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RESEARCH ARTICLE

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The predictive power of farmers' risk attitude measures elicited by experimental methods

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Abstract

Aim of study: Farmers' behavior is shaped by their individual attitudes towards risk. Consequently, an understanding of the heterogeneous risk attitudes among farmers is key to predicting their decision-making. Therefore, there is a need for reliable methods to assess individuals' risk attitudes. The main objective of this paper was to contribute to the existing literature about the external validity of risk attitude measures obtained with diverse experimental methods.

Area of study: Irrigated agriculture in a Mediterranean climate region.

Material and methods: Two different experimental methods widely applied in the agricultural sector were used to elicit farmers' risk attitudes in a sample of irrigators in southern Spain: the Eckel and Grossman lottery-choice task and a self-assessment general risk question. We evaluated the explanatory power of both measures for the farming risk borne by farmers, using an approach based on dispersion measures of farming returns.

Main results: Results revealed stability across these elicitation methods, but the study yielded no evidence of statistical correlation with the farming risk actually borne by farmers, suggesting that it may not be advisable to use these methods for directly predicting farmers' decision-making in modeling exercises.

Research highlights: The most relevant innovation of this paper was the validation approach followed, based on measures assessing the overall level of farming risk borne by individual producers, and the complementary analyses controlling for key variables that could affect farmer risk-taking.

Additional key words: risk preferences; lottery-choice tasks; self-assessment; external validity; agricultural sector; Spain.

Abbreviations used: CRRA (constant relative risk aversion), EG (Eckel and Grossman's approach), EUT (expected utility theory), HL (Holt and Laury's approach), MPL (multiple price lists), R (coefficient of relative risk aversion), SA (self-assessment risk preference measure), SD (standard deviation).

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Introduction

Farming is a risky business. Many sources of risk affect farmers' business performance, potentially causing major losses (Hardaker *et al.*, 2004, pp. 6-7): agricultural production (climatological factors such as hail or drought, and pests affecting yields); markets (price fluctuations); technology (rapid technological innovations); the financial environment (access to credit and variability of interest rates); institutional/legal framework (changes in agricultural and other related policies) and human factors (*e.g.*, farmers' health). This risky environment profoundly influences farmers' decision-making related to farming activities, such as their choices regarding input use, technology adoption, or uptake of policy contracts (*e.g.*, agri-environmental schemes). It also guides their use of risk management instruments, such as crop diversification, agricultural insurance, or long term sale/purchase contracts (Moschini & Hennessy, 2001).

However, it is worth pointing out that the influence of risk varies substantially among farmers since their management behavior is shaped by the individual's risk attitudes. Thus, an understanding of the heterogeneous risk attitudes within farming communities is essential to predict farmers' decision-making and to provide accurate policy conclusions. This requirement underlines the importance of having reliable methods to assess individual farmers' risk attitudes.

Two basic approaches are used for measuring agricultural producers' attitudes towards risk (Iyer *et al.*, 2019):

1. *Observed economic behavior.* This approach relies on econometrics (*e.g.*, Bar-Shira *et al.*, 1997) or mathematical programming models (*e.g.*, Gómez-Limón *et al.*, 2003) representing farmers' decision-making, where risk aversion coefficients are estimated or calibrated to reproduce in-field data about farmers' behavior.

2. *Experimental methods* based on answers to multi-item and scale-based questions (*e.g.*, Hansson & Lagerkvist, 2012) or responses to hypothetical decision situations such as lottery-choice tasks (*e.g.*, Binswanger, 1980). The latter allows individual risk attitudes to be directly determined based on a specific utility function.

Both approaches have drawbacks, but particularly the observed economic behavior methods due to the identification problem inherent in the joint estimation of risk preferences (*i.e.*, risk aversion) and risk perceptions (Just & Just, 2011), and because risk behavior can be confounded with other factors (*e.g.*, resource constraints) actually faced by farmers (Wik *et al.*, 2004). These limitations in measuring farmers' risk attitudes could be overcome by adopting the experimental methods. When conducted under controlled and identical conditions for all participants, such methods have proved to be more effective at isolating farmers' risk preferences in their professional decision-making domain (*i.e.*, farming activity). This explains the popularity of experimental methods in the last decade (Iyer *et al.*, 2019).

However, despite the widespread use of experimental methods to assess farmers' risk attitudes, there is little evidence that the risk aversion measures obtained by these approaches actually reflect real farmers' decision-making behavior. In this sense, only a few studies have examined the predictive power of experimental methods, yielding contradictory conclusions. Hellerstein *et al.* (2013) implemented an experimental method based on a lottery-choice task to elicit risk attitudes in a sample of farmers operating in the US Corn Belt. The authors analyzed how well individual risk attitudes predict farmers' behavior regarding risk-influenced farming decisions, such as diversification or crop insurance. However, their results revealed that more risk-averse farmers were less likely to diversify operations or to take out crop insurance contracts. Thus, they concluded that lottery-choice measures of risk preferences had no explanatory power for predicting real-world farming behavior. Similarly, Menapace *et al.* (2016) analyzed the behavioral validity of three empirical mechanisms for eliciting farmers' attitudes toward risk (self-assessment of risk preferences and two lottery-choice tasks) in a sample of Italian farmers. The resulting risk attitude measures were assessed in terms of their relative ability to explain actual farmer crop insurance purchases. Results showed that one of the versions of the lottery-choice task was the only method that elicited risk attitude measures able to explain farmers' insurance purchasing decisions. Verschoor *et al.* (2016), using a large sample of farmers from Uganda, implemented two empirical methods to assess individuals' risk attitudes based on a single-choice task regarding how individuals allocate an amount of money between a safe and a risky asset. These authors compared both risk preference measures with farmers' risky choice behavior in real life in three different domains (the purchase of fertilizer, the growing of cash crops and the market-orientation) and found that only one of the procedures implemented provided measures of risk aversion that correlated with actual decision-making in all these domains. More recently, Vollmer *et al.* (2017) obtained risk attitude measures using a lottery-choice task for a sample of German farmers and investigated their explanatory power for farmers' production decision behavior, computed as a production function econometrically estimated using panel data. Results showed that farmers with higher risk aversion were less likely to tolerate production risk. Therefore, risk attitudes elicited using this experimental method were proved to properly reflect the risk taken by farmers in real production decisions.

Although these studies reveal interesting results regarding farmers' risk attitudes, they have some limitations that need to be solved to obtain more robust conclusions. In the case of Hellerstein *et al.* (2013), it can be noted that using single choices about risk management instruments to compare individual elicited risk attitudes could provide unreliable results. By way of illustration, just imagine a very risk-averse farmer that only tolerates low levels of risk. This farmer could achieve his/her objective of low-risk decision-making by implementing several risk management instruments. Among other possibilities, he/she could choose a secure crop-mix or, alternatively, cultivate a riskier crop-mix having taken out crop insurance; both options present the farmer with a similar amount of risk. This simple example shows that, although individuals' risk management decision-making actually depends on their risk preferences, analyzing each instrument in an isolated way does not provide a comprehensive view of decision-making, and may well produce potentially misleading results. This suggests that in order to more accurately ascertain whether the risk aversion measures obtained experimentally truly reflect real farmers' decision-making, these elicited risk attitude measures should be compared with variables assessing the overall level of farming risk borne by individual producers (instead of with single-risk instruments). The same implication may be deduced from the studies of Menapace *et al.* (2016), Verschoor *et al.* (2016), and Rommel *et al.* (2019), where elicited risk attitudes were compared with single-risk management strategies, without taking into account the overall risk actually assumed by farmers.

The study of Vollmer *et al.* (2017) considered the squared residuals of the mean production function estimated econometrically as a measure of the production risk taken by individual farmers. They used this measure to examine the external validity of the risk attitude elicited with the experimental task. Some doubts also arise about the accuracy of this way of measuring the risk borne by farmers. In this case, the main concern is the econometric modeling used to estimate the production function; it considers any deviation from the mean production function as being caused by farming risk, although it could be caused by any other factor not explicitly taken into account in the production function. This could lead to a biased estimate of the risk borne by farmers, raising the need for a more accurate way to measure the risk they are willing to tolerate.

Within this framework, the main objective of this paper was to further contribute to the existing literature about the external validity of risk attitude measures obtained using two different experimental methods (the Eckel and Grossman lottery-choice task and a self-assessment general risk question), assessing their explanatory power for actual risk borne by farmers.

Material and methods

Eliciting individual farmers' risk attitudes

Charness *et al.* (2013) reviewed experimental methods used to assess individual risk preferences. They identified the two most prevalent methods: a) stated choices between lotteries, also known as multiple price lists (MPL), most notably those proposed by Eckel & Grossman (2002, 2008) and Holt & Laury (2002); and b) survey questions on the individual's self-reported risk attitudes.

MPL methods are considered the 'gold standard' for assessing individuals' risk preferences, as they offer several advantages over survey methods (Nielsen *et al.*, 2013): a) they allow the estimation of relevant utility function parameters; b) they are incentive-compatible (lottery choices using real payoffs provide incentives for respondents to answer truthfully); and c) they can be designed to control for framing effects.

These methods based on a lottery-choice task can be classified depending on the degree of difficulty for interviewees (Dave *et al.*, 2010): 'simple' elicitation methods tend to be substantially easier for participants to understand than 'complex' ones. An example of a simple method is that proposed by Eckel & Grossman (2002, 2008) (hereafter, EG), in which respondents have to make a single choice from a number of possible gambles, all of which offer a 0.5 probability of winning a higher prize. Among the complex elicitation methods, one of the most widely used is that proposed by Holt & Laury (2002) (hereafter, HL), which requires respondents to make several choices between paired lotteries with probabilities ranging from 0.1 to 0.9.

Engle-Warnick *et al.* (2009), Dave *et al.* (2010), and Reynaud & Couture (2012) compared EG and HL methods for measuring farmers' risk preferences. All of these studies reported that, although they found significant correlations between the assessment of risk coefficients following these two procedures, estimates are not stable across elicitation techniques, revealing differences in both average estimated risk aversion coefficients and preference heterogeneity. Dave *et al.* (2010) argued that these differences may be attributed to the fact that the HL method is more cognitively challenging than the EG one. Thus, although the HL method is more accurate than the EG method, a relevant share of respondents finds the former more difficult to understand, thus potentially leading to biased results. These authors demonstrated that the EG method produce significantly less noisy estimates of risk preferences than more complex elicitation methods, particularly when participants have poorer numerical skills. Reynaud & Couture (2012) pointed out the non-expected utility preferences of farmers as another possible reason explaining differences in risk assessment among these elicitation methods. In this sense, Abdellaoui *et al.* (2011) showed that the use of the HL method reduces noise if expected utility theory (EUT) is fully assumed. However, if the decision-makers under study do not perfectly fulfill all basic EUT assumptions, this elicitation technique cannot provide robust estimates of risk aversion. In contexts where EUT is not able to perfectly represent decision-makers' preferences, the EG method is a better way to elicit individuals' risk attitudes. All these facts justify our choice of implementing the EG approach.

Menapace *et al.* (2016) suggested that misleading predictions using lottery-choice measures of farmers' risk preferences are mainly caused by risk parameters obtained without defining the right context and payoff scale to explain real decision-making. Traditionally, individuals' risk attitude assessments have been implemented using small-stake gambles (payoffs fairly far below the monetary domain of real economic decision) that were not framed in terms of any specific context (gambles considered just as lotteries, rather than related to actual economic decision-making). In fact, there is significant evidence that risk preferences depend on the size of the risky payoff (*e.g.*, Bombardini & Trebbi, 2012) and the context (*e.g.*, Reynaud & Couture, 2012 or Rommel *et al.*, 2019). Thus, only by properly framing MPL methods within the right scale and context can risk preferences be assumed to accurately reflect real farmers' decision-making. For this reason, we recasted the EG approach on a scale and in a context that directly pertained to the risk setting actually faced by farmers. More specifically, the approach followed in this paper was based on gambles representing the respondent's annual profit[1] from his/her farming activity, as shown in Figure 1 and Table 1.

Another relevant issue is the importance of incentive-compatibility in risk elicitation. In this sense, methods which are compatible with financial incentives (those based on lottery choices using real payoffs) are widely acknowledged to yield more accurate estimates regarding individuals' risk attitudes. However, it is also true that the funds required to reflect farm income in developed countries when implementing real sizable lottery-choice tasks are not feasible for research purposes. For this reason, we relied on an alternative incentive mechanism to minimize potential bias arising due to the hypothetical nature of the choice task presented to farmers. Specifically, we used a short cheap-talk script to engage farmers in the risk preference tasks, highlighting the usefulness of their responses to improve risk management in irrigated agriculture.

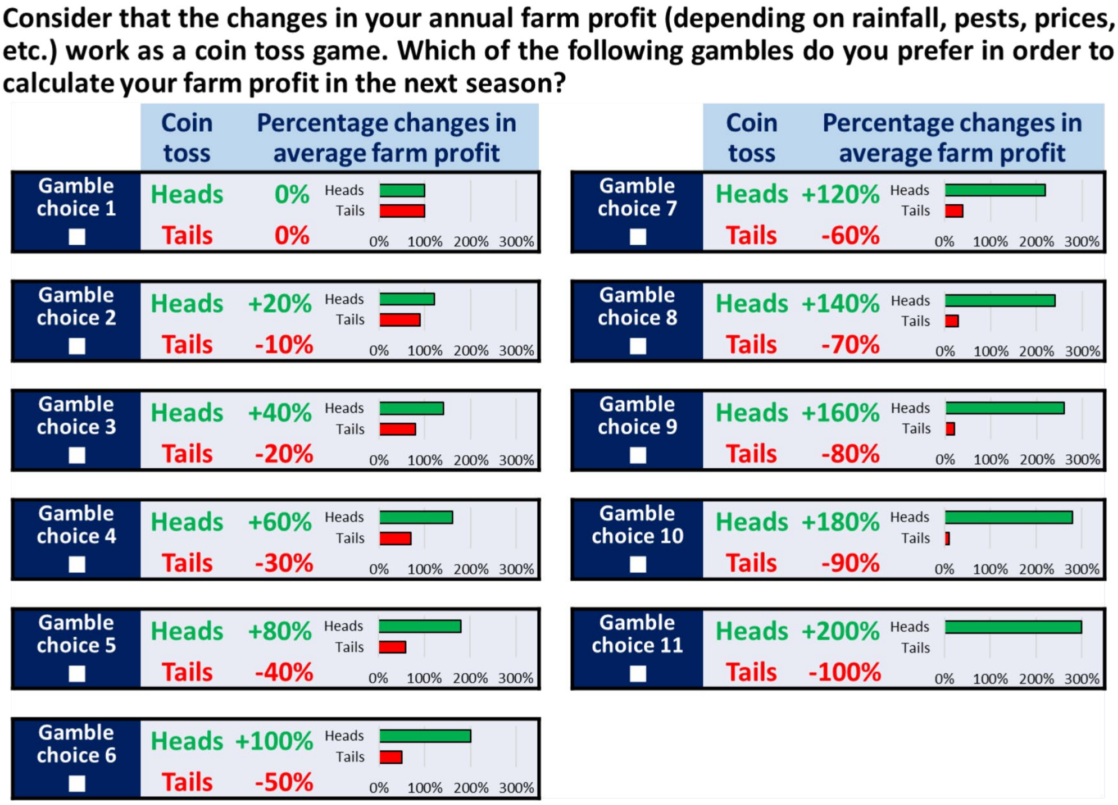

Figure 1. Gamble-choice task.

[1] Farm economic performance can be measured in different ways using well-established concepts such as gross profit, operating profit and net income. However, as shown in the pre-test of the questionnaire, the average farmer participating in the survey was not able to properly distinguish between these concepts. As such, we decided that this 'technical jargon' could lead to the farmers misunderstanding the gamble choice-task proposed, and so we opted to use the general term 'farm profit', as it was correctly understood.

Table 1. Description of the gamble-choice task.

Gamble choice	Probability	Payoff: % of annual farm profit	Expected payoff[a]	Risk[b]	CRRA *R* ranges		
					Max.	Min.	Average
1	50 *vs*. 50	100 *vs*. 100	1.00x	0.00x	4.92	Inf.	5.50
2	50 *vs*. 50	90 *vs*. 120	1.05x	0.15x	1.64	4.92	3.28
3	50 *vs*. 50	80 *vs*. 140	1.10x	0.30x	1.00	1.64	1.32
4	50 *vs*. 50	70 *vs*. 160	1.15x	0.45x	0.72	1.00	0.86
5	50 *vs*. 50	60 *vs*. 180	1.20x	0.60x	0.56	0.72	0.64
6	50 *vs*. 50	50 *vs*. 200	1.25x	0.75x	0.45	0.56	0.50
7	50 *vs*. 50	40 *vs*. 220	1.30x	0.90x	0.37	0.45	0.41
8	50 *vs*. 50	30 *vs*. 240	1.35x	1.05x	0.30	0.37	0.33
9	50 *vs*. 50	20 *vs*. 260	1.40x	1.20x	0.24	0.30	0.27
10	50 *vs*. 50	10 *vs*. 280	1.45x	1.35x	0.16	0.24	0.20
11	50 *vs*. 50	0 *vs*. 300	1.50x	1.50x	0.00	0.16	0.08

CRRA *R*: coefficient of constant relative risk aversion. [a] x = 100% of average annual farm profit. [b] Measured as the standard deviation of expected payoff.

Moreover, we offered them a nonmonetary incentive; namely, a personal risk assessment of their behavior that could be valuable to them in their professional life.

Individuals' responses to the gamble-choice task proposed allowed us to estimate their coefficient of relative risk aversion (R). Based on Moschini & Hennessy (2001), we assumed that farmers' attitude to risk can be modeled relying on the EUT, using a constant relative risk aversion (CRRA) utility function defined as $U(\pi_i) = (\pi_i{}^{1-R_i})/(1-R_i)$, where R_i is the Arrow-Pratt coefficient of relative risk aversion[2] for farmer i, and π_i is the profit from farming activities also for farmer i. While risk preferences vary significantly across farmers, the empirical evidence indicates that the coefficient of relative risk aversion typically varies between 0.5 (slightly risk-averse) and 4 (extremely risk-averse) (Gollier, 2004, p. 31). Table 1 shows the gamble-choice task proposed to cover this wide range of R_i values.

Despite the abovementioned advantages of MPL methods, it is also worth noting that the use of lottery-choice tasks to elicit individuals' risk attitudes entails certain disadvantages (Charness *et al.*, 2013; Nielsen *et al.*, 2013): a) these methods are time-consuming because long explanations must be provided to participants; b) respondents are required to have relatively high numeracy skills (a significant share of potential subjects would fail to understand the procedure). For these reasons, self-assessment survey questions are also commonly used to measure risk preferences. In fact, taking into account that they are easier to administer and comprehend, and can be adapted to different scenarios, they are the best alternative to the lottery-choice task methods (Dohmen *et al.*, 2011).

As with MPL, there are several self-assessment procedures available. The simplest ones rely on a general risk question along the lines of 'On a scale from 0 to 10, where 0 means "not at all willing to take risks" and 10 means "very willing to take risks", how would you assess your personal preference towards taking risks?' (*e.g.*, Meraner & Finger, 2017). More sophisticated procedures have been developed based on multiple-scale items surveys (*e.g.*, Franken *et al.*, 2017) or even longer survey questionnaires to assess individual willingness to engage in risky decision-making across a variety of domains. The DOSPERT psychometric scale proposed

[2] The Arrow-Pratt coefficient of relative risk aversion is defined as $R(\pi) = -\pi\, U''(\pi)/U'(\pi)$. It can be proved that for any risk-averse individual i, expected utility functions $U(\pi_i)$ have two relevant features: $U'(\pi_i) > 0$, implying increasing utility with profit; and $U''(\pi_i) < 0$, that is, decreasing marginal utility. Thus, for a risk-averse individual, $R(\pi_i)$ takes positive values, denoting the level of risk aversion guiding his/her choice-making; the higher $R(\pi_i)$, the more risk-averse the individual is.

by Weber *et al.* (2002), and implemented by authors such as Hansson & Lagerkvist (2012), is a good example of the latter.

Dohmen *et al.* (2011), Maart-Noelck & Musshoff (2014), and Roe (2015) showed that the approach of asking people to provide a global assessment of their willingness to take risks (a general risk question) generates a useful all-round measure of risk aversion. However, results obtained in this way should be taken with caution because these questions are not contextualized to a specific risk domain. Thus, these measures may be of limited applicability when it comes to predicting real farm-level behavior unless they are properly contextualized.

Following Maart-Noelck & Musshoff (2014), Roe (2015), Meraner & Finger (2017), and Brown *et al.* (2019), in our questionnaire, we included a straightforward self-assessment question regarding farmers' risk preferences, contextualized to the farm-level risk domain. Translated from Spanish, the wording of the question was: 'When making decisions regarding your farming activity, do you usually act as a "cautious" farmer, looking for the safest income (even though this would be low), or as a "risky" farmer looking for the highest possible income (even though this would be uncertain)? Please rate yourself on a scale from 0 to 10, where 0 means "highly cautious" and 10 means "highly risky"'. Thus, the individual answers collected using this 0-10 self-assessment scale provided an alternative risk preference measure for each farmer (SA_i).

Stability of risk preferences across elicitation methods

After obtaining the two risk attitude measures for the farmers surveyed using the EG lottery-choice task and a self-assessment procedure proposed, the stability of these results across elicitation methods was examined. The hypothesis to be tested in this sense was that the two methods yield highly correlated results, thus providing evidence that the estimates obtained are not sensitive to the choice of procedure.

There is wide-ranging evidence on the consistency of risk-preference elicitation based on lottery-choice tasks and self-assessment procedures, although contradictory findings have been reported. On the one hand, Dohmen *et al.* (2011), Reynaud & Couture (2012), Nielsen *et al.* (2013), Maart-Noelck & Musshoff (2014), and Meraner & Finger (2017) found a significant correlation between lottery-choice and self-assessment measures of risk aversion. On the other hand, authors such as Verschoor *et al.* (2016) and Menapace *et al.* (2016) concluded that measures of risk preferences are poorly correlated across these alternative methods.

As in most of the previous studies, to examine the stability of risk preferences across elicitation methods, we calculated the Pearson and Spearman rank correlation coefficients between the two experimental measures of risk attitudes. Furthermore, we used Kendall's W statistic to assess the level of agreement between the rankings of farmers according to the two experimental measures elicited. By analyzing the relationship between the two experimentally-measured risk attitude measures (the CRRA R obtained by EG lotteries and the SA measure using a 0-10 scale for self-assessment), we aimed to provide further insights relevant to the abovementioned debate.

Validation of elicitation methods: measuring farmers' risk-taking

Even if the first hypothesis that the two methods used yield highly correlated results were confirmed, it would not necessarily mean that both elicitation methods provided robust estimates of farmers' risk preferences. As such, we tried to validate both measures by evaluating their explanatory power for the level of farming risk borne or tolerated by the farmers, using some variables reflecting the risk actually assumed by farmers (*i.e.*, the variance and the standard deviation of total farm gross margins). Therefore, the second hypothesis to be tested was that a higher measure of elicited risk aversion leads to farmers bearing or tolerating a lower level of farming risk. If this hypothesis was corroborated, it would prove that these estimates of individuals' risk preferences appropriately reflect real farming decisions.

This hypothesis could be confirmed if significant correlation coefficients (Pearson and Spearman rank) were found between the elicited measures of risk aversion and the estimates of the risk borne. Moreover, Kendall's W was used to assess whether there was significant agreement between farmers' rankings according to elicited measures of risk attitudes and estimates of the farming risk borne.

However, the proposed approach for validating empirical measures of risk aversion required variables that accurately capture the overall farm risk borne by farmers. To this end, we followed the traditional approach that measures risk as the variance (or the standard deviation) of agricultural returns (farm profit). The mean-variance (or MV) approach has been widely proved to be consistent with EUT (Hardaker *et al.*, 2004), thus providing a sound theoretical framework for analyzing decision-making under risk in applied economics. Assuming EUT-MV maximizing behavior, farmers choose the whole farm crop-mix accounting for their expected (or mean) returns $E(r)$ and their variance σ_r^2. Under this theoretical framework, when farmers assess different alternatives under risk (*i.e.*, defined as probability functions of return), an increase in the average return leads to an increase in the utility function, while an increase in the variance of return involves a decrease in utility.

The expected return $E\ (r_f)$ and the variance $\sigma^2_{r_f}$ (the subscript f denotes whole-farm plan or crop-mix) of any mix involving w_c (units or proportion) of alternatives prospects c (crops in farming decision-making) were given by:

$$E(r_f) = \sum_{c=1}^{c=C} w_c E(r_c) \quad (1)$$

$$\sigma^2_{r_f} = (w_1 \quad \cdots \quad w_C) \begin{pmatrix} \sigma^2_1 & \cdots & \sigma_{1C} \\ \vdots & \sigma_{cc'} & \vdots \\ \sigma_{C1} & \cdots & \sigma^2_C \end{pmatrix} \begin{pmatrix} w_1 \\ \vdots \\ w_C \end{pmatrix} \quad (2)$$

where $E\ (r_c)$ is the expected return of one hectare of crop c, and $\sigma_{cc'}$ is the covariance of returns of crop c and c' (and the variance of the return of crop c when $c = c'$).

In order to obtain comparable measures of the risk borne by farmers with different farm sizes, the mean and the variance were calculated per farming hectare. Thus, for this purpose, w_c denoted the percentage of farming area devoted to crop c, with $\sum_{c=1}^{c=C} w_c$ equaling one.

The uncertain farm return ($\tilde{r_f}$) was measured in terms of total gross margin (income minus variable costs)[3] per hectare as the weighted sum of uncertain crop gross margins ($\tilde{r_c}$):

$$\tilde{r_f} = \sum_{c=1}^{c=C} w_c \cdot \tilde{r_c} = \sum_{c=1}^{c=C} w_c \cdot [\tilde{p_c} \cdot \tilde{y_c} + s_c + \tilde{\iota_c} - vc_c] \quad (3)$$

where $\tilde{r_c}$ was obtained considering crop prices (p_c in €/kg), yields (y_c in kg/ha), coupled subsidies (s_c in €/ha) and the sum of variable costs, including insurance premia (v_c measured in €/ha)[4]. Note that in expression (3), the crop-mix (w_c), coupled subsidies and the sum of variable costs were considered as deterministic (known in advance), while the remaining elements (prices, yields, and indemnities) were stochastic. Thus, crop gross margins took different values every farming year n ($r_{c,n}$). Accordingly, the expected farm return (expected total gross margin) was calculated as the weighted sum of average crop returns ($\overline{r_c}$) for a period of time (N farming years):

$$E(r_f) = \sum_{c=1}^{c=C} w_c E(r_c) = \sum_{c=1}^{c=C} w_c\, \overline{r_c} = \sum_{c=1}^{c=C} w_c \frac{\sum_{n=1}^{n=N} r_{c,n}}{N} \quad (4)$$

Finally, the variance and standard deviation of farming returns ($\sigma^2_{r_f}$ and σ_{r_f}), measured in €^{2}/ha^2 and €/ha, respectively, were calculated using expression (2) accounting for covariances as follows:

$$\sigma_{cc'} = \frac{\sum_{n=1}^{n=N}\left[r_{c,n} \cdot r_{c',n} - \overline{r_c} \cdot \overline{r_{c'}}\right]}{N} \quad (5)$$

Case study: irrigated agriculture in southern Spain

The proposed methods explained in the previous subsections were implemented in a case study involving a representative sample of irrigation farmers in the province of Córdoba (southern Spain). What makes this such an interesting case study for analyzing the predictive power of farmers' risk attitudes for the overall farming risk borne is the high-risk environment in which these farmers operate, in terms of both production and market risks. As in many other Mediterranean and semi-arid climate regions, it is worth noting that irrigation farmers in the province of Córdoba are especially vulnerable to the risk of drought. This source of uncertainty is becoming increasingly relevant nowadays because of climate change since the frequency and intensity of drought events are growing (IPCC, 2014). Thus, farmers in the selected case study are deeply concerned about uncertainty over the water supply for irrigation, which significantly affects their economic decision-making (crop-mix and other management decisions). In order to manage agricultural risks, these irrigation farmers have a wide variety of risk management instruments available, most notably crop diversification and agricultural insurance.

In the province of Córdoba, irrigated agriculture covers a total of 111,451 ha divided into 21 irrigation districts, managed by a total of 2,083 farmers. This agricultural system is characterized by a typical Mediterranean climate, with hot and dry summers, mild winters, and frequent episodes of hydrological drought. The main crops grown in the selected case study are olives (41%), oranges (16%), wheat (9%), cotton (8%), and vegetables (7%) such as potatoes, garlic, and onions. Irrigated agriculture in the province of Córdoba currently employs modern and efficient irrigation technologies (Gómez-Limón *et al.*, 2013).

The selected case study is sufficiently homogeneous in terms of agroclimatic, economic, social, and cultural conditions. This homogeneity minimizes the potential confounding factors that could affect any research attempting to link real-life behavior and experimental measures (Verschoor *et al.*, 2016).

[3] Total gross margin was considered an accurate enough proxy for 'farm profit' in the short term.

[4] Agricultural insurance is a fairly common risk management strategy among Spanish farmers (Pérez-Blanco *et al.*, 2015). As such, the expression calculating uncertain crop gross margins was expressed in a general form. For insured farmers, $\tilde{r_c}$ was calculated considering both insurance indemnities (as a stochastic income) and insurance premia (as a deterministic cost). For farmers that decided not to insure their crops, $\tilde{r_c}$ was calculated similarly, but without these terms.

Data collection and sample description

In order to achieve the research objectives, we conducted a field survey interviewing a representative sample of farmers operating within the selected case study area. Before administering the questionnaire to each participant, the interviewer carefully explained the objectives of the research and used a short cheap-talk script, as commented above, to engage farmers in the study. Moreover, illustrative material (*i.e.*, Figure 1) was prepared to help participants to fully understand the lottery-choice task. A pretest performed on 20 farmers allowed us to confirm that the whole set of questions, particularly those related to the lottery-choice task, were easily understood by respondents, even those who had only a basic education level.

The questionnaire, which was designed to provide the information needed for the research, was divided into four parts[5]. The first part focused on the main features of the farms: farm size, crop-mix, sources of water, and irrigation techniques. The second part of the questionnaire asked for the average crop yields, the agricultural practices implemented, and about agricultural insurance contracting. The third part sought to determine farmers' risk preferences, following the two experimental methods explained above, that is, the lottery-choice task developed by Eckel & Grossman (2002, 2008) and the self-assessment procedure based on a general risk question. Finally, the fourth part included questions regarding farmers' socio-demographic variables, such as gender, age, percentage of the farming area owned, education level, professional training, farming experience, jobs outside farming, percentage of working time devoted to farming activities, and percentage of agricultural income over total income.

A two-stage sampling procedure was employed to obtain a representative sample of irrigators operating in the province of Córdoba. Firstly, once the sample size had been set (n=200), quota sampling based on irrigation district size was used to determine the number of farmers to be drawn from each of these districts. Secondly, the farmers to be interviewed were randomly selected from each district. The chosen farmers were contacted with the support of the water user associations, agricultural cooperatives, and other farmers' organizations, who strongly encouraged their participation in the survey. Survey implementation involved personal interviews conducted between October and December 2018, a period of time that was specifically chosen to help ensure a high response rate (during these months irrigators have a very low workload). None of the selected farmers refused to take part in the survey, diminishing the risk of selection bias. The final result of this process was 204 completed and validated questionnaires.

The representativeness of the sample was confirmed by chi-square tests for equality of distributions regarding three key variables: farm size, crop distribution, and farmers' age. The null hypothesis of equality of sample and population proportions was not rejected in any case.

Tables 2 and 3 present the descriptive statistics of the sample of irrigators. The average age of the farmers was 54.8 years. They were mostly men (98.5%), with extensive farming experience (30 years). One-third of the participants either had no formal education or had completed only primary school. The average farm irrigated area was 46.8 ha, 92.6% of which was owned by the farmer. The majority of the farmers had another job apart from farming (56.4%), a fact that explains the average value of agricultural income over total farmers' income (62.4%). Just over half of the farmers (52.5%) hedged their farming risks by taking out agricultural insurance.

Table 2. Sample descriptive statistics for metric variables (n=204).

Variable	Unit	Average	SD	Min.	Max.
Farmer's age	Years	54.8	12.3	21.0	83.0
Total farm irrigated area	ha	46.8	85.1	1.0	732.0
Owned land over total farming area	%	92.6	22.4	0.0	100.0
Farming experience	Years	30.0	15.3	2.0	67.0
Percentage of working time devoted to farming activities	%	67.9	34.3	5.0	100.0
Agricultural income over total income	%	62.4	29.2	5.0	100.0

SD: standard deviation

[5] The full questionnaire is available on request.

Table 3. Sample descriptive statistics for categorical variables (n=204).

Variable	Category	Farmers	
		No.	%
Irrigator's gender	0 = Female	3	1.5
	1 = Male	201	98.5
Education level	1 = No formal education	19	9.3
	2 = Primary	48	23.5
	3 = Secondary	62	30.4
	4 = University	75	36.8
Holding a job outside of farming	0 = Do not hold another job apart from farming	89	43.6
	1 = Hold another job apart from farming	115	56.4
Agricultural insurance contract	0 = Do not take out agricultural insurance	97	47.5
	1 = Take out agricultural insurance	107	52.5

The individual information gathered with the survey about crop-mix, average yields, agricultural practices implemented, and insurance contracting was combined with secondary data regarding annual input prices, crop yields, output prices, and subsidies[6]. This made it possible to build historical time series from 2010 to 2017 for crop gross margins ($r_{c,n}$) for each farm following expression (3). These monetary values were initially measured on an actual currency basis, but they were converted to constant currency (2017 euros) considering official annual inflation rates. Finally, the latter series of gross margins were used to estimate individual farmers' expected farm return, the variance, and the standard deviation (SD) of farming returns using expressions (4) and (5) based on their crop-mix.

Results and discussion

Measures of farmers' risk aversion

Table 4 shows participants' responses for the two risk preference elicitation methods, the lottery-choice task and the self-assessment procedure. Regarding the results from the lottery-choice task, the average CRRA *R* coefficient was 2.65 (moderate to high risk-aversion), with the safest alternative (Gamble 1, suggesting extremely high risk-aversion) being the preferred gamble (29.9%). The SD obtained for CRRA *R* (2.03) indicates that farmers' risk aversion was rather heterogeneous. Comparing these values with those reported by other studies in the literature that implement the same EG lottery-choice task, we can conclude that our results are within the range of previous findings. For example, Menapace *et al.* (2016) reported a slightly higher proportion of Italian farmers choosing Gamble 1 (45.9%), leading to an average value of CRRA *R* of 3.71. Engle-Warnick *et al.* (2009) also used a similar EG lottery-choice task to analyze risk aversion among Peruvian farmers, but only included five alternative gambles in the procedure. They found that 37.2% of sampled farmers chose the safest alternative, although the resulting average value of CRRA *R* obtained was moderately lower than in our case study (2.35).

It is also worth pointing out that only 7% of farmers sampled showed CRRA *R* values < 0.5 (low risk-aversion, *i.e.*, preferences close to risk-neutrality; CRRA $R \approx 0$), and none of those chose gambles 9, 10 or 11 (CRRA *R* values < 0.3). This finding points to the fact that risk-averse attitudes were common among all sampled farmers, contrary to the results reported by Reynaud & Couture (2012), Maart-Noelck & Musshoff (2014), or Meraner & Finger (2017), who implemented the HL lottery-task method

[6] These data have been obtained from official statistics (annual crop yields – $y_{c,n}$ – and subsidies – $s_{c,n}$) nd from local agricultural technicians managing accountancy records on agricultural prices, for both output prices ($p_{c,n}$) and input prices. The data on input prices enable the estimation of crop variable costs ($vc_{c,n}$)

Table 4. Gamble choice and self-assessment procedures. Descriptive statistics of results.

Gamble choices procedure				Self-assessment procedure		
Gamble choice	CRRA *R*	Farmers		*SA* scale	Farmers	
		No.	%		No.	%
1	5.50	61	29.9	0	3	1.5
2	3.28	28	13.7	1	10	4.9
3	1.32	54	26.5	2	17	8.3
4	0.86	30	14.7	3	14	6.9
5	0.64	17	8.3	4	14	6.9
6	0.50	8	3.9	5	54	26.5
7	0.41	3	1.5	6	34	16.7
8	0.33	3	1.5	7	29	14.2
9	0.27	0	0.0	8	22	10.8
10	0.20	0	0.0	9	4	2.0
11	0.08	0	0.0	10	3	1.5
Total		204	100.0		204	100.0
Average	2.65			5.20		
SD	2.03			2.15		
Skewness	0.49			-0.34		
Kurtosis	-1.51			-0.32		

CRRA *R*: coefficient of constant relative risk aversion; *SA*: self-assessment risk preference measure; SD: standard deviation.

including gambles to identify risk-seeking preferences and found significant shares of farmers with risk-loving attitudes. This can be explained by a 'task effect' on the farmers' risk preference estimates, leading to significantly greater measures of CRRA *R* with the EG procedure than with the HL one. In fact, all three abovementioned studies report mean values for CRRA *R* of between 0.14 and 0.36.

Concerning results from the self-assessment procedure (see also Table 4), the mean response was 5.20 (SD=2.15). Other studies analyzing farmers' risk attitudes using this same method found similar results, albeit with somewhat higher values for the average and the SD: Nielsen *et al.* (2013) reported a mean of 5.58 and a SD of 2.36; Menapace *et al.* (2016) an average of 5.64 and a SD of 2.26; Meraner & Finger (2017) a mean value of 5.45 (SD=2.19); and Brown *et al.* (2019) an average of 5.86 (SD=2.07).

Regarding the *SA* measurement of risk aversion, it is worth commenting that, as in previous studies implementing this procedure, the results obtained should be taken with caution because the rating scale used for this purpose may be subject to distortion. This is attributable to two main biases: the 'central tendency' bias (respondents' tendency to avoid the extreme response categories); and the 'social desirability' bias (respondents' tendency to choose options that they think are more socially acceptable) (Dimitrov, 2014). In this sense, further research is needed to check whether the measurement obtained with the 0-10 scale is consistent with those of alternative scales (*e.g.*, Likert scales with a different number of options), which would confirm the robustness of this self-assessment procedure.

Farmers' heterogeneity in risk aversion measured through the CRRA *R* and the *SA* scale was analyzed looking for explanatory factors among the socio-demographic features and farm-related variables previously identified in Tables 2 and 3. For this purpose, we calculated the Pearson correlation coefficient between the elicited risk aversion measures and the metric variables of farm/farmer characteristics, and run ANOVA tests to compare the means in case of the categorical variables. The results obtained can be seen in Table 5.

It can be observed that only the farmer's age and his/her experience as a farmer[7] showed a positive and significant correlation with the CRRA *R*, denoting that the older the farmer the more risk-averse he/she was. The same result was reported in most of the related empirical literature (*e.g.*, Gómez-Limón *et al.*, 2003; Picazo-Tadeo & Wall, 2011; Nielsen *et al.*, 2013; Meraner & Finger, 2017; Brown *et al.*, 2019). The rest of the feature variables considered as potential explanatory factors for farmers' risk aversion did not yield statistically significant results. For instance, although the time devoted to agricultural activities or the level of education have been found to influence farmers' risk attitudes (*e.g.*, Feinerman & Finkelshtain, 1996; Abdulkadri *et al.*, 2003; Picazo-Tadeo & Wall, 2011), no statistically significant result confirmed this in our case study.

Surprisingly, none of the analyzed variables was a significant explanatory factor for the farmer's *SA* risk measure.

Table 5. Relationship between farmers' descriptive statistics (metric and categorical variables) and individual elicited measures of risk aversion (CRRA *R* and *SA* scale).

Variable (metric)	Unit	CRRA *R* Pearson (*p*-value)	*SA* scale Pearson (*p*-value)
Farmer's age	Years	0.279*** (0.000)	-0.039 (0.584)
Total farm irrigated area	ha	0.009 (0.894)	0.016 (0.821)
Owned land over total farming area	%	-0.036 (0.606)	0.070 (0.319)
Farming experience	Years	0.275*** (0.000)	-0.111 (0.114)
Percentage of working time devoted to farming activities	%	0.116 (0.097)	-0.055 (0.436)
Agricultural income over total income	%	0.005 (0.938)	0.004 (0.952)

Variable (categorical)	Category	CRRA *R*		*SA* scale	
		Mean	ANOVA test (*p*-value)	Mean	ANOVA test (*p*-value)
Farmer's gender	0=Female	2.33	F=0.076 (0.783)	5.33	F=0.012 (0.915)
	1=Male	2.69		5.20	
Education level	1=No formal education	3.47	F=1.324 (0.268)	4.84	F=0.477 (0.698)
	2=Primary	2.75		5.48	
	3=Secondary	2.56		5.11	
	4=University	2.47		5.19	
Holding a job outside of farming	0=Do not hold another job apart from farming	2.85	F=1.531 (0.217)	5.13	F=0.149 (0.700)
	1=Hold another job apart from farming	2.50		5.25	
Agricultural insurance contract	0=Do not take out agricultural insurance	2.87	F=2.134 (0.146)	5.26	F=0.129 (0.720)
	1=Take out agricultural insurance	2.46		5.15	

CRRA *R*: coefficient of constant relative risk aversion; *SA*: self-assessment risk preference measure.

[7] Logically, these two socio-demographic characteristics of the farmer are directly related because experience increases with age.

Even the variable age turned out not to be significant, despite the high correlation with the two empirical measures of farmers' risk aversion. We hypothesize that potential biases affecting the self-assessment rating scale ('central tendency' or 'social desirability' biases) may be behind this lack of relationship.

Based on this evidence, it can be affirmed that the farmers' attitude towards risk seems to be more dependent on psychological and other personal characteristics rather than on socio-demographic and farm-related variables. Thus, a multidisciplinary approach beyond the analysis implemented here would be required to obtain more conclusive results.

Stability of risk preferences across elicitation methods

The correlation coefficients between the two measures of farmers' risk attitudes (CRRA *R* and *SA*) yielded values of -0.526 (Pearson) and -0.555 (Spearman), both statistically significant at 99.9%. These results confirmed the stability of both methods in the elicitation of farmers' risk attitudes since the negative sign of the coefficients means that a higher CRRA *R* leads to a lower value on the *SA* scale. Consequently, the hypothesis about the stability across elicitation methods −EG lottery-choice task and *SA* scale− could not be rejected. Reynaud & Couture (2012) also reported that risk attitude measures elicited through the EG procedure are correlated with DOSPERT psychometric scales measuring general risk preferences and specific risk attitudes in the financial domain. Nevertheless, both findings are contrary to those of Menapace *et al.* (2016), who found that farmers' risk preference estimates were not stable across the EG lottery-choice task and self-assessment question elicitation techniques; the authors reported a correlation of close to zero (2%) between the two risk aversion measures.

Comparing our findings with those from studies that use lottery-choice tasks other than EG to analyze farmers' risk attitudes, we again see similarities. For instance, using a chi-square test, Maart-Noelck & Musshoff (2014) found a statistically significant relationship between the measures obtained through the HL lottery-task and self-assessment procedures for a sample of German farmers. Similarly, Meraner & Finger (2017) obtained a significant Spearman correlation coefficient of 0.714 between HL and self-assessment measures of risk aversion for a sample of French farmers.

The values of the correlation coefficients obtained for our case study are not among the highest reported in the set of studies that apply lottery-choice tasks and self-assessment elicitation methods and test the stability of the results obtained (*e.g.*, Dohmen *et al.*, 2011; Meraner & Finger, 2017). However, it should be noted that the values of these correlation coefficients were over 0.5, a figure which Nielsen *et al.* (2013) identified as the minimum required for the effect size not to be considered weak (that is, where statistically significant correlation coefficients are obtained but the values are low). Indeed, in their case study, those authors found a statistically significant Spearman coefficient between measures of farmers' risk attitudes obtained by the HL elicitation method and the *SA* scale, but with a weak effect size (0.193).

Although the risk attitude estimates obtained using the two elicitation methods implemented (EG lottery-choice and self-assessment) were measured in different scales and thus are not directly comparable, it seems that farmers were more likely to be cautious when confronted with a lottery-choice task, as most of the responses corresponded to the gambles implying a high level of risk aversion (see Table 4). On the contrary, the self-assessment answers were not concentrated around the values of the scale reflecting the lowest willingness to take risks; nor was a decreasing trend across the scale observed, as was the case in the lottery-choice task. To assess whether the results of the two risk attitude measures differed significantly from each other, as it appears after an initial glance at Table 4, we calculated Kendall's *W*. This non-parametric statistic measures the level of agreement between the rankings of the same sample of objects (farmers in our case) based on different criteria (CRRA *R* and *SA* in our case), ranging from 0 (no agreement) to 1 (complete agreement). Using the R software, the value of the *W* statistic was computed (0.780). Given that the probability distribution of *W* can be approximated by that of a chi-squared distribution (Kendall χ^2=194.84; p=0.000), the null hypothesis that *W* equals 0 was rejected, indicating that risk preference ranking seems to be preserved across methods, as also found in Reynaud & Couture (2012).

External validation of elicitation methods

Based on survey data, different statistics proposed for assessing the amount of farming risk actually borne by irrigators (variance and SD of farming return − $\sigma^2_{r_f}$ and σ_{r_f} − calculated as explained above) were also calculated. Table 6 shows a descriptive analysis of the results obtained. These calculations allowed us to compare the experimental measures of farmers' risk attitudes (CRRA *R* and *SA*) with the amount of farming risk actually borne by those farmers in order to check that the higher the individuals' risk aversion measures, the less risk they assume in their farming activity, as the EUT suggests for risk-averse decision-makers.

The results of the analysis of the correlation and Kendall's *W* between elicited measures of risk attitudes and estimates of the farming risk borne are shown in Table 7. Pearson and Spearman coefficients for every pair of

Table 6. Descriptive statistics of risk borne by farmers.

Variable	Average	SD	Skewness	Kurtosis
Expected return per hectare $(E(r_f))$ (€/ha)	2,013	1,877	2.55	5.95
Variance of return per hectare $(\sigma^2_{r_f})$ (0.000 €^{2}/ha^2)	1,508	2,243	2.01	2.72
SD of return per hectare (σ_{rf}) (€/ha)	985	735	1.34	0.89

SD: standard deviation.

comparisons were rather low (the maximum value was 0.071), and none of those were statistically significant. Moreover, Kendall's *W* showed no significant agreement between farmers' rankings according to elicited measures of risk attitudes and estimates of the farming risk borne (the hypothesis that *W* equals 0 could not be rejected). All of these results may cast doubt on the suitability of experimental measures of risk attitudes for explaining farmers' behavior (*i.e.*, farming risk actually borne). That is, our findings from the case study failed to prove that higher risk aversion implies less farming risk assumed by the farmer. At this point, it should be noted that some previous studies (Hellerstein *et al.*, 2013; Menapace *et al.*, 2016; Verschoor *et al.*, 2016) also questioned the validity of some of these measures for predicting farmers' real behavior.

In this sense, the only relevant previous study is the one by Vollmer *et al.* (2017). These authors tried to externally validate a measure of risk preference based on HL lottery tasks by comparing it with an estimate of the production risk borne, measured as the squared residuals of the Just and Pope's production function calculated using panel data from a sample of German farmers. These authors reported a low, but significant, negative correlation between the two variables (Spearman coefficient=−0.110, *p*=0.013), indicating that the higher the risk aversion, the lower the production risk. This suggests that the experimental risk attitude measure obtained would have (a limited) explanatory power for farmers' risk-influencing decisions in the production process. However, as already pointed out in the Introduction section, the method for assessing risk borne by farmers is questionable since the values obtained as a measure of the farming risk borne could be biased by factors not explicitly considered within the production function estimated.

Taking into account the disappointing results obtained for our case study with the whole sample of farmers (n=204), further analyses were carried out for more specific subsamples. The aim was to explore issues that have yet to be explored, regarding the external validation of experimental measures of farmers' risk attitudes. Therefore, the effect of being a part-time farmer (risk borne from other sources of income outside the agricultural sector) and the role of permanent crops (farming risk borne *vs.* 'accepted' farming risk) were further analyzed.

Descriptive statistics of the sample (see Tables 2 and 3) indicated that *part-time farming* was rather common in the analyzed case study since most of the farmers also

Table 7. Correlation coefficients and Kendall's *W* between experimental measures of risk aversion and farming risk borne for the whole sample of farmers (n=204).

Risk measure	Correlation coefficient and Kendall's *W*	$\sigma^2_{r_f}$	σ_{rf}
CRRA *R*	Pearson (*p*-value)	0.071 (0.313)	0.054 (0.447)
	Spearman (*p*-value)	0.039 (0.585)	0.039 (0.585)
	Kendall χ^2 (*p*-value)	194.8 (0.647)	194.8 (0.647)
SA scale	Pearson (*p*-value)	0.051 (0.465)	0.042 (0.552)
	Spearman (*p*-value)	0.009 (0.899)	0.009 (0.899)
	Kendall χ^2 (*p*-value)	203.4 (0.479)	203.4 (0.479)

CRRA *R*: coefficient of constant relative risk aversion; *SA*: self-assessment risk preference measure.

Table 8. Percentage of agricultural income over total income, and percentage of permanent crops.

Agricultural income over total income	Farmers			Permanent crops	Farmers		
	No.	%	Accum. %		No.	%	Accum. %
0%-≤10%	13	6.3	6.3	0%	45	22.1	22.1
>10%-≤20%	7	3.4	9.7	0%-≤10%	7	3.4	25.5
>20%-≤30%	23	11.3	21.0	>10%-≤20%	7	3.4	28.9
>30%-≤40%	19	9.3	30.3	>20%-≤30%	6	2.9	31.8
>40%-≤50%	25	12.3	42.6	>30%-≤40%	9	4.4	36.2
>50%-≤60%	22	10.8	53.4	>40%-≤50%	6	2.9	39.1
>60%-≤70%	13	6.4	59.8	>50%-≤60%	3	1.5	40.6
>70%-≤80%	24	11.8	71.6	>60%-≤70%	5	2.5	43.1
>80%-≤90%	8	3.9	75.5	>70%-≤80%	4	2.0	45.1
>90%-≤100%	4	2.0	77.5	>80%-≤90%	2	1.0	46.1
100%	46	22.5	100.0	>90%-≤%100	110	53.9	100.0

Accum.: Accumulated.

held other jobs or carried out other economic activities in addition to farming (see detailed information in Table 8). In fact, 42.6% of the farmers sampled obtained less than half of their income from farming activities. For these part-time farmers, the total risk actually borne depends on their portfolio of uncertain sources of income, including both farming and the other non-farming economic activities (*i.e.*, businesses and jobs). This could be a confounding factor when determining the correlation between experimental measures of farmers' risk attitudes and the farming risk they actually take since the latter is only a share of the total risk borne.

A general approach accounting for the total risk borne by farmers who have a portfolio of economic activities could be simplified by considering just two sources of income: farming (*f*)) and non-farming (*nf*) activities, the uncertain returns of which can be denoted as $\widetilde{r_f}$ and $\widetilde{r_{nf}}$, respectively. In this case, the total risk borne by the farmer measured as the variance of total returns can be calculated as follows:

$$\sigma_r^2 = \left(w_f, w_{nf}\right)\begin{pmatrix}\sigma_{r_f}^2 & \sigma_{r_f r_{nf}} \\ \sigma_{r_f r_{nf}} & \sigma_{r_{nf}}^2\end{pmatrix}\begin{pmatrix}w_f \\ w_{nf}\end{pmatrix} \quad (7)$$

where w_f and w_{nf} are the percentages of expected returns from farming and non-farming activities over total expected return, $\sigma_{r_f}^2$ and $\sigma_{r_{nf}}^2$ are the variances of farming and non-farming returns, and $\sigma_{r_f r_{nf}}$ is the covariance between the two returns. Unfortunately, the data needed to calculate expression (7) were not available for every farmer sampled, since the survey focused only on their farming activities. As such, the variance of total returns can be precisely calculated only for those farmers whose unique source of income was farming (full-time farmers). In these cases, since w_{nf}=0, σ_r^2 equals $\sigma_{r_f}^2$.

Focusing the analysis only on full-time farmers (n=46), whose farming risk is the same as the total risk borne, Pearson and Spearman coefficients and Kendall's *W* were again calculated, as shown in Table S1 [suppl.]. Results obtained in this way also yielded non-significant correlation coefficients and Kendall's *W*, leading to similar conclusions regarding the lack of external validation of experimental measures of farmers' risk attitudes estimated with the whole sample of farmers.

In an attempt to expand the analysis to larger subsamples of farmers, some simplifying assumptions allowed us to calculate proxies of the variance and SD of total returns. Thus, it was assumed that non-farming activities do not involve any risk since their returns remain constant every year (*e.g.*, with a permanent, salaried job). Under this assumption, $\sigma_{r_{nf}}^2$=0 and $\sigma_{r_f r_{nf}}$=0, with expression (7) yielding $\sigma_r'^2 = w_f \cdot \sigma_{r_f}^2$ and $=\sigma_r' = w_f^{0.5} \cdot \sigma_{r_f}$ (the prime symbol indicating that this is a proxy of the actual variance and SD of total returns). Considering these proxies of total risk borne by farmers, non-significant correlation coefficients and Kendall's *W* with experimental measures of risk attitudes were obtained for the whole sample (n=204). Similarly, non-significant results were obtained for more restricted subsamples created by progressively filtering for those farmers who had a percentage of income from farming activities equal to or greater than 50% (n=142), 60% (n=117), 70% (n=95), 80% (n=78), and

90% (n=58). These statistical results are available from the authors on request.

Another issue worth exploring was the role of *permanent crops* in farmers' risk-taking decisions. These crops involve important investments in fixed assets that cannot be changed in the short-term (without incurring high grubbing-up costs and income losses). This is especially true for olive and orange groves in the irrigated agriculture of Córdoba province since both permanent crops have long life spans (more than 30 years) and are widely cultivated within the case study area (see Table 8). Under these circumstances, the farming risk borne by these growers can be divided into two parts: the farming risk 'imposed' by the existing permanent crops in their holdings, which cannot be changed in the short-term; and the risk 'accepted' due to their own decision-making when choosing the herbaceous crop-mix every year for the remaining farm area (that not covered by groves). Given this framework, it was assumed that only the 'accepted' farming risk is related to farmers' risk attitudes obtained experimentally. To carry out this analysis, the sample of farmers was filtered according to the percentage of the area devoted to permanent crops. Thus, a subsample comprising only farmers without any permanent crops (n=45) was considered for correlation and Kendall's *W* analyses, as shown in Table S2 [suppl.]. However, non-significant correlation coefficients and *W* statistics were once again found, indicating that experimental measures of risk attitudes were not related to the 'accepted' farming risk.

Complementary correlation and Kendall's *W* analyses were also carried out for larger subsamples comprising farmers who had less than 10% (n=52), less than 20% (n=59), and less than 30% (n=65) of their farming area devoted to permanent crops. In each case, non-significant correlation coefficients and *W* statistics were obtained (results available from the authors on request).

Moreover, an additional correlation analysis was carried out, combining the two issues highlighted above. This correlation analysis took the subsample grouping farmers without other sources of income and without permanent crops (*i.e.*, those whose farming risk borne, estimated as $\sigma^2_{r_f}$ was equivalent to the total risk 'accepted') (n=11). The correlation coefficients and *W* statistics did not yield statistical significance results (available on request). Since the size of this subsample size was very limited and so results may not be sufficiently robust, we repeated the analysis with a larger subsample, selecting those farmers whose farming activities represented more than 80% of their income and who dedicated less than 20% of their farm area to permanent crops (n=27). However, once again the results were non-significant, thus rejecting the hypothesis that the presence of permanent crops was a confounding factor that may be why empirical risk measures did not explain the risk actually taken by farmers.

Finally, we also controlled for the influence of socio-demographic variables on the external validation performed to check that they did not lead to any misleading conclusions. Thus, two additional analyses were carried out. On the one hand, partial correlation coefficients between the two measures of risk attitudes (CRRA *R* or *SA*) and different measures of farming risk borne (variance and SD of farming returns) were calculated controlling for certain variables that may affect the farmers' risk preferences, such as age, educational level or farming experience. However, none of the partial correlation coefficients obtained were statistically significant (results available from the authors on request). On the other hand, the sample was filtered in several ways using these types of socio-demographic variables, obtaining different subsamples and repeating the previous analysis, with no significant results. Therefore, it can be inferred that farmers' socio-demographic characteristics were not behind the lack of statistical correlation between risk attitude measures elicited by CRRA *R* and *SA* and the amount of risk actually borne by farmers.

Conclusions

The main contribution of this research to the existing literature is the proposal of an external validation procedure for risk preference estimates based on their comparison with measures assessing the overall level of farming risk borne by individual producers. Only if this comparison were to yield a significant correlation with a strong enough effect size could it be claimed that individuals' elicited risk preferences appropriately reflect real farming decisions.

Results obtained for the case study considered here revealed stability across EG and self-assessment methods, but there was no evidence of a statistical correlation between these elicitation measures and the measures assessing the actual farming risk taken by farmers. Therefore, the results of experimental methods measuring farmers' attitudes towards risk should be taken with caution since there was no confirmed evidence that they are sufficiently accurate predictors of farmers' decision-making. Thus, the main issue emerging from these findings is the need for more in-depth and holistic approaches when modeling farmers' behavior in *ex-ante* policy analysis.

Although there could be several possible reasons behind the poor predictive power of experimental measures of risk preferences, the most likely explanation is related to the reliance on the theoretical assumption that economic agents are expected utility maximizers. Recent studies show that non-expected utility preferences are widespread among farmers, suggesting that prospect theory (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992) is a more reliable theoretical framework for analyzing farmers' decision-making (*e.g.*, Bocquého *et al.*, 2014; Babcock, 2015; Du *et al.*, 2016; Holden & Quiggin, 2017). This evidence raises the need for new experimental methods designed following the guidelines already set out by Tanaka *et al.* (2010). It also indicates that it is worth testing whether risk preferences based on prospect theory could be externally validated.

The negative results obtained could also be due to the fact that farmers' risk behavior is determined by their risk perceptions, in addition to individuals' risk attitudes (Just & Just, 2016; van Winsen *et al.*, 2014). Further research should focus on jointly analyzing these two variables as factors that are hypothetically able to predict farmers' decision-making (*i.e.*, the farming risk borne).

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