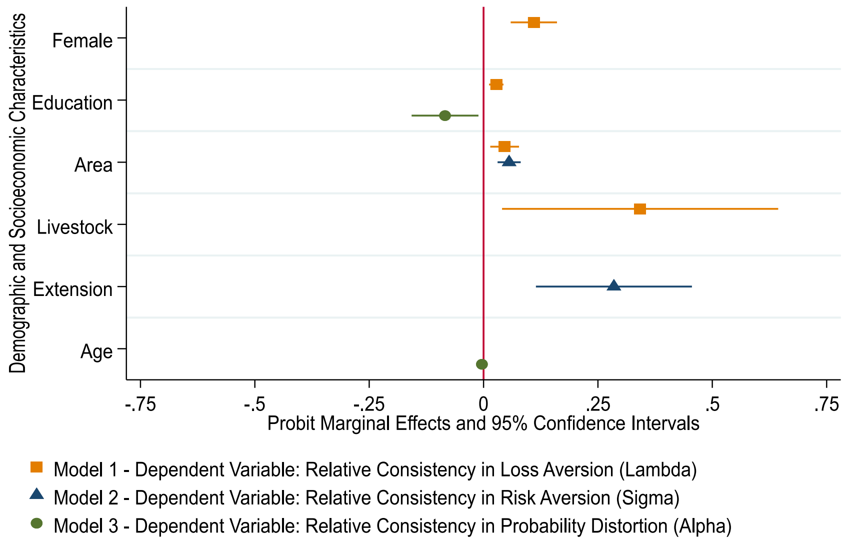

Fig. 4. Empirical correlates of relative consistent farmers' risk preferences.
Note: This figure reports marginal effects at the mean, that is, the marginal effects are estimated for the average person in the sample. See the full probit models marginal effects in the Appendix.

farmers' demographic and socioeconomic characteristics seems to occur mostly for the case of loss aversion (lambda parameter). Farmers that are female, those who have larger farms, are more educated, and own livestock are more likely to exhibit relative consistency in loss aversion.[13] These associations are worth noting because they have implications related with contract farming. Behavioral models have shown that people might work harder under loss contracts than under gain contracts. Loss or clawback contracts are similar to incentives but instead of getting paid at the end of the work – contingent of successful achievement – the clawback or loss contract gives the sellers the money up front and they are forced to give back what they do not achieve related to the agreed level of performance. Recent evidence suggests that people aware of their own high loss aversion will select into loss contracts as a commitment device to improve performance (Imas, Sadoff, & Samek, 2017). Therefore, knowing which farmers' characteristics relate to higher and consistent loss aversion behavior could help improve farmers' performance. For example, government interventions seeking to facilitate the expansion of contract farming – and thus improving agricultural productivity – can provide incentives to processors or buyers to offer loss contracts to growers with high and consistent loss aversion traits. As risk preferences usually go unobserved (Bellemare & Bloem, 2018), the best proxy would be to use the demographic and socioeconomic characteristics identified in the literature. Finally, it is important to recall that only 33% of the sample of farmers in this study exhibited consistency in loss aversion. Thus, given the great inconsistency in risk preferences, flexibility to switch into different type of contracts could be necessary at the individual level.

5. Discussion and conclusions

The objectives of this study were to analyze the consistency of PT risk preferences across experimental sessions and to assess the correlations of individuals' demographic and socioeconomic characteristics with their inconsistencies in risk preferences. To do this, I conducted a within-subject lab-in-the-field experiment with smallholder farmers in Ecuador. Participants played lottery games based on the experimental design of Tanaka et al. (2010) across two consecutive experimental sessions conducted during the same day. In accordance to previous findings, smallholders in the study region are risk averse, distort probability information, and care more about losses than gains.

I found consistency in risk preferences at the sample level; however, at the individual level, results from this study revealed inconsistency in risk-aversion, probability distortion, and loss-aversion. Results are in accordance with previous studies showing that at the individual level, farmers change their risk preferences across experimental sessions (Brown & Healy, 2018; Freeman & Mayraz, 2019). This could be attributed to several factors, including farmer's perception of risk, understanding of the lottery games, and framing effects (Levin, Schneider, & Gaeth, 1998).

Two conceptual frameworks support these results. First, the Conceptual Framework for Preference Stability proposed by Schildberg-Hörisch (2018). In this framework, the standard economic definition of consistency in risk preferences of an individual is relaxed and the assumption of a constant parameter is replaced by a distribution that is characterized by a mean and variance. The variance allows for inconsistency or temporary variation in risk preferences at the individual level, which is in line with my empirical results. Second, the conceptual framework of Conditional Stability by Andersen, Harrison, Lau, and Elisabet Rutström (2008), where consistency in risk preferences is a stable function of states of nature and opportunities that change over time. For both conceptual frameworks, other factors I did not control for in the experimental sessions – such as emotions, self-control, or stress – could have caused the variance or changes in the states of nature (Schildberg-Hörisch, 2018). One of the limitations of this study is that I only conducted two experimental sessions, thus future research can explore the implications of eliciting risk preference parameters for more periods and see if the findings align with the Schildberg-Hörisch's model discussed above.

Findings also come with a caveat. They suggest that modeling prospect theory risk preferences parameters using a deterministic approach – such as that of Tanaka et al. (2010) used in this paper – might not be ideal. Given the great variability in the subjects' choices across the two experimental sessions, a stochastic model could represent a more reasonable approach (Hey & Orme, 1994; Wilcox, 2008, 2011). Accounting for the stochastic nature of individual choice behavior could provide better estimates of PT risk preference parameters, as the error term can capture the variance of subjects that give different

[13] One reason for women showing greater consistency could be that the incentives were more salient for them. This might be due to lower opportunity costs or greater marginal utility of money. Previous studies have argued that incentives can increase focus and lower noise, thus, biases may not be a major problem in some tasks regarding risk (Camerer & Hogarth, 1999).

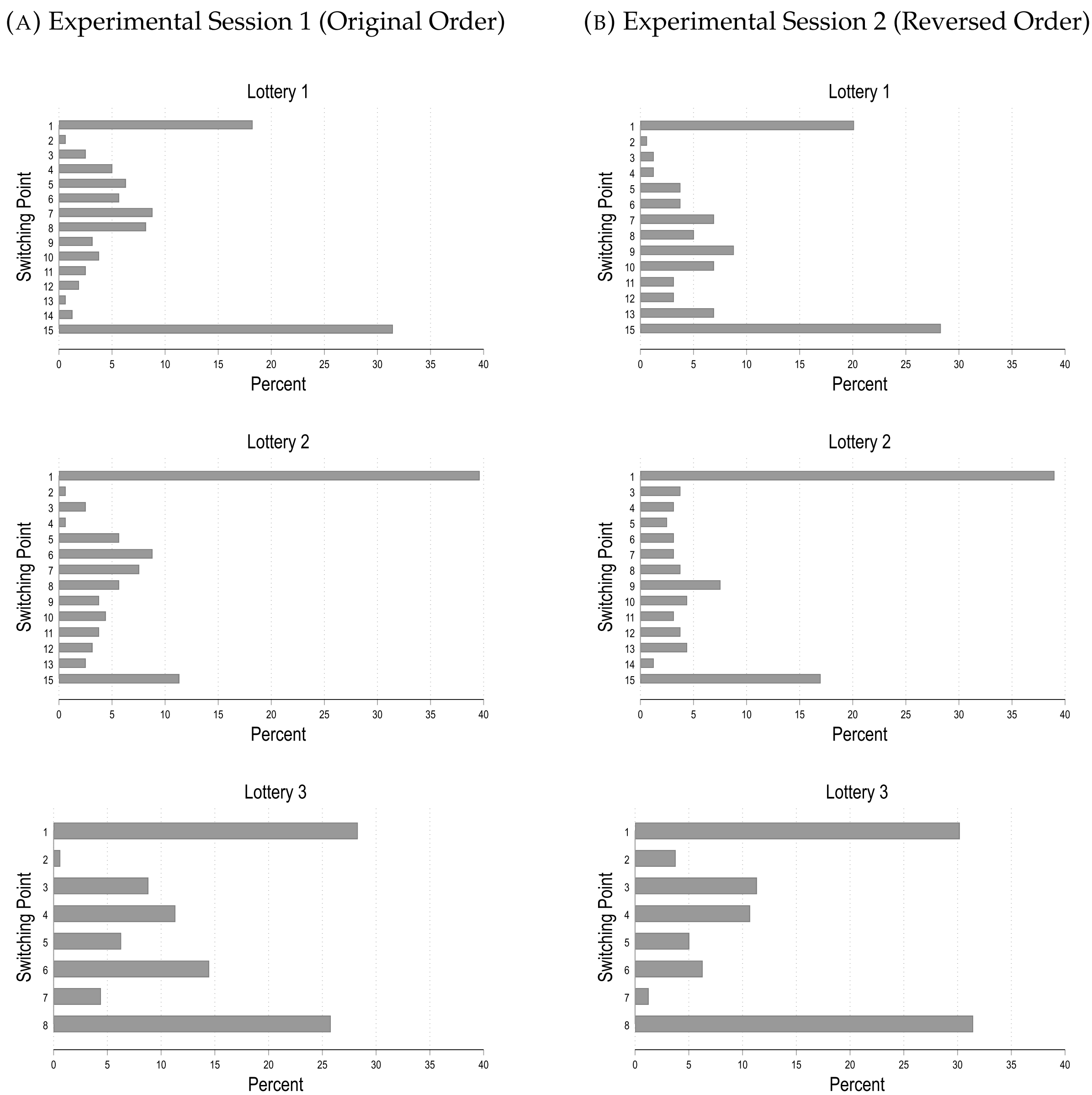

Fig. 5. Percentage of participants and switching points across experimental sessions.
Note: In lotteries 1 and 2, the switching point 15 represents "never switching". In lottery 3, the switching point 8 represents "never switching".

answers to the same question. This is of importance, especially if one wants to evaluate certain economic behaviors or produce inferences, as it could be unwise to rely on the assumption of deterministic choice behavior.

One possibility I did not explore in this paper is that although the order of Tanaka's paired lotteries within each series was doubly reversed to avoid learning effects, they could have still happened. Participants could have memorized the switching points (years) they used in the first experimental session, and subsequently, used these memorized years in the second experimental session — without looking carefully at the new order of the paired lotteries. Fig. 5 illustrates the percentage of participants that switch at specific points in each lottery for each experimental session. The visual assessment signals learning effects and reveals that on average the switching points are consistent across experimental sessions. For example, in lottery 1 the most popular switching points are 15 followed by 1, in both experimental sessions. In lottery 2 the most popular switching points are 1 followed by 15, in both experimental sessions. In lottery 3 there is a similar case. In the experimental design used in this paper, choosing the same switching point at a specific lottery that is played in a different experimental session have strong effects on the approximated PT parameters. This could be one factor driving the inconsistency found in this paper at the individual level. Although this assessment is only speculative, it deserves a closer look by future research. Changing small details in the experimental design has been argued to hold significant effects on choices (Braga & Starmer, 2005; Day et al., 2012; Day & Prades, 2010). Likewise, spatial position could influence visual attention, search dynamics and subject choices (Segovia & Palma, 2021).

Finally, the empirical correlations between *relative consistent* risk preferences and individuals' demographic and socioeconomic characteristics, highlighted one interesting result that deserves a closer look by future research. Specifically, consistency in loss-aversion seems to increase if the operator was female, operates large farms, and has diversified farming enterprises (like livestock). The formulation of agricultural policies can benefit from understanding this consistency in farmers' loss-aversion. For example, the gender of the operator could be crucial in initiatives that might depend on the loss aversion of beneficiaries, such as contract farming and the use of loss contracts.

Future research should clarify why the characteristics mentioned above would affect, if at all, the consistency of loss-aversion, specially with short-time windows.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.socec.2023.101989. It includes all tables and figures of the lotteries presented to participants in the experimental sessions, as well as full probit models marginal effects.

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