The incorporation of subjective risks into choice experiments to test scenario adjustment

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Summary

In choice experiment (CE) applications, subjects are typically assumed to fully accept information given in the status quo (SQ) alternative, however, subjects might adjust such information on the basis of their subjective beliefs. This phenomenon is known as scenario adjustment.

By using a CE field survey, we investigate whether subjects adjust risks portrayed in the SQ using their subjective estimates via a two-stage approach. In the first stage, subjective risks are elicited using the exchangeability method. In the second stage, two treatment groups are designed. In the first group, each subject is presented with a SQ which incorporates her/his own subjective risk estimate, and, hence, no adjustment is required. In the second group, each subject faces a SQ where the presented risk is not consistent with her/his own estimate, and, hence, a mental adjustment to the scenario might take place.

Our modeling results suggest that subjects who are provided with a SQ in which the risk is lower than their own subjective estimates have a higher maximum willingness to pay (WTP) for a risk reduction than subjects provided with a SQ where the risk is consistent with their perceptions. Hence, in this case the scenario adjustment takes place. In contrast, subjects who are presented with a SQ where the risk is higher than their subjective estimates, overreact to the risk information, and have a higher WTP for the risk *reduction than subjects who face a SQ where the presented risk is consistent with their perceived risks. Hence, in this case they appear to go along with the information in the SQ and abandon their subjective estimate*

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1. INTRODUCTION

Discrete choice' modelers have generally assumed that subjects make choices while fully accepting the attribute levels provided by the researcher in the SQ, however, recent Stated Preference studies have shown that subjects often adjust the information given in the SQ on the basis of their prior beliefs and/or expectations (e.g., Burghart et al., 2007; Cameron et al., 2010). These studies have demonstrated the occurrence of the scenario adjustment by simulating subjects' choice-behavior under a full acceptance of attribute levels presented in the SQ alternative (i.e., ex-post simulations). As such ex-post simulated choices may not mirror real decision making processes as they strongly depend on the parameterization of scenario adjustment (Burghart et al., 2007), here, by using a CE field survey, we investigate the extent of scenario adjustment by comparing subjects' choice behavior when the attribute levels presented in the SQ either coincides or does not with subjects beliefs about the SQ. More specifically, we actually elicit preferences, both when the scenario adjustment might take place, and when it might not.

In particular, our CE application examines whether the scenario adjustment takes place when subjects are asked to make choices under risk, and, in particular, to what extent subjects adjust the risk information provided in the SQ on their prior subjective risks. An extensive research within psychology and, to some extent, in economics, has demonstrated that subjects often revise their own risk estimates once they acquire additional risk information. The updating procedure or mechanism that subjects use to revise their prior subjective risks using new information has been not clearly identified yet. Several studies have shown that individuals behave as Bayesians (e.g., Viscusi, 1985; Viscusi, 1989), while others have demonstrated that subjects often overreact to risk information, and, driven by some sort of alarm, they end up having very high risk estimates. This is the so-called alarmist learning behavior (e.g., Viscusi, 1997).

We specifically investigate to what extent a mental adjustment to the SQ scenario takes place in choices over alternative R&D programs which are geared to control the future spread of new apple diseases in the Province of Trento in Italy. As compared to the farmers' standard practice, which is to use pesticide residues, the implementation of new methods, based on natural organism and resistant varieties of apples, will reduce the risk of having contaminated apples in the future. Given this context, a scenario adjustment might easily affect subjects' choices over the alternative R&D programs. In fact, subjects might either make choices by using the provided risk of having contaminated apples given by the researcher in the SQ, or, they might adjust the provided estimates to conform more with those based on their own estimates, if the latter differs from the former. This investigation also helps to identify risk communication strategies that make people more willing to support policies that they may not initially perceive as important based on their prior assessment of risk.

To investigate subjects' choice behavior when the risk level presented in the SQ coincides with perceived or subjective risks[1], we design subject-specific SQ alternatives based on each subject's subjective risk of having contaminated apples in the future. These risk estimates are elicited by using the Exchangeability Method (EM), an elicitation techniques based on de Finetti's notion of exchangeable events (de Finetti, 1937). This method differs from risk elicitation techniques commonly used in SP studies in that it elicits subjective risk estimates by asking subjects to play lotteries containing outcomes occurring in the future (Baillon, 2008; Abdellauoi et al., 2011; Cerroni et al., 2012a). In order to incorporate subjective risks into a CE design, we implement a best-worst pivot CE. Pivot CEs are extensively used in transport economics to generate subject-specific SQ alternatives based on the information that each subject provides about her/his most recent trip. Afterwards, attribute levels of other alternatives are generated by adding or subtracting fixed percentages or values from attribute levels of the SQ alternative (e.g., Hensher and Greene, 2003; Hensher et al. 2011).

In the remainder of the paper, we first review previous studies of mental scenario adjustments. Next, we describe the CE survey used to collect our data, provide testable hypotheses, and present our discounted Expected Utility Theory models of choice. In the final section, we offer some conclusions based on our empirical results.

2. LITERATURE REVIEW

2.1. Scenario adjustment

This paper investigates the adjustment that a subject might make to reduce conflict between provided information and what she/he believes to be true. This phenomenon is becoming commonly known in the CE literature as scenario adjustment (Bughart, 2007; Cameron et al., 2010). Taking this type of adjustment behavior to the extreme, a subject might completely ignore the information provided in the SQ and make choices according to their subjective estimates. Such subjects essentially put zero weight on new information, clinging to their prior, which might be based on some personal knowledge or experience (e.g., Baker et al. 2009).

Two approaches have thus far been identified to deal with scenario adjustment problems in SP studies. Both rely on the collection of additional information about subjects' beliefs or expectations of the levels in one or more key attributes that describe the SQ alternative.

The first approach investigates to what extent the scenario adjustment affects subjects' choices and, hence, their welfare estimates primarily by using simulations. In choice models, additional survey information is interacted with utility parameters to control for the presence of a scenario adjustment. The estimated coefficients of these interaction terms indicate to what extent the adjustment takes place. This information is commonly elicited by using very simple debriefing questions at the end of the survey. For example, researchers ask subjects what would have been the SQ' attribute levels that they expected to face in the choice tasks. By using this approach, some stated choice studies that have incorporated risk as an attribute have detected scenario adjustment and they have demonstrated substantial influence that this phenomenon has on welfare measures (Burghart et al., 2007; Cameron et al., 2010). A criticism of using such ex-post simulated choices is that these might strongly depend on the used econometric specification, and generate biased estimates of the effect that the scenario adjustment produces on subjects' behaviors and implied marginal WTP (Burghart et al., 2007).

In contrast, the second approach avoids scenario adjustment and all potential related issues. This approach, developed in transportation studies, relies on the design of more realistic CE survey by using pivot

[1]The psychology literature refers to subjective estimates of risk as "perceived" risks.

experimental designs based on the subject's most recent actual trip (e.g., Hensher and Greene, 2003; Hensher et al. 2011). To generate such a design, attribute levels of the SQ (characteristics of a recently taken commuting trip) are first obtained from the subjects themselves, and, then, used to design the attribute levels of the other alternatives presented in the choice tasks. Obviously this approach is suspect when the subject did not take a relevant recent trip. One criticism of the Pivot CE approach is that subjects may systematically prefer the realistic SQ alternative over the hypothetical generated alternatives (e.g., Hess and Rose, 2009; Rose and Hess, 2009). Here, we propose that the Pivot CE approach might be used for incorporating subjective estimates into stated choice experiments to better predict choices under conditions of risk.

2.2. Elicitation of subjective probabilities

There is an extensive literature in decision analysis and management science, now spilling over into behavioral and experimental economics, about the elicitation of subjective risks related to financial outcomes, because the method of elicitation may affect the magnitude and precision of the estimated subject risk. Few studies have been done in other fields (e.g., Viscusi, 1990; Wakker and Deneffe, 1996; Cerroni and Shaw, 2012).

In previous stated preference studies (mainly contingent valuation approaches), subjective risks have been commonly elicited by using the so-called direct technique, which basically asks subjects to state the probability that given outcomes will occur in the future (e.g., Viscusi, 1990; Williams and Hammit, 2001). The response could be to an open-ended question or as a marking on a risk ladder. Although the direct approach is very appealing for its simplicity, it may generate biased results as subjects are often not willing and/or able to express probabilities in numerical terms (Zimmer, 1983)[2].

An alternative way for eliciting subjective risks consists in asking subjects to play lotteries. In these indirect risk elicitation techniques the probability estimates are indirectly estimated at the point for which subjects becomes indifferent to playing one lottery instead of another (Spetzler and Stael Von Holstein, 1975).There are many variations on this theme[3], but a rediscovered approach is the exchangeability method (EM). This elicitation technique consists of a set of binary questions in which subjects are asked to bet a certain amount of money on one of the two disjoint subspaces that come from the bisection partition of the whole state space of the variable under study. The sectioning process depends on subjects' betting-behavior, and proceeds until subjects become indifferent to bet on one disjoint subspace rather than on the other. When this point is reached, subjects are assumed to perceive those subspaces as equally likely (Spetzler and Von Holstein, 1975). This method allows eliciting several percentiles of each subject's cumulative distribution function (CDF) of the random variable under study. This approach is particularly appealing because outcomes are not associated to probability measures, and, hence, unlike other techniques, it does not force individuals to process numerical probability estimates (e.g., Baillon, 2008; Abdellaoui et al., 2011, Cerroni and Shaw, 2012)[4].

3. OBJECTIVE AND TESTABLE HYPOTHESES

Recall from above that in the first stage of the approach we use each subject's subjective risks that given outcomes will occur are elicited, and, in the second stage, the sample is split into two treatment groups to explore their marginal WTP (MWTP). In the Subjective SQ (SSQ) treatment, the risk presented in the SQ is consistent to each subject's risk estimate, while in the Objective SQ (OSQ) treatment, it is not. The OSQ treatment group is further split into two other sub-groups. In one, the risk depicted in the SQ is lower than

[2] One might argue that, subjective risks do not need to be elicited, but they can be inferred from subjects' choices. Unfortunately, in this study, the elicitation of subjective risks is necessary to investigate how subjects react when provided with risk information which differs from their prior risk estimates.

[3] To keep the paper of a manageable length we refer interested readers to Cerroni et al. (2012a).

[4] In a recent study, Cerroni et al. (2012a) have shown that the validity of subjective probabilities elicited via the EM depends on the ordering of questions and the provision of monetary incentives to subjects based on their betting-behavior during the tasks. However, the issue of validity is beyond the scope of this paper.

each subject's estimate (OSQ_{LOW}), while, in the other, it is higher than that (OSQ_{HIGH}).

This approach implies the incorporation of subjective risks, elicited using the EM method, into the CE's experimental design by using the pivot approach. To our knowledge, our investigation represents the first attempt to use the pivot CE to create SQ alternative which are consistent and coherent with subjective risks related to future outcomes.

The scenario adjustment is investigated by testing the following specific hypotheses[5]:

Hypothesis 1.

H_0: $MWTP_{SSQ} \geq MWTP_{OSQ\_LOW}$

H_1: $MWTP_{SSQ} < MWTP_{OSQ\_LOW}$

If the null hypothesis (H_0) is rejected, subjects who belong to the OSQ_{LOW} treatment positively adjust the risk information provided in the SQ on their estimates. Because they make choices having in their own mind SQ's attribute levels that are greater than those provided in the SQ, their estimated MWTP is greater than those for subjects who belong to the SSQ treatment. In contrast, if the null hypothesis (H_0) is not rejected, subjects who belong to the OSQ_{LOW} fully accept the risk information given by the researcher (i.e., there is no scenario adjustment), or they negatively adjust the risk information provided in the SQ because they overreact to such information.

Hypothesis 2.

H_0: $MWTP_{SSQ} \leq MWTP_{OSQ\_HIGH}$

H_1: $MWTP_{SSQ} > MWTP_{OSQ\_HIGH}$

Here, if the null hypothesis (H_0) is rejected, subjects who belong to the OSQ_{HIGH} treatment group negatively adjust the risk estimate provided in the SQ due to their subjective estimates. These subjects have lower MWTP than subjects who belong to the SSQ treatment because they make decisions consistent with their lower subjective risk estimate. In contrast, if the null hypothesis (H_0) is not rejected, the scenario adjustment does not occur, or it occurs in the opposite direction (i.e., positive adjustment), as they overreact to such information.

4. METHODOLOGY

4.1. Exchangeability method

In our application of the EM, the random variable under study is the number of apples, (*a*), produced in the Province of Trento that will contain pesticide residues in 2030 if farmers control the spread of new

[5] These hypotheses allows testing the scenario adjustment within the Expected Utility Theory framework. In other non-standard theories of decision making under risk and uncertainty, such as Cumulative Prospect Theory and Rank Dependent Utility Theory, the reference point affects subjects' choices.

diseases by using pesticides. Only the 50th percentile of each subjects' CDF is elicited ($a_{1/2}$). In the first step of the EM, subjects are asked to express the lower and upper bounds of the state space of variable a (S_a), defined as a_{min} and a_{max}. These bounds contain all outcomes that have a non-zero probability to occur. For example, if subject i believes that $a_{i,min}$=70 and $a_{i,max}$=86, then, she/he implicitly assumes that only outcomes belonging to this range will occur.

In the second step of the EM, subject i is asked to answer a series of binary questions that reveal the 50th percentile of the her/his subjective CDF ($a_{i,1/2}$). In the first binary question, S_a is divided at a point a_1 into two prospects, say $A_1=\{a_{min}<x<a_1\}$ and $A_1'=\{a_1\leq x<a_{max}\}$, where $a_1=\{a_{min}+[(a_{max}-a_{min})/2]\}$. To our subject i, $a_{i,1}=\{70+[(86-70)/2]\}=78$ apples, and, thus, the first binary question asks her/him to bet on prospect $A_1=\{70<x<78\}$ or prospect $A_1'=\{78\leq x<86\}$. If prospect A_1 is chosen by the subject i, the implication is that she/he believes the probability of occurrence of the sub-event $A_1$is greater than that of the sub-event A_1', so that $P(A_1)\geq P(A_1')$ and $a_{i,1}\geq a_{i,1/2}$, and thus, $P(70<x<78)$□□$P(78$□$x<86)$ and 78□□$a_{i,1/2}$. This process is repeated until subject i reaches a value $a_{i,1+z}$ (with z=1,2,...,n) such that she/he is indifferent between A_{1+z} and A_{1+z}'. When this point is reached, it follows that $P(A_{1+z})=P(A_{1+z}')$ and $a_{i,1/2}=a_{i,1+z}$. For example, assume that subject i was indifferent between prospect $A_{1+z}=\{70<x<74\}$ and prospect $A_{1+z}'=\{74\leq x<76\}$, this implicitly means that $P(70<x<74)=P(74\leq x<76)$ and $a_{i,1/2}$=74. To conclude, our subject i believes that there is 50% chance that the number of apples containing pesticide residue will be between 70 ($a_{i,min}$) and 74 ($a_{i,1/2}$), and another 50% chance that it will be between 74 ($a_{i,1/2}$) and 86 ($a_{i,max}$). For simplicity's sake, at the end of the task, subject i is presented with a summary screen-shot in which he/she is informed that, based on her/his choice-behavior, there is 50% chance that the number of apples containing pesticide residues will be 74 ($a_{i,1/2}$), at the worst, and another 50% chance that it will be 86 ($a_{i,max}$), at the worst. As a check, each subject is asked to confirm her/his estimate[6].

4.2. Best-worst pivot choice experiment

After having interviewed 34 subjects during three focus-group meetings, three key attributes were selected to describe the effect of the R&D programs on the presence of pesticide residues in apples. These are:

(i) the maximum number of apples containing pesticide residues in a sample of a hundred in 2030 (N),

(ii) the probability of this number N occurring (P), and

(iii) the annual tax in euro that taxpayers of the Province of Trento must pay over the period between 2012 and 2030 if they want R&D programs to be launched in 2012 (T).

In the CE application, each subject is presented with 12 choice tasks, containing each of three alternatives. Using the best-worst approach, subjects are asked to select the most and least preferred alternatives in each choice task. In the best-worst version of the CE, the subject first chooses either their most or least preferred alternative. If subjects first provide their most (least) preferred alternative, then they are next asked to indicate their least (most) preferred alternative among those that remain[7].

In the SQ alternative, no R&D program is launched by the Province of Trento and, thus, farmers will have to control any new diseases by spraying new pesticides in 2030. Given the very long time-horizon for events to evolve, the number of contaminated apples in 2030 cannot be known with certainty, thus the SQ is portrayed as a lottery which consists of two prospects, Prospect A and B. In Prospect A, there is a given

[6]The majority of our subjects confirmed estimates inferred from their choice-behavior.
[7] See Scarpa et al. (2010) for advantages and disadvantages of using best-worst CE.

chance $P(N_{A,SQ})$that the maximum number of contaminated apples in 2030 will be $N_{A,SQ}$; in Prospect B, there is a given chance $P(N_{B,SQ})$ = 1- $P(N_{A,SQ})$ that the maximum number of contaminated apples in 2030 will be $N_{B,SQ}$. As any R&D program is implemented, there is no tax to pay in the SQ alternative (Table 1a).

As noted above, in addition to the SQ, which allows subjects to reject the other alternatives in favor of the baseline scenario, subjects are presented with other two alternatives in every choice task. In these two alternatives, the Province of Trento will launch an R&D program to develop new methods to control new disease in 2030. These methods are described to reduce the number of apples containing pesticide residues in 2030, as compared to the baseline scenario depicted in the SQ alternative. In this case, each hypothetical alternative presented in each choice task is a lottery which consists of two prospects, Prospect A and B. In Prospect A, there is a given chance $P(N_{A,R\&D})$that the maximum number of contaminated apples in 2030 will be $N_{A,R\&D}$; in Prospect B there is a given chance $P(N_{B,R\&D})$ =1- $P(N_{A,R\&D})$that the maximum number of contaminated apples in 2030 will be $N_{B,R\&D}= N_{B,SQ}$. As R&D programs will reduce the presence of pesticide residues in apples, and, thus $N_{A,R\&D}<N_{A,SQ}$, we have generated three levels for $N_{A,R\&D}$ by using the pivot approach, and more specifically, the following algorithms, $N_{A,SQ}$ – 40%, $N_{A,SQ}$ – 60%, and $N_{A,SQ}$ – 80% (Table 1b). On the other hand, as the effectiveness of R&D programs is highly uncertain, and, thus, $P(N_{A,R\&D})\leq P(N_{A,SQ})$ and 1-$P(N_{A,R\&D})\geq$1-$P(N_{A,R\&D})$,we created the pivoted four levels for $P(N_{A,R\&D})$ by using the following algorithms, $P(N_{A,SQ})$- 0%,$P(N_{A,SQ})$ - 50%, $P(N_{A,SQ})$ – 80%,and $P(N_{A,SQ})$ – 90% (Table 1b)[8].

The selected levels for the tax attribute (*T*) were the following, 15€, 30€, 50€, and 80€ (Table 1b). These levels were determined to be appropriate based on previous related studies (e.g., Florax et al., 2005), as well as taking into account focus group participants' opinions and expectations about R&D programs and their costs.

In this study, we used a Bayesian *D*-efficient homogeneous pivot design that has been generated through a two-step procedure (Ferrini and Scarpa, 2007). In the first step, by running a pre-test CE survey[9] prior coefficients of our attributes were estimated, and, then used to generate a *D*-efficient design. Given our 3×4^2 factorial design of our pre-test study, we generated a simple optimal orthogonal design with four blocks of 9 choice tasks by using Ngene 1.1.1. Reference levels and segment weights of our homogeneous pivot design were obtained by examining the median percentile estimates of the number of apples containing pesticide residues in 2030 elicited via the EM by Cerroni et al. (2012a). A homogeneous pivot design was chosen, rather than a heterogeneous one, because the former allows us to generate a single design that can be used for all individual-specific SQ alternatives. As subjects face the same basic experimental design whatever treatments they belong to, confounding factors due to the use of different designs across treatments are avoided[10].

Table 1a. Attribute levels for the SQ

Attribute	Prospect A	Prospect B
Maximum number of apples containing pesticide residues in 2030	$N_{A,SQ}$	$N_{B,SQ}$
Probability of occurrence	$P(N_{A,SQ})$	1-$P(N_{A,SQ})$
Yearly tax to pay in the period 2012-2030		0€

[8]Our experimental design ensures that the probabilities sum to one in each lottery.
[9] The sample of the pre-test survey consists of 80 randomly selected subjects in the Province of Trento.
[10]The number of simulate respondents was 500, the number of Halton random draws was 800.

Table 1b. Attribute level for R&D plans

Attribute	Prospect A	Prospect B
Maximum number of apples containing pesticide residues in 2030	$N_{A,SQ}$ – 40% $N_{A,SQ}$ – 60% $N_{A,SQ}$ – 80%	$N_{B,SQ}$
Probability of occurrence	$P(N_{A,SQ})$ – 0% $P(N_{A,SQ})$ – 50% $P(N_{A,SQ})$ – 80% $P(N_{A,SQ})$ – 90%	1-[$P(N_{A,SQ})$ – 0%] 1-[$P(N_{A,SQ})$ – 50%] 1-[$P(N_{A,SQ})$ – 80%] 1-[$P(N_{A,SQ})$ – 90%]
Yearly tax to pay in the period 2012-2030	15€ 30€ 50€ 80€	

4.3. Experimental treatment and sampling procedure

After The final sample of subjects consists of 797 taxpayers who reside in the Province of Trento. Data were collected by trained interviewers using the computer-assisted personal interviewed (CAPI) system which consists of face-to-face interviews usually conducted at respondents' home or business using a portable personal computer.

The Subjective SQ (SSQ) treatment group consists of 487 subjects randomly selected from the full sample of 797 people, and the Objective SQ (OSQ) treatment group has 310 randomly selected subjects.

In the Subjective SQ each subject *i* is presented with an SQ alternative (No R&D Program) which specifies the baseline risk. The Subjective SQ consists of Prospect A, where there is a 50% chance that the maximum number of contaminated apples in 2030 will be $N_{A,SQ} = a_{i,1/2}$, which is from the 50th percentile estimates of each subject's CDF obtained using the EM. For prospect B, there is a 50% chance that the maximum number of contaminated apples in 2030 will be $N_{B,SQ} = a_{i,max}$, the 100th percentile estimates of each subject's CDF. Recall that here there is no tax for subjects to pay for the SQ alternative. An example of choice cards presented to subjects who belong to this treatment group is provided in Tables 2, while summary statistics of attribute levels are presented in Table 4a.

Table 2. Choice Task 1 for subject *i* in the SSQ treatment

	R&D Program X		R&D Program Y		NO R&D Program	
	Prospect A	Prospect B	Prospect A	Prospect B	Prospect A	Prospect B

Maximum number of apples containing pesticide residues in 2030	$a_{i,1/2}$–80%	$a_{i,max}$	$a_{,1/2}$-40%	$a_{i,max}$	$a_{1/2,i}$	$a_{i,max}$
Probability of occurrence	10%	90%	25%	75%	50%	50%
Yearly tax to pay in the period 2012-2030	15€		50€		0€	

In the Objective SQ treatment, each subject *i* is similarly presented with the SQ alternative, however this risk is provided to the subject, and differs from the one she/he expressed through the EM. Subject *i* was assigned to one treatment subgroup, rather than to the other, based on her/his 50th percentile estimate ($a_{i,1/2}$), previously elicited by using the EM. In fact, if subjects *i's* 50th percentile estimate falls between 76 and 100 apples ($76 \leq a_{i,1/2} \leq 100$), she/he belongs to the SQ_{LOW} treatment, while if it falls between 50 and 74 apples ($50 \leq a_{i,1/2} \leq 74$), she/he belongs to the SQ_{HIGH} treatment.

As an example, in the Objective SQ_{LOW} treatment, if subjects *i's* 50th percentile estimate falls between 76 and 86 apples ($76 \leq a_{i,1/2} \leq 86$), the SQ alternative's Prospect A reports that there is a 50% chance that the maximum number of contaminated apples in 2030 will be $N_{A,SQ}$=65, which is lower than 50th percentile estimates of each subject's CDF ($a_{i,1/2}$), while Prospect B informs the subject that there is a 50% chance that the maximum number of contaminated apples in 2030 will be $N_{B,SQ}$=75,which is lower than the 100th percentile estimates of each subject's CDF ($a_{\max,i}$). Summary statistics of attribute levels presented to subject in this treatment group are reported in Table 4b, while a choice card example is offered in Table 3.

Table 3. Choice Task 1 for subject *i* in the OSQ_{LOW} treatment

	R&D Program X		**R&D Program Y**		**NO R&D Program**	
	Prospect A	**Prospect B**	**Prospect A**	**Prospect B**	**Prospect A**	**Prospect B**
Maximum number of apples containing pesticide residues in 2030	65–80%	75	65-40%	75	65	75
Probability of occurrence	10%	90%	25%	75%	50%	50%
Yearly tax to pay in the period 2012-2030	15€		50€		0€	

As an example, in the objective SQ_{HIGH} treatment, if subjects *i's* 50th percentile estimate falls between 50 and 66 apples ($50 \leq a_{i,1/2} \leq 66$), Prospect A reports that there is a 50% chance that the maximum number of contaminated apples in 2030 will be $N_{A,SQ}$ =75, which is higher than 50th percentile estimates of each subject's CDF ($a_{i,1/2}$), and Prospect B informs that there is a 50% chance that the maximum number of contaminated apples in 2030 will be $N_{B,SQ}$=85, which is higher than the 100th percentile estimates of each subject's CDF ($a_{i,max}$)[11].

The “splitting” rule presented above aims to generate the equivalent sample size across subgroups and was defined using experimental results by Cerroni et al. (2012a) which pertain to the number of subjects who have the same 50th percentile estimates of the numbers of apples containing pesticides in 2030. The reliability of this approach is supported by the fact that both treatment groups consist of 155 subjects. Unfortunately, this procedure may have affected the composition of our subsamples which, in this study, should be similar across treatment groups, as key socioeconomic variables likely affect willingness to pay for R&D programs. However, having data on these variables allows control via additional econometric modeling. To detect variables that must be included in the choice models to control their effect on WTP, a very simple logit selection model was estimated, described below. In this model, the probability of belonging to the OSQ_{LOW} or the OSQ_{HIGH} treatment groups rather than to the SSQ treatment depends on a set of variables defining the socioeconomic status and attitudes of subjects, which the literature pertaining to food choices under conditions of risk has shown to be relevant in explaining subjects' behavior[12].

Table 4a. Summary statistics of variables in the Subjective SQ treatment

Variable	N. Obs.	Mean	St. Dev	Min	Max

[11]Two diverse SQ alternatives were designed for each objective SQ treatment groups because of the deep uncertainty surrounding scientific predictions of the number of apples containing pesticides in 2030 in the Province of Trento.
[12] Results are available under request

	SQ	R&D	SQ	R&D	SQ	R&D	SQ	R&D	SQ	R&D
N_A	5,844	5,844	76.480	30.590	6.530	12.813	64	13	98	59
N_B	5,844	5,844	87.188	34.874	9.710	14.863	66	13	100	60
$P(N_A)$	5,844	5,844	0.5	0.225	0	0.175	0.5	0.05	0.5	0.5
$1\text{-}P(N_A)$	5,844	5,844	0.5	0.775	0	0.175	0.5	0.5	0.5	0.95
T	5,844	5,844	0	43.750	0	24.337	0	15	0	80
REDD		5,844		17,012.320		11,103.230		5,000		120,000

Table 4b. Summary statistics of variables in the Objective SQ_{LOW} treatment

Variable	N. Obs.		Mean		St. Dev		Min		Max	
	SQ	R&D	SQ	R&D	SQ	R&D	SQ	R&D	SQ	R&D
N_A	1,860	1,860	68.290	27.316	4.699	11.338	65	13	75	45
N_B	1,860	1,860	78.290	31.316	4.699	12.948	75	15	85	51
$P(N_A)$	1,860	1,860	0.5	0.225	0	0.175	0.5	0.05	0.5	0.5
$1\text{-}P(N_A)$	1,860	1,860	0.5	0.775	0	0.175	0.5	0.5	0.5	0.95
T	1,860	1,860	0	43.750	0	24.341	0	15	0	80
REDD		1,860		25,870.970		19,022.490		5,000		120,000

Table 4c. Summary statistics of variables in the Objective SQHIGH treatment

Variable	N. Obs.		Mean		St. Dev		Min		Max	
	SQ	R&D	SQ	R&D	SQ	R&D	SQ	R&D	SQ	R&D
N_A	1,860	1,860	87.967	35.187	5.134	14.539	75	15	90	54
N_B	1,860	1,860	97.967	39.187	5.134	16.155	85	17	100	60
$P(N_A)$	1,860	1,860	0.5	0.225	0	0.175	0.5	0.05	0.5	0.5
$1\text{-}P(N_A)$	1,860	1,860	0.5	0.775	0	0.175	0.5	0.5	0.5	0.95
T	1,860	1,860	0	43.750	0	24.341	0	15	0	80
REDD		1,860		25,451.610		13,931.760		5,000		120,000

5. MODELING, ESTIMATION, AND WELFARE MEASURES

5.1. Discrete choice modeling

As our subjects are asked to make choices over lotteries, we implement an Expected Utility Theory (EUT) model which assumes that subject i makes a choice over j alternatives, with $j = 1,...,J$, by using an expected utility maximization rule. Like Random Utility models (RUM), our models also assume that the utility that subject *i* attaches to each alternative *j* is decomposed into two parts, $V_{i,s,j}$ that is the part of the utility observed by the researcher, and $\varepsilon_{i,s,j}$ that is the one cannot be observed by the researcher, so that, $U_{i,j}= V_{i,j}+ \varepsilon_{i,j}$. While researchers can model $V_{i,j}$, they can only make assumptions of the distribution that $\varepsilon_{i,j}$ follows.

The basic EUT approach, following von Neuman and Morgenstern (1947), assumes that subjects have rational preferences over lotteries *L* implying risky outcomes x_n with $n = 1,.., N$. An outcome is risky when it occurs with a given probability, $P(x_n)<1$, such that $\sum_1^N P(x_n)=1$. The conventional EUT assumes that the probability is well known to the decision maker. Under the EUT (in discrete form), the utility of lottery *L* is described as follows:

Equation 1

$$U(L)=\sum_1^N P(x_n)\times U(x_n)$$

As each alternative *j* presented in our choice tasks depicts a lottery involving two risky prospects, the discounted utility ($U_{i,,j}$) that subject *i* attaches to alternative *j* is the sum of the utility that she/he attaches to Prospect A ($W_{i,A,j}$) and the utility that she/he attaches to Prospect B ($W_{i,B,j}$). Note that, each year $n=\{1,\dots,N\}$ over the period between 2012 and 2030, the annual tax (*T*) is taken away from each subject's yearly income (INC_i)[13], so that, the parameter ($INC_i– T_j$) enters in the conditional indirect utility function. Given this framework.

Equation 2

$$U_{i,j}=W_{i,j,A}+W_{i,j,B}+Y_{i,j}+\varepsilon_{i,j}$$

where:

Equation 3

$$W_{i,j,A}=\left\{P(N_{A,j})\times\left[\beta_{0,j}+\beta_{N,i}\times\frac{N_{A,j}^{1-r_N}}{1-r_N}+\beta_{INC,j}\times\left(\frac{(INC_i-T_j)^{1-r_{INC}}}{1-r_{INC}}\right)\right]\right\}\times\sum_{n=1}^N\frac{1}{(1+\delta)^n}$$

[13]We assume constant income over the period between 2012 and 2030. Were it to grow, if income effects are present, then we underestimate WTP. We could assume a constant growth rate in income for all subjects, but we cannot know if this would hold for everyone in the sample.

Equation 4

$$W_{i,j,B} = \left\{ \left[1 - P\left(N_{A,j}\right)\right] \times \left[\beta_{0,j} + \beta_{N,i} \times \frac{N_{B,j}^{1-r_N}}{1-r_N} + \beta_{INC,j} \times \left(\frac{(INC_i - T_j)^{1-r_{INC}}}{1-r_{INC}} \right) \right] \right\} \times \sum_{n=1}^{N} \frac{1}{(1+\delta)^n}$$

In the model presented above, the parameter β_0 is the alternative specific constant related to each alternative *j*. As it is evident in Equation 3 and 4, we investigate the presence of an unobserved between-subject heterogeneity for the coefficient $\beta_{N,i}$. After having tested diverse distributional forms (normal, lognormal, SB Johnson), the triangular distribution was chosen to model this random parameter. To our knowledge, only a few CE studies have modeled a random parameter related to risky outcomes (e.g., Hensher and Li, 2012).

The *r* parameters included in the modeling, r_N and r_{INC} correspond to coefficients of constant relative risk aversion (CRRA). Although the usual assumption is that risk preferences are consistent across sources of risk, recently, risk attitudes have been empirically shown to be context-dependent (Riddel, forthcoming), hence, we estimated two different CRRA coefficient here, the parameter r_N accounts for a subject's risk attitude with respect to the number of contaminated apples in our fruit bowls in 2030, while the parameter r_{INC} represents the subjects' risk attitudes with respect to income. The CRRA coefficient's specification used in our model has been extensively implemented in economic experiments investigating risk attitudes or preferences for monetary or financial outcomes (e.g. Andersen et al., 2006; 2008).

As noted above, our subjects are asked to pay a yearly tax in the period between 2012 and 2030, and thus, our model incorporates a standard financial rate of discount, δ. The estimated coefficient of this parameter provides a measure of the average sample discount rate that subjects used in their temporally dependent choices (e.g., Burghart et al., 2007).

The vector $Y_{i,j}$ consists of all socioeconomic and variables that the estimated selection model has shown to affect the composition of treatment group. They are incorporated in the model to control their potential influence on subjects' choice-behavior and, hence, on their MWTP estimates. To create differences in utilities over alternatives, each of these variables is normalized to zero when it is associated to the SQ alternative (Train, 2003). More specifically, these variables indicate subject's apple consumption habit (*APPLES*), consumer association membership (*C_ASS*), job typology (*PROD*), age (*AGE*), gender (*FEMALE*), and life insurance taking (*LIFE*).

5.2. Estimation procedure and welfare measures

As noted above, in each choice task, subjects are asked to state their best and least preferred alternatives in a set of three alternatives *j*, say *j1*, *j2*,and *j3*. Assuming decision-making procedure and recalling from above that we use the best-worst approach, we estimate models presented above by using a standard "exploded" MMNL (Scarpa et al., 2010), where the probability of occurrence of each ranking option is obtained as follows:

Equation 5

$$P\left[ranking\left(j_1, j_2, j_3\right)\right] = \frac{e^{V_{i,j_1}}}{\sum_{j=j_1,j_2,j_3} e^{v_{i,j}}} + \frac{e^{V_{i,j_2}}}{\sum_{j=j_1,j_2,j_3} e^{v_{i,j}}}$$

In our investigation, for a risk reduction related to the presence of pesticide residues in apples, the MWTP are estimated using the following specification, which of course follows from the usual definition of the marginal rate of substitution:

Equation 6

$$MWTP = \left(\frac{\partial U_{i,j}}{\partial N_{A,j}} + \frac{\partial U_{i,j}}{\partial N_{B,j}} \right) \Bigg/ \left(\frac{\partial U_{i,j}}{\partial (INC_i - T_j)} \right)$$

This specification implies that the MWTP for risk reduction is the following:

Equation 7

$$MWTP = \frac{\beta_{N,i} \left\{ \left(P_{A,j} \times N_{A,j}^{-r_N} \right) + \left[\left(1 - P_{A,j} \right) \times N_{B,j}^{-r_N} \right] \right\}}{\beta_I \times (INC_i - T_j)^{-r_{INC}}}$$

This equation implies that MWTP estimates depend on both the number of apples containing pesticides in 2030 (*NA,j* and *NB,j*) and the probability of this amount occurring (*PA,j*) presented in the risky prospects of each alternative. In their turn, as a pivot experimental design is used, *NA,R&D*, *NB, R&D*, *PA, R&D*, and *PB, R&D* that are presented in the R&D programs depend on both the number of apples containing pesticides in 2030 (*NA,SQ* and *NB,SQ*) and the probability of this amount occurring (*PA,SQ* and *PB,SQ*) that are presented in the SQ alternative. Finally, MWTP estimates also depend on both each subject's yearly income (*INCi*) and the yearly tax to pay in order to get the R&D program implemented (*Tj*). Given that, these welfare measures incorporate risk and are not expected to be of the same order of magnitude of certainty-related marginal WTP measures.

6. RESULTS

6.1. Discrete choice models

By using a mixed multinomial logit (MMNL) estimation procedure, three discounted Expected Utility Theory (EUT) models are estimated, one for each treatment group, the Subjective SQ (SSQ model), the Objective Low SQ (OSQ_{LOW} model), and the Objective High SQ (OSQ_{LOW} model).

In all of the specifications, coefficients of alternative specific constants related to R&D programs *x* and *y* ($\beta_{ASC\_R\&Dx}$ and $\beta_{ASC\_R\&Dy}$) are positive and statistically significant. As the R&D programs are generic and unlabelled, these coefficients do not diverge much within the same model, although $\beta_{ASC\_R\&Dx}$ is always slightly greater than $\beta_{ASC\_R\&Dy}$ (Table 5). This result suggests that subjects consistently prefer R&D programs rather than the SQ alternative, even when they are presented with a pivot experimental design tailored to their expectations about attribute levels. While many transportation studies have shown that pivot CEs induce subjects to prefer the SQ rather than other alternatives (scenario rejection or status quo effect) (Hess and Rose, 2009). Now, the SQ alternatives in our pivot CE are not designed with real experience taken into account, but rather, on the basis of probabilistic expectations about future outcomes. Hence, our subjects likely perceive the SQ scenario to be as hypothetical as the other alternatives, and, hence, they do not have any reason to systematically prefer the SQ. We also investigate the presence of unobserved between-subject heterogeneity in the coefficient of the variable N (β_N), the number of contaminated apples in 2030. Unobserved heterogeneity is detected in all the models. The estimated mean ($\beta_{N\mu}$) of such distribution is always negative and statistically significant, while the estimated standard deviation ($\beta_{N\sigma}$) is always lower than the estimated mean, indicating that each subject's N parameter is negative (Table 5). This means that the probability of choosing an alternative increases when the number of contaminated apples decreases, which is as expected. However, as the coefficients of the variable N in the OSQ models are much lower than in the SSQ model, we conclude that when subjects are presented with SQ's risk levels that diverge from their expected ones, the models have a relatively low explanatory power (Table 5).

The coefficient on the income term *INC-TAX* (β_{INC}) indicates the marginal utility of net yearly income: the annual income left after having paid the yearly tax in the period between 2012 and 2030 for having a R&D program. The yearly income remains intact if the SQ is chosen. Estimated coefficients are negative and statistically significant in all specifications, and, thus, the probability of choosing an alternative increases when the amount of money to pay in tax decreases, as is also expected (Table 5).

In all the models, the coefficient r_N is negative and statistically significant, meaning that subjects are overall risk takers, or risk loving with respect to the number of contaminated apples. However, the subjects who belong to the SSQ are only moderately risk-loving in the SSQ (r_N= -0.535), while others more strongly prefer to take risks (r_N= -2.410 in the OSQ_{LOW} and (r_N= -3.550 in the OSQ_{HIGH} model). Risk preference is an empirical issue, and here preferences are consistent with willingness to take a gamble on the potential loss from the bad apples. This result is consistent with some previous empirical studies which have shown that the way of framing outcomes of a gamble strongly affects subjects' risk preferences. In particular, if outcomes are framed as a loss, subjects becomes risk seeking, while, if outcomes are framed as gains subjects are risk averse (e.g., Tversky and Kahneman, 1981; Kanheman and Tversky, 1984). In this application, the fact that attribute N is clearly framed as a loss (number of contaminated apples out of 100 apples) likely influences subjects willingness to "seek" the health risk[14].

In contrast, the coefficient r_{INC} is positive and statistically significant, meaning that subjects are overall risk averse with respect to their monetary income. All subjects are moderately risk averse in the income dimension, whatever group treatment they belong to (r_{INC}=0.297 in the SSQ, r_{INC}=0.054 in the OSQ_{LOW}, and r_{INC}=0.197 in the OSQ_{HIGH} model) (Table 5). This highlights the importance of not assuming that risk preferences for income carry over to the health risk.

The coefficient δ indicates the financial discount factor that subjects use during their choices, and is statistically significant only in the SSQ model (δ =0.460). It is assumed to be constant over the period. This suggests that subjects in the SSQ treatment groups have a discount factor of about 0.46, while, on average, other subjects have a discount factor which is not significantly different from zero (Table 5)[15].

Other socioeconomic and attitudinal variables that influence subjects' choice-behavior and, hence,

[14] It is likely that if the random variable under study was the number of free-pesticide apples (expressed in line with a gain in health risk), then, subjects were risk averse.

[15] It is quite possible that for long-term decisions, the average person's discount rate is in fact close to zero, meaning that they value the future the same as the present.

their MWTP estimates were incorporated in the models to control for potential differences in the subsamples. Those variables only partially affect subjects' choice behavior (see Table 5).

Table 5. Mixed Multinomial Logit estimation of discounted EUT models

	SSQ	OSQ_{LOW}	OSQ_{HIGH}
$ASC\_R\&D_X$	0.318*	0.632**	1.54*
	(0.106)	(0.314)	(0.222)
$ASC\_R\&D_Y$	0.278*	0.546***	1.28*
	(0.0928)	(0.276)	(0.187)
N_μ^a	-0.0014*	-2.07e-6*	-8.85e-08*
	(3.22e-05)	(4.80e-08)	(2.04e-09)
N_σ^a	0.0007*	1.72e-06*	-1.81e-09*
	(0.000206)	(2.05e-07)	(1.22e-10)

r_N	-0.535*	-2.410*	-3.550*
	(0.0822)	(0.109)	(0.0139)
INC	0.257*	0.036***	0.209**
	(0.0951)	(0.0211)	(0.103)
r_{INC}	0.297*	0.054***	0.197***
	(0.0185)	(0.0351)	(0.0493)
δ	0.460**	0.919	6.91
	(0.219)	(0.793)	(1.80e+308)
$APPLE_X$	0.076*	-0.150*	-0.220*
	(0.0117)	(0.0163)	(0.0186)
$APPLE_Y$	0.080*	-0.148*	-0.194*
	(0.0115)	(0.0149)	(0.0170)
T_CON_X	0.344*	-0.228	-0.322
	(0.0874)	(0.156)	(0.206)
T_CON_Y	0.309*	-0.294***	-0.488*
	(0.0849)	(0.156)	(0.142)
$PROD_X$	-1.12e-05*	-1.76e-05***	-1.11e-5**
	(1.62e-06)	(2.88e-06)	(5.29e-06)
$PROD_Y$	-1.24e-05*	-1.66e-05*	-8.80e-6
	(1.80e-06)	(2.95e-06)	(5.63e-06)
$GENDER_X$	-0.150*	-0.074	-0.233
	(0.0558)	(0.110)	(0.142)
$GENDER_Y$	-0.250*	-0.108	-0.135***
	(0.0560)	(0.107)	(0.0727)
AGE_X	-0.001	0.008**	0.008**
	(0.000254)	(0.00396)	(0.00394)
AGE_Y	-0.001	0.010*	0.005
	(0.000317)	(0.00392)	(0.00373)
$LIFE_X$	0.335	0.383**	-1.71
	(0.0740)	(0.171)	(1.80e+308)
$LIFE_Y$	0.267	0.259	-0.488*
	(0.0743)	(0.168)	(0.142)
LL(0)	-10,471.042	-3,332.673	-3,332.673
LL(β)	-8,399.744	-2,471.542	-2,700.016
Rho	0.198	0.258	0.190
N	11,688	3,720	3,720

*1% significance level; **5% significance level; ***10% significant level

6.2. *Willingness to pay*

Mean yearly MWTP estimates (per taxpayer) for a marginal reduction in the risk of having contaminated apples in 2030 are estimated for each treatment group (SSQ, OSQ_{LOW}, and OSQ_{HIGH}) by using the formula in Equation 7 presented above[16,17]. Given our framework, several MWTP calculations can be

[16] MWTP is assumed to be constant over time, and, hence, can be aggregated over time. Using a discount rate, we could calculate the present value, but all subjects are assumed to have the same discount rate as the average one implied in estimation.

[17] We note that MWTP measures can be used to calculate changes in consumer surplus that given changes in utility imply.

undertaken. However, we focus on those which allow us to investigate the scenario adjustment by testing Hypothesis 1 and 2 presented above. In particular, we only estimate MWTP that are comparable across treatment groups, more specifically, MWTP that relates to given baseline risks presented in the SQ alternative. More specifically, we have estimated MWTP related to the following SQ alternatives:

i. $SSQ_{(65\text{-}50\%,75\text{-}50\%)}$, and $OSQ_{LOW(65\text{-}50\%,75\text{-}50\%)}$,

ii. $SSQ_{(75\text{-}50\%,85\text{-}50\%)}$, $OSQ_{LOW(75\text{-}50\%,85\text{-}50\%)}$, and $OSQ_{HIGH(75\text{-}50\%,75\text{-}50\%),}$

iii. $SSQ_{(90\text{-}50\%,100\text{-}50\%)}$, and $OSQ_{HIGH(90\text{-}50\%,100\text{-}50\%)}$.

For example, the $SSQ_{(65\text{-}50\%,75\text{-}50\%)}$ is the estimate from subjects who belong to the SSQ treatment group and face a SQ alternative in which there is 50% chance to have 65 contaminated apples (Prospect A) and 50% chance to have 75 contaminated apples (Prospect B) (Table 6).

Given the fact that MWTP estimates depend also on the risk reduction that each R&D program produces, here, MWTP are inferred about 4 different risk reduction scenarios out of the 12 available for each selected SQ alternative. These reduction scenarios are the following:

i. $N_{A,SQ}$– 40% with $P_{A,SQ}$ -90%, and $N_{B,SQ}$ with 1-($P_{A,SQ}$ -90%)

ii. $N_{A,SQ}$– 40% with $P_{A,SQ}$ -0% chance, and $N_{B,SQ}$ with 1-($P_{A,SQ}$ -0%)

iii. $N_{A,SQ}$– 80% with $P_{A,SQ}$ -90%, and $N_{B,SQ}$ with 1-($P_{A,SQ}$ -90%)

iv. $N_{A,SQ}$– 80% with $P_{A,SQ}$ -0% chance, and $N_{B,SQ}$ with 1-($P_{A,SQ}$ -0%)

Finally, because MWTP estimates involve an income effect, the estimates are assessed by assuming that the average or typical subject has a yearly income equal to €50,000 and that the R&D program yearly costs €30.

Inferred yearly MWTP estimates per taxpayer are quite reasonable. The MWTP ranges from €0.01 to €1.39 in the SSQ treatment, from €0.17 to €2.79 in the OSQ_{LOW}, and from €1.26 to €24.97 in the OSQ_{HIGH} (see Table 6). A previous study which has investigated subjects' preferences for reducing health risks due to pesticide residues in Northern Italy, has found a MTWP per household per month of about €0.48 (lower bound €0.01 and upper bound €0.87) (Travisi and Nijkamp, 2008).

In each treatment, when the number of contaminated apples increases in the prospects of the SQ alternative, then MWTP estimate for a given risk reduction increases. For example, MWTP of a subjected presented with $SSQ_{(90,100)}$ for a risk reduction i (equal to 0.139) is greater than MWTP of a subject who faces $SSQ_{(75,85)}$ (equal to 0.126) (Table 6).

Second, in each treatment, when the probability of a given reduction in the number of contaminated apples increases, then MWTP increases. For example, MWTP of a subject presented with $SSQ_{(65\text{-}50\%,75\text{-}50\%)}$ for a risk reduction ii (equal to 0.179) is greater than that for a risk reduction i (equal to 0.116) (Table 6).

Third, in each treatment, when the reduction in the number of contaminated apples increases, being the probability of the reduction constant, then MWTP decreases. For example, MWTP of a subject who face $SSQ_{(65\text{-}50\%,75\text{-}50\%)}$ for a risk reduction i (equal to 0.179) is greater than that for a risk reduction iii (equal to 0.096) (Table 6). This is due to the fact the subjects are risk loving with respect to the number of contaminated apples.

Table 6. Marginal willingness to pay for risk reductions

SQ	$N_{A,SQ}$-40% 0.05 $N_{B,SQ}$ 0.95	$N_{A,SQ}$-40% 0.50 $N_{B,SQ}$ 0.50	$N_{A,SQ}$-80% 0.05 $N_{B,SQ}$ 0.95	$N_{A,SQ}$-80% 0.50 $N_{B,SQ}$ 0.50
$SSQ_{(65\text{-}50\%,75\text{-}50\%)}$	0.118	1.179	0.096	0.963
$OSQ_{LOW(65\text{-}50\%,75\text{-}50\%)}$	0.204	2.048	0.172	1.720
$SSQ_{(75\text{-}50\%,85\text{-}50\%)}$	0.126	1.265	0.103	1.032
$OSQ_{LOW(75\text{-}50\%,85\text{-}50\%)}$	0.278	2.787	0.232	2.237
$OSQ_{HIGH(75\text{-}50\%,85\text{-}50\%)}$	1.392	13.928	1.263	12.636
$SSQ_{(90\text{-}50\%,100\text{-}50\%)}$	0.139	1.385	0.113	1.129
$OSQ_{HIGH(90\text{-}50\%,100\text{-}50\%)}$	2.497	24.971	2.250	22.504

6.3. *Hypothesis testing*

Hypothesis 1 is tested by comparing MWTP inferred from subjects who face $SSQ_{(65\text{-}50\%,75\text{-}50\%)}$, $OSQ_{LOW(65\text{-}50\%,75\text{-}50\%)}$, $SSQ_{(75\text{-}50\%,85\text{-}50\%)}$, $OSQ_{LOW(75\text{-}50\%,85\text{-}50\%)}$. On the other hand, Hypothesis 2 is tested by comparing MWTP inferred from subjects presented with $SSQ_{(75\text{-}50\%,85\text{-}50\%)}$, $OSQ_{HIGH(75\text{-}50\%,75\text{-}50\%)}$, $SSQ_{(90\text{-}50\%,100\text{-}50\%)}$, and, finally, $OSQ_{HIGH(90\text{-}50\%,100\text{-}50\%)}$. Our hypotheses are tested by using a simple t-test (Table 7).

We reject the null hypothesis for Hypothesis 1, that MWTPs for given risk reductions provided by subjects whose expected SQ's risk levels were equal to those presented in the SQ (SSQ treatment) were greater than or equal to the MWTP estimates for the subjects whose own expected SQ's risk levels were higher than those given in the SQ (OSQ_{LOW} treatment) (at the 1% significance level). We conclude that these subjects do not fully accept the information given in the SQ, and they positively adjust the risks to conform with their perceived risks. Subjects in the OSQ_{LOW} treatment group make choices by using a risk of having contaminated apples greater than the risks used by subjects in the SSQ treatment, and, hence, the former group has higher MWTP for risk reductions than the latter group. These results are consistent across the various levels of risk reductions (Table 7).

Turning to Hypothesis 2, we fail to reject the null hypothesis that the MWTP estimates for risk reductions inferred from subjects whose expected SQ's risk levels were equal to those given in the SQ (SSQ treatment) are lower than or equal to those obtained from subjects whose expected SQ's risk levels were smaller than those presented in the SQ (OSQ_{HIGH} treatment) (Table 7). In this case, we expected subjects who adjust the information provided in the SQ on their expectations (OSQ treatment) to have lower MWTP for risk reductions than the others. In fact, subjects should negatively adjust the information given in the SQ, on their expectations. In contrast, subjects who belong to the OSQ_{HIGH} treatment have higher MWTP than the others. Such a result is again consistent across diverse risk reductions (Table 7). We might speculate that, when subjects find in the SQ risk of having contaminated apples substantially higher that they expected, they might feel some sort of alarm that induce them to irrationally pay more than what they would have paid if this information was not given. This would be consistent with the alarmist learning theory by Viscusi (1997) under which subjects put a lot of weight on high risk information, and take alarmist decisions that are not consistent with a rational Bayesian learning model.

Table 7. One sided t test for comparing marginal willingness to pay

H_0	$N_{A,SQ}$-40% 0.05 $N_{B,SQ}$ 0.95	$N_{A,SQ}$-40% 0.50 $N_{B,SQ}$ 0.50	$N_{A,SQ}$-80% 0.05 $N_{B,SQ}$ 0.95	$N_{A,SQ}$-80% 0.50 $N_{B,SQ}$ 0.50
MWTP_ $SSQ_{(65\text{-}50\%,75\text{-}50\%)}$ ≥	-368.392***	-369.561***	-385.725***	-383.320***

MWTP_ $OSQ_{LOW(65\text{-}50\%,75\text{-}50\%)}$				
MWTP_ $SSQ_{(75\text{-}50\%,85\text{-}50\%)}$ ≥ MWTP_$OSQ_{LOW(75\text{-}50\%,85\text{-}50\%)}$	-487.493***	-487.225***	-497.112***	-499.776***
MWTP_ $SSQ_{(75\text{-}50\%,85\text{-}50\%)}$ ≤ MWTP_ $OSQ_{HIGH(75\text{-}50\%,85\text{-}50\%)}$	-12,999.920	-12,991.150	-14,327.540	-14,324.360
MWTP_$SSQ_{(90\text{-}50\%,100\text{-}50\%)}$ ≤ MWTP_ $OSQ_{HIGH(90\text{-}50\%,100\text{-}50\%)}$	-19,730.590	-19,736.340	-21,247.120	-21,183.070

*1% significance level; **5% significance level; ***10% significant level

7. CONCLUSIONS

In this paper, we have investigated to what extent scenario adjustment occurs in choice experiments that involve risk, using an innovative two-stage approach that relies on the comparison of willingness-to-pay estimates obtained in different treatment groups. In the first treatment group, the subjects are presented with a status quo alternative where the risk of having contaminated apples in 2030 is consistent with their subjective estimates, while, in the second, they are presented with a status quo alternative where the risk of having contaminated apples in 2030 is not consistent with their own risk estimates.

To investigate these issues we have also incorporated subjective risks, elicited via a novel approach such as the exchangeability method, into our choice experiment's design by using a pivot experimental design. Some previous stated-preference investigations have only introduced subjective probability estimates in econometric modeling, but to our knowledge, never into the stated choice context designs. Thus our investigation here breaks some new ground in modeling risky stated choice behavior.

We found that subjects when provided with risk that are lower than perceived ones, adjust attribute levels on their expectations, and express marginal willingness to pay for risk reduction higher than those that they would have provided taking choices by using status quo's risk information. In contrast, subjects who face a risk of having contaminated apples higher than the expected one, do not negatively adjust attribute levels on their expectations, but, they, driven by some sort of panic, overreact to this information and irrationally pay more than what they would have paid if they fully accepted the SQ's information.

Our investigation has shown that information provided by researchers in the status quo alternative substantially affects subjects' choices. This might have very crucial policy implication, in the sense that financial support for public policies might be driven by the strategy used to communicate new information, which in this case relates to risk. The implication of our work is that stated-preference studies might become very helpful in identifying the most effective way to communicate risk information that makes people willing to support policies that are not perceived to be important yet.

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