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How many bad apples are in a bunch? An experimental investigation of perceived pesticide residue risks

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Abstract

Subjective risks of having contaminated apples elicited via the Exchangeability Method (EM) are examined in this study. In particular, as the experimental design allows us to investigate the validity of elicited risk measures, we examine the magnitude of differences between valid and invalid observations. In addition, using an econometric model, we also explore the effect of consumers' socioeconomic status and attitudes toward food safety on subjects' perceptions of pesticide residues in apples. Results suggest first, that consumers do not expect an increase in the number of apples containing only one pesticide residue, but, rather, in the number of those apples with traces of multiple residues. Second, we find that valid subjective risk measures do not significantly diverge from invalid ones, indicative of little effect of internal validity on the actual magnitude of subjective risks. Finally, we show that subjective risks depend on age, education, a subject's ties to the apple industry, and consumer association membership.

Highlights

- Subjects think that apples containing multiple residues will increase in the future

- Valid subjective risks do not statistically diverge from those of invalid ones

- Subjective risks depend on socioeconomic and attitudinal variables

How many bad apples are in a bunch? An experimental investigation of perceived pesticide residue risks

1. Introduction

Despite progress that international and national authorities have made toward ensuring food safety (e.g., food-labeling, packaging, inspections), food-related risks still get the attention of a substantial proportion of consumers. For example, approximately 30 percent of all Europeans remain concerned about health consequences of pesticide residues in food (European Commission, 2010).

As both short- and long-term health outcomes induced by food safety are often uncertain, people's own risk estimates become crucial for understanding their choice-behavior towards food products or policies (Kivi and Shogren, 2010)[1]. In fact, several empirical investigations have shown that subjective risks often dictate consumers' choices far more than science-based risk predictions would, especially when subjective estimates differ from science-based ones (e.g., Jakus et al., 2009). There might be two general reasons why such a discrepancy exists. First, while science-based risk estimates are simple averages based on frequency values for homogenous populations, individual subjective risks are heterogeneous, and causes for this heterogeneity can be observed or unobserved. For many individuals, their subjective risks might be accurate, and not truly equal to the average population risk. Second, some individuals may make mistakes in processing risk-related information, and formulate estimates that are higher or lower than the science-based predictions. Much of what economists know about subjective risks has been borrowed from initial work by psychologists (e.g., Slovic, 1987).

Although an extensive literature has shown that subjective risks related to financial outcomes affect people's choices in several branches of applied economics

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[1] Here, risk is intended to mean the probability that a given outcome occurs.

(see Manski, 2004 for a review), a relatively small number of studies have investigated the influence that subjective risks related to health outcomes have on people's behavior related to their everyday choices. A few studies have primarily coped with estimates of health risks related to smoking behavior (e.g., Viscusi, 1990; Gerking and Khaddaria, 2011) as well as drinking contaminated water (e.g., Jakus et al., 2009; Shaw et al., 2012). Unfortunately, little has been done to investigate whether subjective health risks related to food safety affect people's economic choices in their everyday life. A relatively small number of studies have shown that consumers' numerical estimates of health risks (i.e., mortality rate) due to the presence of pesticide residues in fresh fruit and vegetables drive their preferences for pesticide-free fresh fruit and vegetables in hypothetical markets (e.g., Hammit, 1990; van Ravenswaay and Hoehn, 1991; Buzby et al., 1998).

In contrast to other studies, here we mainly examine the risk of having contaminated apples. In particular, we investigate consumers' subjective probabilities that given proportions of apples produced in the Province of Trento (Italy) will contain pesticide residues in the future. Given that pesticide residues have consequences on health, consumers' expectations about the future presence of pesticide residues in apples likely affect their support for an agricultural policy that the Province of Trento is planning to incentivize the production of pesticide-free apples. The investigation of consumers' preferences for this policy becomes particularly important because the saleable gross production of apple is approximately 23 percent of the entire agricultural saleable gross production in the Province of Trento (P.A.T., 2010).

The bulk of the literature which has investigated subjective risks related to food safety has barely taken into account the fact that elicited risks might not be valid[2]. An exception is the artefactual field experiment conducted by Cerroni et al. (2012) in which the validity of subjective risks elicited via the Exchangeability Method (EM) (Baillon, 2008; Abdellaoui et al., 2011), an innovative elicitation techniques based on the notion of exchangeable events (de Finetti, 1937), has been tested. In this study, the validation procedure is based on the de Finetti's notion of coherence under which risk estimates are coherent if and only if they obey to all axioms and theorems of Probability Theory (de Finetti 1937; 1974a; 1974b).

Investigating the validity of subjective risks contributes to better understand people's choices under risk and uncertainty. In fact, the inclusion of invalid observations in subjective expected utility or other non-expected utility models used to predict decision-making processes might generate biased results, especially if invalid observations systematically differ from valid ones in terms of magnitude. For example, if invalid subjective risks are systematically lower (or greater) then valid ones, consumers' willingness to support agricultural policies might be underestimated (or overestimated).

Given that, in this current paper, by drawing on Cerroni et al.'s (2012) results on the validity of subjective risks elicited via the EM, we more carefully analyze the actual discrepancy between valid and invalid risk estimates. In other words, we measure the differences in terms of magnitude, which goes beyond the previous study. Furthermore, we also econometrically identify attitudinal and socio-economic factors that shape subject's perceptions, comparing our results with previous findings.

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[2] In contrast, one might use observed purchases or transactions as a way of revealing individuals' sense of risk, but identification issues may easily arise in the effort to uncover the risks and sort these out from other influences on purchases.

The remainder of the paper is laid out as follows. In the next section, we review previous studies dealing with perceptions of pesticide residues and its consequences on human health. Next, we define the aims of the current study and provide detailed information about the experimental design. Finally, we offer a discussion of our results.

2.   Subjective risks and pesticide residues

Many stated-preference (SP) studies have investigated the role of consumers' perceptions of health outcomes due to pesticide residues in determining food-purchasing behavior. In general, these studies have shown a negative correlation between people's perceptions of health outcomes due to pesticide residues and willingness to purchase products which contain those chemical substances. Many food products have been considered, ranging from general unlabeled ones (e.g., Misra, et al., 1991; Eom, 1994; Rimal, et al. 2008) to specific types of fresh fruit and vegetables (e.g., Fu et al., 1999; Boccaletti and Nardella, 2000).

Most previous studies have not focused on subjective risk estimates expressed in a numerical fashion, but on people's concern about the severity of health consequences due to food safety. For example, individuals have been asked to indicate the presence of health risks using simple descriptive labels (e.g. high, medium, or low), likert or other numerical scales.

Eom (1994) has elicited subjects' concern about the presence of pesticides in general commercially grown food products by using a likert scale between 0 (no risk) and 10 (very serious risk). This study has found that the average concern across consumers was quite high, around 6.6. The same approach was taken by Fu et al. (1999), but for fresh fruit and vegetables. In this case, the average level of concern was extremely high, exceeding 6, on a scale between 0 and 7. In their experimental auction for residue-free foods, Roosen et al. (1998) have used a simple scale of concern (1 to 5)

to investigate the influence of subjective perceptions on consumers' bidding behavior. The approach recently used by Rimal et al. (2008) to elicit people's perceptions of pesticide residues in food was even simpler. In fact, individuals were simply asked to state whether the problem of pesticides in food was serious, moderate or inexistent, and the finding was that more than half the subjects chose the serious option.

Boccaletti and Nardella (2000) have improved the approach used by Misra et al. (1991) implementing a Likert Attitude Scaling Procedure, where individuals are asked several questions and, then, an individual-specific score is calculated to measure the concern about pesticide residues on fresh fruit and vegetables. The mean score across consumers was 78 on the maximum of 100, where the latter value is not a probability per se, but simply indicates very high concern.

Several scholars have questioned whether perceptions measured on some scale, as done in some of the studies above, are good indicators of risk (e.g., Viscusi and Hakes, 2003). At the very least, one would have to make strong assumptions to re-map from a 0 to 10 discrete response scale to a 0 to 1 unit interval. This could be done for example, to get a relevant risk measure, which is of course a continuous variable on the unit interval. Simple recoding would of course make it impossible to obtain other risk estimates than in 10 percent jumps (10, 20, 30 percent etc.).

While these simple efforts are appealing, they are lacking in that they do not provide the information that would be ideal in actual modelling risky behaviours. In fact, measures of concern, or other responses which are not numerical measure cannot be directly used in either an expected utility or subjective expected utility framework, (Manski, 2004). Hence, many other studies have paid closer attention to the elicitation of actual numerical risk measures. In most of these studies the elicitation scheme is simple, and people are just asked to state risk estimates. The specific magnitude of the outcome that will happen is typically first presented, and individuals are then asked

about the probability of this occurring to others (e.g., Viscusi 1990, asked people to guess how many smokers out of 100 will get, or die from, lung cancer), or to themselves, but many variations in presentation are possible. The techniques which directly elicit subjective risks are called direct methods (Spetzler and Von Holstein, 1975).

Extensive research, much of which is in the psychology literature, has shown that people do not easily understand numerical risks (especially small ones), and, given that, has suggested different approaches (i.e., frequencies) for making people willing and able to state their best estimates (e.g., Gigerenzer and Hoffrage, 1995; Hammit and Graham, 1999; Corso et al., 2001).

Several studies have shown that mortality risks be couched as deaths per 100,000 or some other number in the population, avoiding small decimal place numbers that are confusing. Buzby et al. (1998) have asked subjects their own subjective probability of dying from consuming fresh products containing pesticides in a similar manner, specifically, as the annual number of deaths per 1 million individuals. Since this probability-estimation task may be difficult for laypeople, subjects in both of these studies were provided with risk ladders showing probability of dying from more-familiar causes of death. The mean probability estimate was roughly 43 deaths per million in the population, per year.

Williams and Hammit (2001) have used this same basic technique to examine the annual fatality rate per 1 million in the population of the United States for several categories of food hazards, and one of these was also the presence of pesticide residues in food. Generally, consumers perceived the probability of dying due to pesticides as being greater than that related to either natural toxins or microbial pathogens. In particular, to conventional buyers, the annual median fatality rate because of pesticide

residues on fresh products was 50 per million, while, to organic food buyers, the rate was 200 per million.

Although direct methods are very easy to design and implement, they have been questioned because of the quality or accuracy of the elicited subjective risks. In the cognitive psychology literature the ability, or more specifically, the willingness of subjects to put efforts in expressing their belief in numerical risk estimates, has been extensively debated. The elicitation of numerical risks is of course easy and feasible, but reliable results are not guaranteed (Manski, 2004).

An alternative way of eliciting subjective risks consists of using subjects' choices, most often made over lotteries and gambles. In particular, risk measures are indirectly estimated by the researcher at the points for which people show their indifference between lotteries or gambles, which can be thought of as games that the subjects play. These techniques which indirectly elicit subjective risks are called indirect methods (Spetzler and Von Holstein, 1975). Those methods are assumed to be less demanding than direct methods from a cognitive point of view as subjects are not asked to directly express a numerical risk, but to compare risky outcomes and choose the most likely one (Spetzler and Von Holstein, 1975).

To our knowledge, the first application of an indirect technique in eliciting subjective risks of having pesticide residues in food is represented by the Cerroni et al. (2012)'s artefactual field experiment (Harrison and List, 2004). In particular, that study has elicited numerical subjective probabilities that given proportions of apples will contain pesticide residues by using the EM. This technique consists of a set of binary questions in which subjects are asked to bet a given amount of money on a given outcome rather than on an alternative one. Subjective risks are indirectly inferred at the point for which subjects show their indifference for betting on one of the two outcomes. The fact that the outcomes derive from a bisection procedure of the whole state space of

the random variable under study, make binary questions chained, in the sense that the outcomes presented in one questions depend on the outcome that has been chosen in the previous question. One innovative aspect of this elicitation technique consists in asking subjects to focus on the severity of the outcome under study, rather than on the probability of a given outcome to occur. This investigation into outcomes is rare, as compared to attention paid by previous studies to subjective probabilities of endpoint risks, such as human mortality or morbidity rates (Kuhn and Budescu, 1996).

The study by Cerroni et al. (2012) also represents the first attempt to investigate the influence that incentive compatibility has on the internal validity of elicited subjective risks related to food safety outcomes. In fact, when monetary incentive are provided to subjects based on their betting behavior, chained elicitation mechanism such as the EM are presumed to induce subjects to not state their real beliefs, but to strategically behave to get better rewarded. To test whether internal validity of elicited subjective risk estimates depends on incentive compatibility four experimental treatments have been designed. More specifically, subjects were provided with monetary incentives in two treatments, but they were not in the remaining two. Each of these treatments was divided into two other treatment, in one treatment, subjects were aware of the chained structure of the EM because questions were sequentially ordered, while in the other treatment, subjects were not aware of method as questions were randomly ordered. A detailed description of treatment groups will be provided below.

As noted above, valid estimates have been identified by using a validation procedure based on the de Finetti's notion of coherent subjective probabilities (de Finetti, 1937; 1974a; 1974b). In particular, risk measures elicited via the EM are valid if and only if the certainty equivalents that subjects are asked to express about specific lotteries are equal. These lotteries involve the two risky outcomes that subjects were indifferent between during the EM procedure. In the EM framework, this ensures that

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subjective risks satisfy de Finetti's notion of coherence. Certainty equivalents were elicited by using another experimental game which will be described in more details below, the Certainty Equivalent Game (CEG).

Investigating the validity within each treatment group, Cerroni et al. (2012) have found that subjects provided with real monetary incentives and random questions more likely return valid estimates. Examining the validity of each elicited subjective risk estimates, they found that the proportion of valid estimates is 29.72 percent in the sample. In particular, they showed that the proportion of valid subjective risks is 39.13 percent when real monetary incentives and random questions were provided to subjects, followed by 29.86 percent when monetary incentives were not provided and questions were randomly ordered, 26.26 percent when real monetary incentives were provided, but questions were sequentially ordered, and 22.22 percent when monetary incentives were not provided and questions were sequentially ordered. This suggests that in each treatment group there is a relatively small portion of valid subjective risk estimates, and the real compensation with sequential responses out-performs the other treatments.

In our view, as subjective risks are often incorporated in the standard subjective expected utility or other non-standard theories of decision-making under risk and uncertainty to model and predict behavior, the identification of valid risk estimates becomes crucial to obtain highly predictive models, and thus, reliable findings on subjects' choice behavior. This is particularly true if valid observations systematically differ from invalid ones in terms of magnitude. In the latter case, failure to recognize valid subjective risks might induce us to over- or underestimate subjects' true expectations, and hence, to wrongly predicts their behavior.

3.   Objectives

By drawing on Cerroni et al.'s (2012) investigation and using the same dataset they have used in their analysis, we first investigate subjective risks of having contaminated apples. Second, we examine the potential discrepancy between valid and invalid subjective risks to fully understand whether failure to recognize validity implies an over- or underestimation of consumers' true probability estimates. Finally, we estimate a behavioral model to identify attitudinal and socio-economic factors that affect the subject's risk estimates of pesticide residues in apples. This information will help policy makers to target their risk communication campaigns at given interest groups of the population and, hence, gain public support for the Province of Trento's pesticide risk reduction policy.

4. The empirical application

4.1. *The case study*

The fire blight is a bacterial disease that has damaged and killed apple plants in the Province of Trento since 2003 (EMF, 2006). The current infestation rate which is the number of days in which the infestation occurs in the blossoming period is less than 1 percent. The infestation rate depends on climatic parameters such us temperature and precipitation. In this region of Italy, farmers currently adopt preventative measures based on pesticide usage in the form of copper compounds or Acibenzolar-S-metile to control the mild negative consequences that fire blight has on apple production. However, the future increase of the infestation rate, which is predicted to reach 17 percent in 2030, might eventually induce farmers to use new pesticides for preventative and curative control of fire blight. One candidate is the antibiotic streptomycin, currently forbidden under Italian law, but which has been already used in U.S., Germany, Belgium, and The Netherlands to control fire blight (Németh, 2004).

4.2. *The sample and the dataset*

The pool of sample subjects is the same used by Cerroni et al. (2012) and consists of 80 individuals between 18 and 70 years age who live in the Province of Trento. The sample is not, strictly speaking, randomly selected because subjects were recruited outside food markets, but it is still quite generally representative of people living in this Province because most of the people in the region go shopping in those markets at some point or another. A show-up fee of €25 was given toeach participant as a compensation for agreeing to come into the experimental lab of the University of Trento to take part in the experiment.

The dataset consists of 1,200 probability estimates, 400 for each of the three random variables under study which are: the number of apples, a, containing at least one residue in a sample of 100 apples in 2030[3], the number of apples, r, containing at least two residues (multiple residues) in a sample of 100 apples in 2030[4], and the number of days, g, during which the infestation will occur during the blossoming period in 2030[5]. The latter variable g was added because of the potential link between the development of fire blight and the presence of pesticide residues in apples. For each random variable, five risk estimates have been elicited from each subjects, the lower bound (g_0, a_0, and r_0), the 25th percentile ($g_{1/4}$, $a_{1/4}$, and $r_{1/4}$), the 50th percentile ($g_{1/2}$, $a_{1/2}$, and $r_{1/2}$), the 75th percentile ($g_{3/4}$, $a_{3/4}$, and $r_{3/4}$), and the upper bound (g_1, a_1, and r_1).

These variables were selected after having interviewed approximately 20 focus group subjects. The year 2030 is chosen because the best available science predicts that the heavy development of new phytopathology, as the fire blight, will start approximately twenty years from now in the Province of Trento.

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[3] The apple containing residues are those containing at least one residue beyond the level of 0 mg/kg.
[4] The apple containing residues are those containing at least two residues beyond the level of 0 mg/kg.
[5] The blossoming period usually occurs in April in the Province of Trento.

4.3. *Experimental Treatments*

As noted above, selected sample participants were randomly assigned to four treatment groups. Each subsample is presented with a different experimental design: the real monetary incentives-sequential questions with 23 subjects (TRS), the real monetary incentives-random questions with 22 subjects (TRR), the hypothetical monetary incentives-sequential questions with 16 subjects (THS), and the hypothetical monetary incentives-random questions with 19 subjects (THR).

In the hypothetical treatments (THR and THS), subjects are only given the show-up fee, while in the real incentives treatments (TRR and TRS), each subject has the chance to win up to an additional €100 based on their choices during the experimental games. More specifically, one randomly selected individual from each group (TRR and TRS) can actually earn additional €100 based on her/his choices during the experiment. The subject to be paid is randomly selected at the end of the experiment by drawing a numbered chip from a bingo cage (Cage 1). All subjects have the same equal chance of being the winner because the total number of chips in the bingo cage is equal to the total number of participants in each session and subjects are informed of this. One of the questions each subject answers during the experiment is also randomly selected to be played out for the payoff. In this case, we use another cage (Cage 2) that contains as many numbered chips as the number of questions that the respondent answered during the experiment. The selected participant wins the additional €100 if and only if the event she/he had chosen in the drawn question contains the value of the random variable under consideration that the Edmund Mach Foundation (EMF) predicts. Such science-based predictions of risk have been frequently used by experimental researchers (for example, see Fiore et al., 2009). Of course, this specific incentive scheme may have induced subjects to guess the science-based estimated instead of expressing their own subjective risks. Subjects may have had private information about the science-based risk

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estimates or some reason for not trusting the Edmund Mach Foundation' s (EMF's) studies and predictions[6]. We assume that subjects' risk estimates have been not distorted away from their own beliefs by our incentive scheme for two main reasons. First, our subjects are average consumers and are unlikely to have had any information about the science-based risk estimate because the latter had not been disseminated to the public when the experiment was conducted.

In addition, based on our focus group interviews, we believe that the population of the Province of Trento highly trusts the EMF, and would have no reason to have a strongly different personal prior. In one question of the survey, subjects were asked to state their level of trust in the EMF on a scale between 0 (very low) and 4 (very high), and their average level of trust was around 2.6. None of the subjects expressed a very low level of trust and only 3 subjects out of 80 expressed a low level of trust. Given this information we do not think elicitation to correspond with the EMF prediction is a large problem for the study. As noted by Baillon (2008) and echoed in Cerroni and Shaw (2012) the simplest strategy for consumers to play the game is just to state their real beliefs. In this context, we assume that our incentive scheme has induced subjects to state their real beliefs, or at least, to invest more cognitive effort into doing that (Cerroni et al., 2012).

One feature of the sample worth noting is that we do have a few apple producers, and these subjects may indeed have more information than others do. However, their preferences do not influence average beliefs because there are so few of them (3 out of 80).

The only difference between the random (THR and TRR) and sequential treatments (THS and TRS) is the order of the questions. In fact, in sequential treatments subjects are presented with sequentially ordered questions, and, hence, they are aware of

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[6] We thank an anonymous reviewer for suggesting this possibility.

the chained structure of the EM, while, in the random treatments, subjects face randomly ordered questions which hide the presence of chained questions. More precisely, in the sequential treatments, the order in which percentiles of each subject's CDF are elicited is the following: $g_{1/2}$, $g_{1/4}$, $g_{3/4}$, $a_{1/2}$, $a_{1/4}$, $a_{3/4}$, $r_{1/2}$, $r_{1/4}$, and $r_{3/4}$. In the random treatments, the order in which the percentiles of each subject's CDF are elicited is the following: $g_{1/2}$, $a_{1/2}$, $r_{1/2}$, $g_{1/4}$, $a_{1/4}$, $r_{1/4}$, $g_{3/4}$, $a_{3/4}$, and $r_{3/4}$.

5. Methods

5.1. *The elicitation of subjective risks: the Exchangeability Method*

In this section, we briefly describe the EM, the technique used by Cerroni et al. (2012) to elicit subjective risks. The EM consists of multiple binary questions where subjects are only asked to bet a certain amount of money on one of the two disjoint subspaces in which the whole state space of the variable under study has been previously divided based on their choices. When subjects become indifferent to bet on one disjoint subspace rather than on the other, they are assumed to perceive those subspaces as equally likely (Spetzler and Von Holstein, 1975). This method allows eliciting several point estimates of the individual cumulative distribution function (CDF) of the random variable under study for each experimental subject. Interested readers may find additional details about the EM in Abdellaoui et al. (2011), Baillon (2008), and Cerroni and Shaw (2012).

The EM is applied to elicit risks of three random variables, a, r, and g. As the EM is formally described in Cerroni et al. (2012), for brevity's sake, here, we only describe the application of the EM that concerns the number of apples containing at least one residue in a sample of 100 apples in 2030 (variable a). At the beginning of the game, subjects are asked to express the lower (a_0) and upper bounds (a_1) of the event space A.

In this way, the individual-specific range outside of which subjects are essentially certain that the outcome cannot happen at all is identified. Assume that subject i states that a_0 is equal to 60 apples and a_1 is equal to 76. This means that she/he believes that the probability that the portion of apples containing at least one pesticide residue in 2030 will be outside these bounds (i.e. less than 60 and greater than 76) is equal to zero.

The second step involves asking a series of questions to establish the value of $a_{1/2}$ that corresponds with the 50th percentile of the subjective CDF, the median estimate. The first binary question is generated by splitting the event space in two prospects by using the following algorithm, $60 + [(76 - 60)/2] = 68$. It follows that the first binary question implies a choice between prospects $A_1=\{60<x<68\}$ and $A_2=\{68\leq x<76\}$ (Figure 1). Following the first choice, the exercise is repeated using a bisection of the chosen prospect. For example, if subject i has chosen prospect $A_1=\{60<x<68\}$, the second binary question asks subjects to choose between prospects $A_3=\{60<x<64\}$ and $A_4=\{64\leq x<68\}$. The bisectioning process goes on until the subjects become indifferent between the two prospects; at this point, the median point $a_{1/2}$ of each subject's CDF is estimated. This estimate indicates that there is a 50 percent chance that the number of apples that will contain at least one pesticide residue in 2030 will be equal to or less than $a_{1/2}$. A similar process can be followed to determine as many other points for the individual's subjective CDF as is desired, depending on limitations of the subjects' attention spans. Here, the 25th percentile ($a_{1/4}$) and the 75th percentile ($a_{3/4}$) are also elicited. Before asking our subjects to play the EM, they were provided with a description of the relevant scenario, as well as precise information about the values that the random variables under study had in the last ten years (from 2000 to 2009),

5.2.   *The validity of subjective risks: the Certainty Equivalent Game*

In this section, we briefly describe an additional experimental game that was implemented by Cerroni et al. (2012) to facilitate the identification of valid risk measures, the Certainty Equivalent Game (CEG)[7]. In the CEG, subjects are presented with two choice tasks, say CT1 and CT2, both containing six binary questions, each asking subjects to choose between a gamble and a certain amount of money (Figure 2).

Next, we provide an example of the CEG that concerns the number of apples containing at least one residue in a sample of 100 apples in 2030 (variable a). Assume that subject i provides us with an estimate of $a_{1/2}$ that is equal to 66 apples, in CT1 she/he has to choose between options A (place a bet of €x on the fact that a is lower than 66) or B (take the certain amount of money $z = 0, 25, 49, 51, 75,$ and €100). For the second choice task CT2, she/he has to choose between options A (a bet of €x on the fact that a is greater than or equal to 66) or B (take the amount of money $z = 0, 25, 49, 51, 75,$ and €100). The certainty equivalent for the lottery described in option A is determined by looking at the first question of the six in the choice task in which the subject switches from choosing option A to choose option B (the amount of money). The CEG is played for the 25th percentile ($g_{1/4}$, $a_{1/4}$, and $r_{1/4}$), the 50th percentile ($g_{1/2}$, $a_{1/2}$, and $r_{1/2}$), and the 75th percentile ($g_{3/4}$, $a_{3/4}$, and $r_{3/4}$). The CEG allows identification of valid risk estimates at both the sample and individual level. In the former case, the sample provides valid risks if and only if CE estimates related to CT1 and CT2 does not statistically differ from each other. At the individual level, each specific risk estimate is valid if and only if the CE estimates related to CT1 and CT2 are equal.

6.   Results

6.1.   *The analysis of subjective risks*

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[7] Cerroni et al. (2012) tested also the reliability of elicited risk estimates via the EM by implementing the Repeated Exchangeability Game. However, here, we only focus on the validity and, hence, the CEG is taken into account.

On average, estimated bounds of variable a suggest that the subjects believe the number of contaminated apples out of 100 will be between 56 and 75. Using information from the estimated 25th percentile, we argue that subjects believe there is only a 25 percent chance that the number of apples containing pesticides will be lower than or equal to 66. Using average values for the 50th and the 75th percentiles it appears that the subjects attach a 50 percent chance to the fact that the number of bad apples will be lower than or equal to 69, and 75 percent chance to the fact that this number will be lower than or equal to 71 apples (see the basic statistics in Table 1 and Figure 3). Taking into account that the number of apples with at least one pesticide residue at present (in 2009) is 63 out of 100 (Italian Ministry of Health, 2010), we conclude that subjects do not in fact perceive an increase in the number of apples containing at least one pesticide residue by the year 2030 to be particularly substantial and, very likely.

Following the same general approach, we interpret percentile estimates related of the r variable, which is the number of apples containing multiple residues in a sample of 100 apples in 2030. In this case, we found that the lower bound (r_0) is about 31, the 25th percentile ($r_{1/4}$) is 42, the 50th percentile ($r_{1/2}$) is 45, the 75th percentile ($r_{3/4}$) is 48, and the upper bound (r_1) is 52 (again, see Table 1 and Figure 3). As might be expected, the average percentile estimates of r are always smaller than those of variable a (Figure 3) because the number of apples with multiple residues should always be lower than the number of apples with at least one residue. However, given that 31 apples, out of the 63 containing at least one residue, have multiple residues in 2009 (Italian Ministry of Health, 2010), we deduce that subjects perceive an increase in the number of apples with multiple residues to be quite significant and likely. For example, they think that there is 75 percent chance that the number of apples with multiple residues will be 48 at the worst.

To summarize, although subjects believe that the number of apples containing one residue or more will not significantly increase by the year 2030, they predict that the number of apples containing multiple residues (more than one) will significantly increase. This means that the number of apples containing only one pesticide residue will decrease, but the number of apples with multiple residues will significantly grow by the year 2030.

Considering the infestation rate which is the number of days in which the infestation will occur during the blossoming period in 2030, we found that the lower bound (g_0) is 6, the 25th percentile ($g_{1/4}$) is 8, the 50th percentile ($g_{1/2}$) is 9, the 75th percentile ($g_{3/4}$) is 10, and the upper bound (g_1) is 12 (see Table 1 and Figure 4). Given the fact that the number of days in which the infestation actually occurred in 2000, 2005, and 2010 was very close to zero, we conclude that subjects perceive the infestation rate in 2030 as being quite high and likely.

6.2. *The difference between valid and invalid subjective risks*

Using results on validity obtained by Cerroni et al. (2012) via the Certainty Equivalent Game, for each random variable, we compare the magnitudes of valid and invalid estimates at both the sample and individual levels. At the sample level, we found here that the valid estimates are lower than invalid ones for each percentile (the 25th, the 50th, and the 75th) of each variable (a, r, and g) (Table 2). However, by using the Kolmogorov-Smirnov (KS) and Mann-Whitney U (MWU) tests, we found that the discrepancy between the magnitudes of valid and invalid estimates is not statistically significant for all variables, a, g, and r (Table 3). Hence, even if our results suggest that failure to recognize validity might induce researchers to overestimate subjects' true risk estimates, this finding is not statistically supported.

Next, the valid and invalid estimates are compared at the individual level. For the random variables a and r, we found the same pattern as before, the 25th, the 50th, and the 75th percentiles are lower in valid estimates as compared to invalid ones (Table 2). Using the KS and MWU tests, we found that such a discrepancy between valid and invalid estimates is not statistically supported for variable a, while it is for variable r. In particular, valid estimates of 25th percentile ($r_{1/4}$) are statistically lower than the corresponding invalid ones (Table 4).

We found a different pattern for the variable g; valid estimates of the 25th and 75th percentiles ($g_{1/4}$ and $g_{3/4}$) are greater than the corresponding invalid estimates, while valid estimates of the 50th percentile ($g_{1/2}$) are lower than invalid ones (see columns 3 and 4 in Table 2). However, these results are not statistically supported by the KS and MWU tests (Table 4).

In general, the valid estimates are smaller than the invalid ones in variable a and r, but greater in variable g. However, we note that such discrepancies are statistically supported only for variable r, but not for a and g. For what concern r, mistakes appear here to result in upward bias, and thus, failure to recognize validity results in an overestimation of subjects' average probabilistic expectations.

6.3. *Factors shaping subjective risks*

To further analyze the factors that explain subjects' probabilistic expectations of both the number of apples containing pesticide residues and the fire blight's infestation rate, we estimate three empirical models (see Table 5 for the definition of the explanatory variables used in the econometric model).

Given that our dependent variables are all essentially fractions, we do not estimate our models (Model 1, 2, and 3) by using a simple OLS estimator, although many apply the linear probability model to such data. Here, we use the Generalized Linear Model

(GLM) along with robust standard errors (Papke and Woolridge, 1996). Observations in 80 groups are clustered because each subject provides three different percentile estimates (25th, 50th, and 75th percentile) for each random variable under study (g, a, and r), and these may be correlated.

The general empirical specification common to the three models is:

$$y_{i,s} = \beta_0 + \beta_1 PERCENTILE_{i,s} + \beta_2 VALIDITY_{i,s} + \beta_3 ATTITUDE_{i,s} + \\ + \beta_4 APPLE\_LINK_{i,s} + \beta_5 SOCIOECONOMIC_{i,s} \tag{1}$$

In Model 1, the dependent variable (y) is each subject's estimates of the number of days in which the infestation will occur during the blossoming period in 2030 (g), in Model 2, each subject's estimates of the number of apples containing at least one residue in a sample of 100 apples in 2030 (a), and in Model 3, each subject's estimates of the number of apples containing multiple residues in a sample of 100 apples in 2030 (r).

In all models, we examine whether 25th, 50th, and 75th percentile estimates differ from each other by using the set of dummy variables *PERCENTILE* which consists of variable $25^{th}PERC$, $50^{th}PERC$, and $75^{th}PERC$. As we expected, the 50th and 75th percentile estimates ($50^{th}PERC$ and $75^{th} PERC$, respectively) are statistically greater than the 25th percentile estimates ($25^{th} PERC$) at the 1 percent significance level (see Table 6).

In addition, we investigate the difference between valid and invalid estimates in terms of magnitude by creating another variable, called *VALIDITY*, defined below. Cerroni et al. (2012) demonstrated that subjects were more likely express valid risk estimates when they were provided with monetary incentives and randomly ordered questions, but we actually compare the magnitude of risk measures elicited from

subjects who belong to the "real incentives-random questions" treatment (*TRR*) with risk estimates elicited from subjects who belong to the other treatments (*TRS*, *THR*, and *THS*). To accomplish this, the *VALIDITY* variable is comprised of four dummy variables (*TRS*, *TRR*, *THS*, and *THR*), each taking a value equal to 1 if and only if the subjects belong to the experimental treatment that the variable represents, and equal to zero otherwise.

Consider Model 2 (*a*) and 3 (*r*) in Table 6. The positive signs of variables *TRS*, *THR*, and *THS*'s coefficients are consistent with result from non-parametric testing which show that average invalid estimates are greater than valid ones. However, estimated coefficients are not statistically supported in either Model 2 (*a*) or Model 3 (*r*) (Table 6). In Model 1, we found that *TRS*' coefficient has the expected positive sign, while *THR* and *THS*'s coefficients are negative, meaning that invalid observation are lower than valid ones. However, none of the coefficients are statistically significant (Table 6).

The composition of the vector *ATTITUDE* used to explain the random variable *g* strongly differs from that used to explain the other variables, *a* and *r*. For what concerns Model 1 (*g*), *ATTITUDE* captures subjects' trust in the IPCC's predictions about climate change (*IPCC_AV*, *IPCC_HIGH*, and *IPCC_VHIGH*) and their beliefs about the human and/or natural determinants of this phenomenon (*CC_HN, CC_H*, and *CC_HH*). In the former case, the subjects were informed about the positive correlation between the fire blight's infestation rate and climatic conditions during the presentation of the experimental instructions, and we predict that subjects who highly trust the IPCC' predictions (*IPCC_HIGH* and *IPCC_VHIGH*) will provide higher estimates of the number of days in which the infestation will occur during the blossoming period in 2030 (*g*) than those who partially trust IPCC' predictions (*IPCC_AV*). The coefficient of the variables *IPCC_HIGH* and *IPCC_VHIGH* have the positive and statistically

significant expected signs (Table 6). Our results also indicate that the subjects who believe that climate change is only due to human activities (*CC_HH*) perceive the infestation to be more likely than subjects who blame the climate change on both natural and human processes (*CC_HN*) (Table 6). The results, which are statistically significant at the 1 percent level, are consistent with some of the psychology literature about perceptions of risk, which has shown that people commonly perceive technology-induced risks to be higher than nature-induced ones (e.g., Slovic, 1987).

In Model 2 (*a*) and Model 3 (*r*), the variables relating to *ATTITUDE* captures subjects' beliefs about the future usage of pesticides to control apple disease (*PEST_AV*, *PEST_HIGH*, and *PEST_VHIGH*) and subjects' trust in Edmund Mach Foundation's predictions about the fire blight's infestation rate (*EMF _AV*, *EMF_HIGH*, and *EMF_VHIGH*). As we expected, subjects who agree on the fact that farmers will mainly use pesticides in the future (*PEST_HIGH* and *PEST_VHIGH*) provide higher estimates of the number of apples that will contain residues than subjects who do not agree with that (*PEST_LOW*). However these results are not statistically significant in either Model 3 (*r*) or Model 2 (*a*) (Table 6).

Next, we hypothesize that subjects who trust the Edmund Mach Foundation's predictions which show that the fire blight's infestation rate will increase from the 1 percent of 2010 to the 17 percent of 2030 (*EMF_HIGH* and *EMF_VHIGH*), have higher percentile estimates of the number of apples containing pesticide residues in 2030 than subjects who do not trust EMF's predictions (*EMF_LOW*). This hypothesis is supported by some of the results, i.e., the positive and significant coefficients of the variables *EMF_HIGH* and *EMF_VHIGH* in Model 2 (*a*) at the 10 percent significance level, while it is not statistically supported in Model 3 (*r*) (Table 6).

The *APPLE_LINK* variable vector, which consists of four diverse dummy variables, *APP_PROD*, *APP_IND*, *CONSUMER*, and *CONS_ASS*, is present in all

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models. In Model 1 (*g*), subjects who produce apples (*APP_PROD*) provide lower estimates of the number of days in which the fire blight's infestation will occur during the blossoming period in 2030 than the others (at the 5 percent significance level). This finding is not surprising because farmers have a better knowledge of the actual low infestation rate in the Province of Trento. As might be expected, farmers (*APP_PROD*) self-protect their own profession, expressing lower estimates of the number of apples that will contain residues in 2030 than others, however, the negative coefficient of the variable *APP_PROD* is statistically significant in Model 3 (*r*), but not in Model 2 (*a*) (Table 6).

In contrast to farmers, some subjects who work in apple processing and marketing (*APP_IND*) have generally higher estimates of pesticide residues in apples than others, and the positive coefficient is statistically significant in Model 2 and 3 at the 1 percent level (Table 6). This is likely due to the fact that people who are involved in the apple industry have better knowledge that chemicals are commonly used to control apple diseases than laypersons, but, unlike farmers, they do not appear to be interested in promoting a healthy brand image.

While the fact that the number of apples consumed weekly (*CONSUMER*) does not affect estimates regarding the fire blight's infestation rate (*g*) is perhaps not surprising, it is striking that this variable only partially influences the consumers' perceptions of pesticide residues in apples (*a* and *r*). The variable *CONSUMER* is negative and statistically significant in Model 2 (*a*) at the 1 percentlevel, but it is not significant in Model 3 (*r*) (Table 6). The negative sign of this variable in Model 2 might be due to the fact that subjects who consume apples perceive the risk of contamination as low. In contrast, we found that members of consumer associations (*CONS_ASS*) who are assumed to be very concerned about pesticide residues have higher estimates of both

a and *r* than the others (Table 6). The coefficient of this variable is positive and statistically significant at the 1 percent level in both Model 2 and Model 3.

We have used the same set of socioeconomic variables in all our models. Although we found that women (*FEMALE*) have higher risk estimates, as frequently found in the literature about risk perceptions (e.g., Flynn et al., 1994; Krewski et al., 1994; Lin, 1995; Hamilton, 1985; 1995), the coefficients are not statistically significant in all of our models.

We found contrasting results for the age of subjects (*AGE*). A person's age may serve as a proxy for experience with one or more types of risk. Related to the variable *g* (Model 1), we found that elderly subjects have higher estimates of the infestation rate than the others (at the 10 percent significance level). This result is consistent with the previous literature on age and health risks (e.g., Krewski et al., 1994; Williams and Hammit, 2001). In contrast however, we found that the number of apples containing pesticide residues decreases with age in Model 2 (*a*) and 3 (*r*) (5 and 1 percent significance level, respectively) (Table 6). This result may be due to the fact that younger consumers are expected to be more sensitive to food-safety issues than older ones because they are considering a longer period of life left in front of them, but it is somewhat surprising because older consumers might be viewed to be more vulnerable to health risks than younger ones[8].

We also found some contrasting results about the effect of education on risk perception. Education is likely related to cognitive ability to process risk information, but might also relate to experience and general knowledge about health risks. Results based on Model 1 (*g*), support the hypothesis that more educated subjects (*UNIVERSITY*) have lower estimates of the infestation rate than the others

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[8] As one anonymous referee argued, elderly subjects are more sensitive to food safety issues than younger ones because they more likely suffer chronic complications that put them at risk from food safety hazards. However, we note that as 2030 is quite far in the future, elderly subjects might not care much about these chronic complications.

(*SEC_SCHOOL*). This is consistent with what some others have found: see Dosman et al. (2001) and Williams and Hammit (2001). However, in Model 2 (*a*) and 3 (*r*), we found that people with a master degree have higher estimates of apples containing pesticides than people with lower education levels (5 and 1 percent significance level, respectively) (Table 6). Again, this divergence may be due to the fact that highly educated subjects (those with graduate degrees) may be more sensitive to food-safety issues than moderately educated subjects.

Subjects with higher annual net income (*INCOME*) perceive the number of apples containing pesticides to be higher than the others with lower annual income. However, the positive sign of the income variable is statistically significant only in Model 2 (a).

Among all of the estimated models explaining the perceptions of pesticides, Model 2, which pertains to the number of apples with one or more residues (*a*), is more predictive than Model 3, which pertains to the number of apples with multiple residues (*r*) (Table 6). There are various hypotheses that may explain the lower explanatory power of Model 3. First, this may be related to the discrepancy between valid and invalid probability estimates detected at the individual level for variable *r*, second, boredom and fatigue may have mattered, given that half of the sample assessed the variable *r* at the end of the experiment, while in the other half the order of questions has been randomized.

In summary, the results of our econometric analysis support many of the predictions we had about the potential factors shaping people's perceptions of the fire blight's infestation rate and the presence of pesticide residues in apples, especially those related to being a farmer, having consumer association membership, having ties with apple industry, and the roles of the demographic variables age, and education. Even using our innovative risk elicitation approach here, we have several results that are quite consistent with previous studies that investigated the same issues with different

techniques. Where our results differ from the literature we believe there are plausible explanations of those discrepancies.

7. Conclusion

Elicited subjective risks are important because they often explain behavior under risk and uncertainty better than science-based risks do. These subjective estimates can be used in risk-oriented behavioral models that incorporate them, such as the subjective expected utility model, or non-expected utility models. In general, empirical results in previous studies have indicated that consumers have a high level of anxiety about such contaminants in food. Using data elicited via an indirect technique such as the Exchangeability Method, which we apply in an artefactual field experiment, we have shown that subjects are in fact not very concerned about a general increase of pesticide residues in apples at a key policy-related future date, but they are more concerned about the presence of multiple residues in apples.

The main contribution of this paper consists of investigating the discrepancy between valid and invalid subjective probabilities. Our results suggest that valid estimates are smaller than the invalid estimates of the number of contaminated apples (variables a and r in the paper), but risk estimates are larger for the number of days in which the fire blight's infestation will occur in the blossoming period (g). We note that such discrepancies are statistically supported only for variable r , indicating that number of apples that will contain multiple residues. This highlights the fact that as researchers and policy makers, our failure to recognize valid subjective risks might not actually imply an over- or underestimation of consumers' true probability estimates, and, hence, affect their choice behavior.

Our econometric analysis explores factors shaping perceptions of pesticide residues in apples and provides other useful information that simple ANOVA-style

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experimental tests do not provide. For example, we found that the average apple consumer in our subject pool is not particularly concerned about pesticide risks; in fact their expectations about the presence of pesticide residues do not statistically differ between apple consumers and non-consumers. In contrast, members of consumers associations and subjects who actually work in the apple industry (excluding farmers) are very sensitive to the problem, as they show higher risk estimates than the others. We also found that young and highly educated can be expected to be more sensitive to food-safety issues.

Such results have quite important food safety policy implications, given the fact that consumers' subjective probabilities of pesticide residues in apples might affect their financial support for policies which the Province of Trento is planning to promote the production of pesticide-free apples. For example, based on our results policy makers should communicate and promote their policies by highlighting the fact that these reduce the risk of having apples containing multiple pesticide residues if they want public support. In addition, food policy specialists should focus their risk communication campaigns towards average consumers and less educated people in the population.

As a final caveat, we note that our subjects were asked to answer questions about risky outcomes pertaining to a future policy period, in the year 2030. It is possible that some subjects discount the future differently than others do, and discount rates and subjective risks could well be related to one another, which could affect each subject's risk estimates. For example, some individuals might use higher discount rates to reflect their sense that the distant future is quite risky. To the extent that all subjects do this in our subject pool, this may not present a significant problem, but if this tendency is mixed among individuals, it may. In future studies, researchers should try to simultaneously estimate discount rates and subjective risks within the context of the EM

approach that we have implemented here. To our knowledge, thus far no one has considered the elicitation of both simultaneously within the context of the EM.

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Table 1. Summary statistics of percentile estimates

Variable	Obs.	Mean	Median	St.Dev.	Min	Max
$g_0{}^{a,d}$	80	6.176	5.000	4.677	1.000	29.000
$g_{1/4}{}^{a,e}$	80	7.912	6.750	5.879	0.205	29.250
$g_{1/2}{}^{a,f}$	80	9.175	7.500	6.320	0.500	29.500
$g_{3/4}{}^{a,g}$	80	10.250	9.000	6.228	0.750	29.750
$g_1{}^{a,h}$	80	11.925	10.500	6.072	1.000	30.000
$a_0{}^{b,d}$	80	56.354	60.000	20.455	4.000	90.000
$a_{1/4}{}^{b,e}$	80	65.637	68.000	21.879	5.000	96.000
$a_{1/2}{}^{b,f}$	80	69.200	72.000	21.907	6.000	98.000
$a_{3/4}{}^{b,g}$	80	71.187	74.500	21.896	8.000	99.000
$a_1{}^{b,h}$	80	75.450	80.000	21.706	10.000	100.000
$r_0{}^{c,d}$	80	31.392	32.000	16.381	4.000	82.000
$r_{1/4}{}^{c,e}$	80	42.387	38.000	19.066	5.000	90.000
$r_{1/2}{}^{c,f}$	80	44.875	41.000	18.941	6.000	92.000
$r_{3/4}{}^{c,g}$	80	47.700	43.000	19.334	8.000	93.000
$r_1{}^{c,h}$	80	51.825	47.000	19.241	12.000	100.000

[a] the number of days during which the infestation will occur during the blossoming period in 2030.
[b] the number of apples containing at least one residue in a sample of 100 apples in 2030
[c] the number of apples containing at least two residues in a sample of 100 apples in 2030.
[d] the lower bound.
[e] the 25th percentile.
[f] the 50th percentile.
[g] the 75th percentile.
[h] the upper bound.

Table 2. Average valid and invalid percentile estimates

Variable	Valid at the sample level		Invalid at the sample level		Valid at the individual level		Invalid at the individual level	
	Obs.	Mean	Obs.	Mean	Obs.	Mean	Obs.	Mean
$g_{1/4}$ [a,d]	23	7.326	53	8.149	19	9.421	34	8.500
$g_{1/2}$ [a,e]	23	8.434	53	9.473	35	8.228	43	9.674
$g_{3/4}$ [a,f]	23	9.583	53	10.512	14	10.071	32	9.031
Tot.	69	-	171	-	68	-	109	-
$a_{1/4}$ [b,d]	23	62.691	53	66.823	23	64.260	44	69.431
$a_{1/2}$ [b,e]	23	67.304	53	69.964	27	61.629	53	73.056
$a_{3/4}$ [b,f]	23	69.652	53	71.807	21	68.619	32	68.625
Tot.	69	-	171	-	71	-	129	-
$r_{1/4}$ [c,d]	23	38.782	53	43.842	23	37.913	41	48.293
$r_{1/2}$ [c,e]	23	41.826	53	46.105	29	39.103	51	48.156
$r_{3/4}$ [c,f]	23	45.608	53	48.543	22	41.409	35	45.485
Tot.	69	-	171	-	74	-	127	-

[a] the number of days during which the infestation will occur during the blossoming period in 2030.
[b] the number of apples containing at least one residue in a sample of 100 apples in 2030.
[c] the number of apples containing at least two residues in a sample of 100 apples in 2030.
[d] the 25th percentile.
[e] the 50th percentile.
[f] the 75th percentile.

Table 3. Comparison of valid and invalid percentile estimates at the sample level

Null Hypothesis	Mann-Whitney U Test	Kolmogorov-Smirnov Test
H_0	z	D
$g_{valid} = g_{invalid}$ [a]	.819	.197
$g_{1/4,\ valid} = g_{1/4,\ invalid}$ [a,d]	.818	.197
$g_{1/2,\ valid} = g_{1/2,\ invalid}$ [a,e]	.820	.161
$g_{3/4,\ valid} = g_{3/4,\ invalid}$ [a,f]	.729	.197
$a_{valid} = a_{invalid}$ [b]	1.069	.180
$a_{1/4,\ valid} = a_{1/4,\ invalid}$ [b,d]	1.069	.180
$a_{1/2,\ valid} = a_{1/2,\ invalid}$ [b,e]	.607	.167
$a_{3/4,\ valid} = a_{3/4,\ invalid}$ [b,f]	.340	.184
$r_{valid} = r_{invalid}$ [c]	1.053	.197
$r_{1/4,\ valid} = r_{1/4,\ invalid}$ [c,d]	1.058	.197
$r_{1/2,\ valid} = r_{1/2,\ invalid}$ [c,e]	.777	.141
$r_{3/4,\ valid} = r_{3/4,\ invalid}$ [c,f]	.670	.127

[a] the number of days during which the infestation will occur during the blossoming period in 2030.
[b] the number of apples containing at least one residue in a sample of 100 apples in 2030.
[c] the number of apples containing at least two residues in a sample of 100 apples in 2030.
[d] the 25th percentile.
[e] the 50th percentile.
[f] the 75th percentile.
* $p < .01$
** $p < .05$
*** $p < .10$

Table 4. Comparison of valid and invalid percentile estimates at the individual level

Null Hypothesis	Mann-Whitney U Test	Kolmogorov-Smirnov Test
H_0	z	D
$g_{valid} = g_{invalid}$ [a]	-.002	.069
$g_{1/4,\ valid} = g_{1/4,\ invalid}$ [a,d]	-.828	.278
$g_{1/2,\ valid} = g_{1/2,\ invalid}$ [a,e]	.962	.166
$g_{3/4,\ valid} = g_{3/4,\ invalid}$ [a,f]	-.910	.236
$a_{valid} = a_{invalid}$ [b]	1.485	.116
$a_{1/4,\ valid} = a_{1/4,\ invalid}$ [b,d]	.893	.182
$a_{1/2,\ valid} = a_{1/2,\ invalid}$ [b,e]	1.632	.236
$a_{3/4,\ valid} = a_{3/4,\ invalid}$ [b,f]	.027	.122
$r_{valid} = r_{invalid}$ [c]	.732	.113
$r_{1/4,\ valid} = r_{1/4,\ invalid}$ [c,d]	2.017**	.348**
$r_{1/2,\ valid} = r_{1/2,\ invalid}$ [c,e]	1.865***	.236
$r_{3/4,\ valid} = r_{3/4,\ invalid}$ [c,f]	.443	.181

[a] the number of days during which the infestation will occur during the blossoming period in 2030.
[b] the number of apples containing at least one residue in a sample of 100 apples in 2030.
[c] the number of apples containing at least two residues in a sample of 100 apples in 2030.
[d] the 25th percentile.
[e] the 50th percentile.
[f] the 75th percentile.
* $p < .01$
** $p < .05$
*** $p < .10$

Table 5. Description of variables presented in Model 1, 2, and 3

Variable	Definition	Mean	St.Dev.	Min	Max
G_GLM	Percentage of days in which the infestation will occur during the blossoming period in 2030	.287	.453	0	1
A_GLM	Percentage of apples containing at least one residue in a sample of 100 apples in 2030	.375	.485	0	1
R_GLM	Percentage of apples containing more than one residue in a sample of 100 apples in 2030	.325	.469	0	1
25th PERC	Observations related to the 25th percentile of g, a, and r	.333	.471	0	1
50th PERC	Observations related to the 50th percentile of g, a, and r	.334	.471	0	1
75th PERC	Observations related to the 75th percentile of g, a, and r	.333	.471	0	1
TRS	= 1 if the subject belongs to the "Real Incentives-Sequential Questions" treatment, = 0 otherwise	.275	.446	0	1
TRR	= 1 if the subject belongs to the "Real Incentives-Random Questions" treatment, = 0 otherwise	.287	.452	0	1
THS	= 1 if the subject belongs to the "Hypothetical Incentives-Sequential Questions" treatment, = 0 otherwise	.237	.425	0	1
THR	= 1 if the subject belongs to the "Hypothetical Incentives-Random Questions" treatment, = 0 otherwise	.200	.400	0	1
IPCC_MED	= 1 if the subject trusts in IPCC's predictions of temperature and precipitation,[a] = 0 otherwise	.012	.111	0	1
IPCC_HIGH	= 1 if the subject highly trusts in IPCC's predictions of temperature and precipitation,[a] = 0 otherwise	.238	.426	0	1
IPCC_VHIGH	= 1 if the subject very highly trusts in IPCC's predictions of temperature and precipitation,[a] = 0 otherwise	.750	.433	0	1
CC_H&N	= 1 if the subject believes that the climate change is due to both human activities and natural processes,[b] = 0 otherwise	.600	.490	0	1
CC_H	= 1 if the subject believes that the	.337	.473	0	1

	climate change is mostly due to human activities,[b] = 0 otherwise				
CC_HH	= 1 if the subject believes that the climate change is only due to human activities,[b] = 0 otherwise	.062	.242	0	1
PEST_LOW	= 1 if the subject believe that farmers will unlikely use pesticides in the future,[c] = 0 otherwise	.050	.218	0	1
PEST_MED	= 1 if the subject believe that farmers will maybe use pesticides in the future,[c] = 0 otherwise	.200	.400	0	1
PEST_HIGH	= 1 if the subject believe that farmers will likely use pesticides in the future,[c] = 0 otherwise	.537	.499	0	1
PEST_VHIGH	= 1 if the subject believe that farmers will very likely use pesticides in the future,[c] = 0 otherwise	.213	.409	0	1
EMF_LOW	=1 if subjects little trusts EMF's predictions of fire blight's infestation risk in the future,[d] = 0 otherwise	.038	.190	0	1
EMF_MED	=1 if subjects trusts EMF's predictions of fire blight's infestation risk in the future,[d] = 0 otherwise	.412	.493	0	1
EMF_HIGH	=1 if subjects highly trusts EMF's predictions of fire blight's infestation risk in the future,[d] = 0 otherwise	.475	.500	0	1
EMF_VHIGH	=1 if subjects very highly trusts EMF's predictions of fire blight's infestation risk in the future,[d] = 0 otherwise	.075	.263	0	1
CONSUMER	The number of apples consumed by the subject in a week	3.700	5.160	0	20
CONS_ASS	= 1 if the subject is a member of a consumer association, = 0 otherwise	.062	.242	0	1
APP_PROD	= 1 if the subject is an apple producer, = 0 otherwise	.037	.190	0	1
APP_IND	= 1 if the subject is tied to apple processing and marketing, = 0 otherwise	.187	.391	0	1
AGE	Age in years	33.625	13.213	19	68
FEMALE	= 1 if the subject is female, = 0 otherwise	.436	.499	0	1
SEC_SCHOOL	= 1 if the subject has this education level,[e] = 0 otherwise	.183	.389	0	1
HIGH_SCHOOL	= 1 if the subject has this education	.512	.503	0	1

	level,[e] $= 0$ otherwise				
UNIVERSITY	= 1 if the subject has this education level,[e] $= 0$ otherwise	.300	.465	0	1
INCOME	The yearly net income in 2010 in thousand €	.189	.195	.075	.115

[a] We ask subjects whether IPCC's predictions will happen surely, very likely, maybe, not likely, or never.

[b] We ask subjects if they believe that climate change is due to, only human activity, mostly human activity, human activities and natural processes, mostly natural processes, and only natural processes.

[c] We ask people if they agree with the statement saying that farmers mostly use chemical control against apple diseases, 0=strongly disagree, 1=disagree, 2=do not know, 3=agree, 4=strongly agree.

[d] We ask subjects whether FEM's predictions about fire blight will happen surely, very likely, maybe, not likely, or never.

[e] We ask subjects their education level, elementary school, secondary school, high school, university.

Table 6. Generalized Linear Model Estimation

Variable	Model 1 (*G_GLM*)	Model 2 (*A_GLM*)	Model 3 (*R_GLM*)
50th PERC	.220***	.179***	.108***
75th PERC	.395***	.283***	.231***
TRS	.206	.369	.276
THR	-.245	.131	.051
THS	-.116	.071	.246
IPCC_HIGH	1.261**	-	-
IPCC_VHIGH	1.416***	-	-
CC_H	-.181	-	-
CC_HH	.860***	-	-
EMF_MED	-	.823	-.271
EMF_HIGH	-	1.141***	.403
EMF_VHIGH	-	2.790***	.530
PEST_MED	-	.326	.472
PEST_HIGH	-	.113	.336
PEST_VHIGH	-	.210	.405
APP_PROD	-1.057**	-.069	-1.112***
APP_IND	.411	.848***	.902***
CONSUMER	-.007	-.058***	-.015
CONS_ASS	-1.235***	1.196***	1.004***
FEMALE	.085	.181	.054
AGE	.015*	-.026**	-.012*
HIGH_SCHOOL	-.809**	.249	.291
UNIVERSITY	-1.373***	0.796**	.675***
INCOME	.001	.001***	.001
CONSTANT	-2.138***	-.572	-.942
LOG P.L.§	-99.855	-98.318	-107.073

* $p < .01$, ** $p < .05$, *** $p < .10$
§ Log Pseudo-Likelihood

Figure 1: An example of the binary question of the Exchangeability Method for the variable *a*.

I prefer to bet 100€ on the fact that the number apples containing at least one pesticide residues in 2030 will be:

□	□
smaller than 64	greater than or equal to 64

Figure 2: An example of the Certainty Equivalent Game for the variable *a*.

In each of the following question, do you prefer to play the lottery presented in Option A or do you prefer to take the amount of money presented in Option B?

Option A			Option B
	□	□	0€
	□	□	25€
You win 100€ if the number apples containing at least one pesticide residues in 2030 will be SMALLER THAN 64	□	□	49€
	□	□	51€
0€, otherwise	□	□	75€
	□	□	100€

In each of the following question, do you prefer to play the lottery presented in Option A or do you prefer to take the amount of money presented in Option B?

Option A			Option B
	□	□	0€
	□	□	25€
You win 100€ if the number apples containing at least one pesticide residues in 2030 will be GREATER THAN OR EQUAL TO 64	□	□	49€
	□	□	51€
0€, otherwise	□	□	75€
	□	□	100€

Figure 3: The average number of days in which the infestation will occur during the blossoming period in 2030.
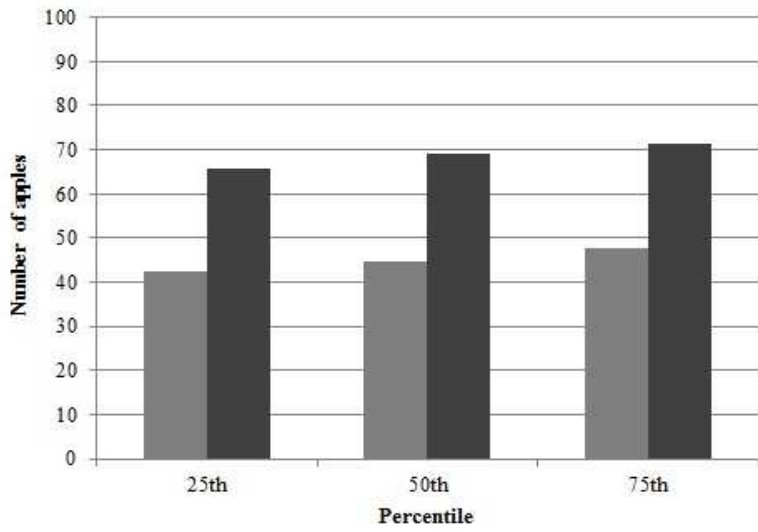

Figure 4: The average number of apples containing residues in a sample of 100 apples in 2030.