Beliefs and preferences for food-safety policies: A discrete choice model under uncertainty[1]

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Abstract

Outcomes of food polices are highly uncertain. Therefore, public's support for these policies depends on individuals' beliefs and the provision of scientific information. Using data collected from a discrete choice experiment survey, we explore whether new information regarding a food-safety policy influences respondents' support, while controlling for risk and time preferences. Additionally, we examine if support depends on whether information is perceived as either good or bad news. Results from the estimation of parametric error component logit models, based on Expected Utility Theory and Rank Dependent Utility Theory, suggest that good and bad news affects preferences and welfare measures.

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Outcomes of food polices are highly uncertain. Therefore, public's support for these policies depends on individuals' beliefs and the provision of scientific information. Using data collected from a discrete choice experiment survey, we explore whether new information regarding a food-safety policy influences respondents' support, while controlling for risk and time preferences. Additionally, we examine if support depends on whether information is perceived as either good or bad news. Results from the estimation of parametric error component logit models, based on Expected Utility Theory and Rank Dependent Utility Theory, suggest that good and bad news affects preferences and welfare measures.

1. Introduction

A recent publication by the European Food Safety Authority (EFSA, 2016) revealed that 97.1% of food samples contained pesticide residues within the legal limits in 2014. The same publication pointed out that health risks due to the presence of pesticide residues in fresh food cannot be ruled out (EFSA, 2016). Therefore, while monitoring of pesticide residues in food is mandatory in the European Union (EU) (EC No 396/2005), new scientific research and development (R&D) programmes are funded to generate alternatives to pesticides (Antle, 2015).

Policy makers need ex-ante evaluations of these programmes to make informed decisions. Because R&D programmes have long term and uncertain benefits, it has been recently argued that welfare evaluation should incorporate behavioural factors, such as subjective beliefs, risk attitudes and time preferences (Harrison, 2011; Colen *et al*., 2016). Stated-preference (SP) approaches are often used to measure welfare benefits associated to R&D programmes, but rarely follows Harrison's recommendation.[1]

In this paper, we conduct a survey, in which subjective beliefs, time preferences and risk attitudes are elicited using different tasks and methodologies. Subjective beliefs are elicited using the Exchangeability Method (EM) (Baillon, 2008). Time preferences are elicited using the multi price list (MPL) format (Coller and Williams, 1999). Risk preferences are elicited using a discrete choice experiment (DCE) aiming to investigate taxpayers' preferences for different R&D policies geared to reduce the risk of having pesticide residues in apples in the future. Each DCE alternative is framed as a binary policy lottery with two states of the worlds, each characterized by the probability that a given number of apples will present pesticide in the

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[1] Other approaches to evaluate ex-ante the welfare of public policy are randomized control trials and simulation-based studies. For a good review of strengths and limitations of these approaches, we refer interested readers to Harrison (2011) and Colen *et al*. (2016).

future.[2] Such a complex survey design allows estimating welfare benefits generated by the R&D programmes, while controlling for probabilistic beliefs, risk and time preferences.

The evaluation of welfare benefits can be influenced by public information campaigns that are based on available scientific evidence (Weiss and Tschirhart, 1994). The goals of these campaigns are to make institutional actions more transparent and increase public support for policies that are perceived as important yet. The public's acceptance of new information is extremely difficult to predict and depends, among other factors, on personal probabilistic beliefs (e.g., Manski, 2004). There is a substantial amount of empirical work that investigates the influence of probabilistic beliefs on public support for food policies (e.g., Fox, Hayes and Shogren, 2002; Lusk, Schroeder and Tonsor, 2014).

In this paper, we contribute to this strand of the literature in two ways. First, we investigate whether choice behaviour and welfare measures for the R&D programmes are affected by information regarding future levels of contaminated apples. In particular, we test if the effect of information depends on whether this is perceived to be good or bad news (hereafter, the "good-bad news effect"). Recent works suggest that people are more willing to accept good rather than bad news regarding personal traits (Eil and Rao, 2011) and this paper aims to test if this phenomenon occurs in the food-safety domain.

Second, we model choices over food-safety policy lotteries using Expected Utility Theory (EUT) (von Neumann and Morgenstern, 1944) and Rank Dependent Utility Theory (RDUT) (Quiggin, 1982) to identify the theoretical framework that best "predicts the facts" in a food-policy setting. Very few studies estimating welfare benefits of food safety policies have investigated potential deviations from EUT. A noticeable exception is a non-hypothetical DCE

[2] The idea of policy lottery was first introduced by Stern (2007: 163ff.) and then re-proposed by Harrison (2011).

investigation by Lusk, Schroeder and Tonsor (2014), which models choices for hormone and antibiotic-free meat products using EUT and RDUT.[3]

2. Beliefs, information and food policy evaluation

2.1. Probabilistic beliefs and food policy evaluation

The influence of probabilistic beliefs on decisions has been examined in many branches of applied economics (Manski, 2004) and public economic support for food-safety policies is no exception. The effect of qualitative probability judgements on preferences for safe food products or food-safety polices has been widely investigated in this literature, leading mostly to ad hoc modelling of risk reductions (e.g., Misra et al., 1991; Buzby et al., 1998; Lusk and Coble, 2005; Marette, Roe and Teisl, 2012; Malone and Lusk, 2017).[4]

There are only few DCE studies that examine the impact of (numerical) subjective probabilities over binary outcomes on such preferences in a more formal model of risky behaviour (Teisl and Roe, 2010; Lusk, Schroeder and Tonsor, 2014). These works elicit subjective probabilities of food-borne illnesses (i.e., being hill or not) and investigate their influence on preferences for treated or untreated meat products.[5] Treatments are irradiation or ethylene gas processing in Teisl and Roe (2010), and hormones or antibiotics in Lusk, Schroeder and Tonsor (2014). None of these studies attempts to elicit subjective probability distributions over continuous outcomes and control for risk and time preferences. To the best of our

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[3] A more comprehensive review of the literature on comparing theories of choice under risk and uncertainty is presented in the online Appendix 1a.

[4] An example of question used to elicit qualitative probability judgements is the following: "How do you assess the likelihood of event x occurring? Very likely, Don't know, Very Unlikely" or "How do you assess the likelihood of event x occurring on scale from 1 to 10?".

[5] An example of question used to elicit subjective probabilities is the following: "What is the chance that you will become ill due to the possible use of added growth hormones or antibiotics?".

knowledge, we are the first attempting to control for the effect of subjective probability distributions, risk and time preferences when evaluating welfare benefit using a DCE survey.

2.2. The role of information and policy evaluation

The influence of probabilistic information on beliefs and choice behaviour is another popular research field in economics. There is a very large volume of literature related on the topic and results are far from being conclusive. Some studies show that, when people are provided with information, they update their prior belief in a Bayesian fashion (e.g. Viscusi, 1985; 1989; 1990), but others react in a variety of complicated ways (e.g. Viscusi and Magat, 1992; Cameron 2005a). Information might simply be ignored (i.e., conservatism bias as defined by McFadden and Lusk, 2015), or at the other extreme, an individual could discard their prior beliefs altogether.

Disseminating scientific information regarding food policies may well have an effect on people's economic support for such policies, especially if beliefs differ from objective probability measures. The literature on this topic is relatively scarce.[6] A noticeable exception is Fox, Hayes and Shogren's (2002) experimental investigation. This study indicates that both subjective probabilities and information of foodborne health risks explain consumers' preferences for irradiated pork. Their experiment also shows that preferences for irradiated pork depend on (non-probabilistic) positive and negative descriptions of this technology (i.e. irradiation). In this study, consumers appear to weigh negative descriptions of foodborne health risks more than positive ones.

[6] Few works have investigated the extent to which consumers revise their prior non-probabilistic beliefs about genetically modified food in the light of new non-probabilistic information from different sources (e.g., Huffman *et al.*, 2007; McFadden and Lusk, 2015; Malone and Lusk, 2017).

The influence of positive and negative probabilistic information has been examined in other domains than food. A recent experimental study has shown that while respondents react differently to positive and negative feedback regarding personal traits (i.e., intelligence and beauty), they tend to discount or discard negative information in ways that are inconsistent with Bayes' rule (i.e., the good-bad news effect) (Eil and Rao, 2011). The present paper is the first attempt to test the good-bad news effect in the context of food-safety policies and measure its implications on welfare evaluation.

2.3. Elicitation of numerical probabilistic beliefs related to food-safety outcomes

The literature on eliciting numerical probabilistic beliefs for financial outcomes is vast and a number of approaches are available (Andersen et al., 2014; Trautmann and van de Kuilen, 2015). Part of this literature relies on hypothetical surveys (see Manski, 2004 for a review). The other on financial incentives and incentive compatible methods (see Harrison, 2014 for a discussion). These methods generally ask respondents to choose between lotteries or prospects. The implied probabilities are estimated using the points at which a subject becomes indifferent between choosing one lottery and choosing another (Spetzler and Stael Von Holstein 1975). There are many variations on the theme: outcome or probability matching method, quadratic or linear scoring rules, and others.[7] It is also important to distinguish between approaches that elicit subjective probabilities over binary outcomes (e.g., Andersen et al., 2014; Harrison et al., 2014), and more informative approaches that elicit subjective probability distributions over continuous outcomes (e.g., Di Girolamo et al., 2015; Harrison et al., 2015; 2017).

There is little research investigating how these approaches can be adapted to elicit

[7] This list is far from being exhaustive. See Andersen *et al*. (2014) and Trautmann and van de Kuilen (2015) for further reviews of this literature.

numerical probabilistic beliefs related to food-safety outcomes. This literature mostly focuses on the elicitation of subjective probabilities over binary outcomes using the "direct" elicitation approach and non-incentivised procedures. This approach just asks respondents to state the probability that given food-safety outcomes will occur in the present or in the future (e.g., Fox, Hayes and Shogren, 2002; Teisl and Roe, 2010; Lusk, Schroeder and Tonsor, 2014). Results may be inaccurate for two reasons. First, the hypothetical nature of the question. Second, people are often not willing and/or able to express numerical probabilities directly (Manski, 2004).

Only a small number of studies have attempted to elicit subjective probability distributions over continuous food-safety outcomes using incentivised procedures, such as the exchangeability method (EM) (e.g., Cerroni, Notaro and Shaw, 2012; 2013). In the present paper, a non-incentivised version of the EM is used (Baillon, 2008, Abdellauoi *et al*., 2011). The EM consists of a set of binary questions. In each question, subjects are asked to bet on one of two disjoint subspaces of the whole state space of the random variable under study (i.e. number of contaminated apples). These subspaces are identified by sequentially dividing the (remaining portion of the) state space using a bisection process. The advantages of the EM as compared to other direct and indirect approaches is that participants are not asked to process numerical probabilities (at all) during the procedure and they are exposed to only one source of uncertainty (Cerroni, Notaro and Shaw, 2012; 2013). In addition, the EM allows eliciting several percentiles of each subject's cumulative distribution function (CDF) for the random variable under study. The hypothetical nature of our study may affect the validity of elicited beliefs. Cerroni, Notaro and Shaw (2012) show that the validity of beliefs elicited via the EM increases when monetary incentives are provided.[8]

3. Empirical application

The food-safety policy considered in our study aims at reducing the risk of having apples contaminated by pesticides in the Province of Trento (Italy) in 2030. More specifically, we investigate preferences for the R&D programs geared to develop new methods to control apple diseases that are predicted to infest apple orchards in the area in the near future.[9] These R&D programs would identify natural organisms that are antagonists of causal pathogens, and develop resistant varieties of apples that will be unaffected by new diseases. Funding for these programs will be raised by asking the population of the Province of Trento to pay a tax that consists of a yearly sum over the entire period between 2012 and 2030.

If proposed R&D programs are not implemented, farmers will likely fight new diseases by applying higher quantities of existing pesticides and/or treating apples with other new and more effective pesticides. This will affect the presence of pesticide residues on apples in 2030, which is already quite high today (Italian Health Ministry, 2010).[10] In contrast, the implementation of such R&D programs is geared to lower the risk of having contaminated apples in 2030.

However, either way, the consequences in terms of pesticide residues in apples cannot be precisely predicted by the scientific community and therefore remains rather uncertain.

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[8] Harrison (2014) provides a review of pros and cons of hypothetical surveys and incentivised scoring rules. The empirical analysis conducted in his work shows that subjective beliefs elicited via hypothetical survey can differ from those elicited via incentivised scoring rules.

[9] An example is the fire blight, a bacterial phytopathology that has damaged and killed a number of apple orchards in the Province of Trento since 2003 (Edmund Mach Foundation, 2006). According to the best available forecasts, a future spread of this disease in apple orchards of the Province of Trento is expected in the future, with significant damages in 2030 (unpublished results by Edmund Mach Foundation).

[10] According to scientific data, 63 apples out of about 100 contain pesticide residues, albeit well below the legal limit (Italian Health Ministry, 2010).

4. Methods

4.1. The Exchangeability Method

In our application of the EM, the random variable under study is the number of apples (out of 100) that will contain pesticide residues in the year 2030, if farmers control the spread of new diseases by using pesticides (a). In theory, the EM can be used to elicit as many points for each individual's subjective CDF as the researcher wants to attempt to identify. Here, however, we attempt to elicit only the 50th percentile ($a_{1/2}$) and the end-points of each respondent's CDF is elicited (a_{max}).[11]

In the first step of the EM, respondents 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 of occurring. For example, if subject i believes that $a_{i,min}$=70 and $a_{i,max}$=86, then, she/he implicitly assumes that only outcomes within 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 her/his subjective CDF ($a_{i,1/2}$) (Figure 1). The first binary question presents two prospects that are identified by dividing the state space S_a at a point a_1 which is calculated as $a_1=\{a_{min}+[(a_{max}-a_{min})/2]\}$. For subject i, $a_{i,1}$ is equal to $\{70+[(86-70)/2]\}=78$ apples and the first binary question asks her/him to bet on prospect $A_1=\{70<x<78\}$ or prospect $A_1'=\{78\leq x<86\}$. This process is repeated until subject i is indifferent between the two prospect A_{1+z} and A_{1+z}'. At this stage, we infer that she/he attaches the same probability to these prospects $P(A_{1+z})=P(A_{1+z}')$, and we are able to identify the 50th percentile of her/his subjective CDF ($a_{i,1/2}$).

[11] We decided to elicit only three points of each respondent's probability distribution to keep the survey of a manageable length to respondents. The survey was already rather cognitively demanding and we did not want to undermine the quality of collected data. However, we acknowledge that the elicitation of additional percentiles of each respondents' subjective belief distribution would have been possible (see for example, Cerroni et al., 2012).

For example, assume that subject i is indifferent between prospect $A_{1+z}=\{70<x<74\}$ and prospect $A_{1+z}'=\{74\leq x<78\}$, this implicitly means that $P(70<x<74)=P(74\leq x<78)$ and $a_{i,1/2}=74$.

I prefer to bet 100€ on the fact that the number of apples that contains pesticide residues in 2030 is:

☐	☐
smaller than 78	greater than or equal to 78

Figure 1 Example of a binary question of the Exchangeability Method

4.2. The policy-lottery based discrete choice experiment

Preferences are elicited via a best-worst pivot DCE.[12] Pivot designs are used in transportation studies to create realistic DCE surveys based on respondents' recent and familiar commuting trip (e.g., Greene and Hensher, 2003). Best-worst DCEs are used to elicit the full weak rank-ordering by asking respondents to select the most (or best) and least preferred (or worst) alternatives in each choice task (e.g, Finn and Louviere, 1992).

In the present DCE study, three key attributes were identified to describe a reduction in the content of pesticide residues in apples generated by R&D programs using information collected in three separate focus-group meetings. These attributes are:

[12] More details on strengths and limitations of these DCE designs are provided in the online Appendix 1b.

(i) the number of apples containing pesticide residues out of a sample of a hundred in 2030 (*x*),

(ii) the probability of this number *x* 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*).

Each subject is presented with 12 choice tasks, each containing three alternatives.[13] Each alternative is a binary policy lottery with two states of the world (*a* and *b*). In Figure 2, we present an example of a choice task.

Figure 2 Example of Choice Task for subject *i*

	R&D Program A		**R&D Program B**		**NO R&D Program**	
Number of apples containing pesticide residues in 2030	26	75	13	75	65	75
Probability of occurrence	50%	50%	10%	90%	50%	50%
Yearly tax to pay in the period 2012-2030	30€		50€		0€	

In the opt-out alternative, the Province of Trento does not launch any R&D program and farmers will have to control new diseases by spraying pesticides that are available in 2030. Using

[13] We used a Bayesian *D*-efficient homogeneous pivot design (Ferrini and Scarpa, 2007; ChoiceMetrics, 2011).

the example in Figure 2, the opt-out alternative is portrayed as a binary lottery, in which there is a chance $p(x_{a,oo}) = 0.5$ that the number of contaminated apples in 2030 will be $x_{a,oo} = 65$ (state of the world a) and a chance $p(x_{b,oo}) = 1- p(x_{a,oo}) = 0.5$ that this number will be $x_{b,oo} = 75$ (state of the world b). As no R&D program is implemented, there is no tax to pay in the opt-out alternative.

The other two alternatives describe the scenarios under which the Province of Trento will launch R&D programs, in 2012. These programs potentially reduce the number of apples containing pesticide residues in 2030. Each hypothetical alternative is a lottery, in which there is a chance $p(x_{a,R\&D})$ that the number of contaminated apples in 2030 will be $x_{a,R\&D}$ (state of the world a) and a chance $p(x_{b,R\&D}) =1- p(x_{a,R\&D})$ that this the number will be $x_{b,R\&D}= x_{b,oo}$ (state of the world b).

Note that the attribute $x_{b,R\&D}= x_{b,oo}$ and is constant across policy lotteries in the same choice task. In our example in Figure 2, $x_{b,R\&D} = x_{b,oo} = 75$. In contrast, the attribute $x_{a,R\&D} < x_{a,oo}$ because the R&D programs aim to reduce the number of contaminated apples in 2030. The attribute $x_{a,R\&D}$ can take one of the pivoted values below:

i) $x_{a,oo} * 0.6 = 39$,

ii) $x_{a,oo} * 0.4 = 26$, or

iii) $x_{a,oo} * 0.2 = 13$.

The attribute $p(x_{a,R\&D}) \leq p(x_{a,oo})$ because the R&D programs may not be effective. Four pivoted levels for the attribute $p(x_{a,R\&D})$ were designed using the formulas below:

i) $p(x_{a,oo}) * 1 = 0.5$,

ii) $p(x_{a,oo}) * 0.5 = 0.25$,

iii) $p(x_{a,oo}) * 0.2 = 0.1$ or

iv) $p(x_{a,oo}) * 0.1 = 0.05$.[14]

These algorithms were not shown to respondents in the instructions and choice tasks. Respondents only see the final numerical outcomes (see online Appendix 2). The selected levels for the tax attribute (t) were the following, 15€, 30€, 50€, and 80€, to be paid by each taxpayer, in each year between 2012 and 2030. Tax levels were identified by conducting research on previous taxation schemes introduced by the Province of Trento to finance agricultural policies and using data collected in our focus groups.[15]

As face-to-face interviews were conducted, respondents were guided through each choice task by a trained interviewer to facilitate comprehension (see online Appendix 2).[16] Respondents were also presented with a practice choice task.

4.3. Multi price list format for time preferences

Time preferences for financial outcomes are elicited using the MPL format, which is commonly implemented in number of experimental studies (e.g., Coller and Williams, 1999; Harrison, Lau and Williams, 2002; Andersen et al., 2008; 2013; 2014). In our hypothetical task, respondents have to choose between Option B, in which respondents pay a fixed sum equal to

[14] It follows that the attribute $p(x_{b,R\&D})$ can take one of the values below: i) $1- p(x_{a,R\&D}) = 0.5$, ii) $1- p(x_{a,R\&D}) = 0.75$, iii) $1- p(x_{a,R\&D}) = 0.90$, or iv) $1- p(x_{a,R\&D}) = 0.95$

[15] Summary statistics of attribute levels and observed choices are provided in the online Appendix 1c.

[16] Subjects were told that there is a NO R&D Program scenario in which there is 50% chance of having 65 contaminated apples out of 100 apples and 50% chance of having 75 contaminated apples out of 100 apples. Then, they were instructed that there is a R&D Program A, which implies a scenario where there is 50% chance of having 26 contaminated apples out of 100 apples and 50% chance of having 75 contaminated apples out of 100 apples. Finally, they were told that there is a R&D Program B, which implies a scenario where there is 10% chance of having 13 contaminated apples out of 100 apples and 90% chance of having 75 contaminated apples out of 100 apples. More details are provided in the online Appendix 2.

M_B=€415 in 19 years, and Option A, in which respondents pay a lower sum equal to M_A=€415 - €x today.[17,18] The amount of money x is increasing over choices (from choice 1 to 9) and generates a range of annual discount rates from 0.5% to 10% (see Figure 3). The payment in Option B was fixed at €415 because this was the estimated average tax that respondents were willing to pay over the period 2012-2030 to implement a R&D program in the pilot study conducted to test the survey. This design was implemented to reduce the influence of stakes' level on elicited time preferences.

[17] We acknowledge the potential effect of hypothetical bias on elicited time preferences (see discussion on Andersen et al., 2014).

[18] In this paper, we elicit time preferences over losses rather than gains because we are interested in discounting behaviour over tax-based payments. There is a relatively extensive literature on the asymmetry between discount rates elicited in the loss and gain domain, but the discussion of this issue is beyond the scope of this paper (see discussion in Abdellaoui, Bleichrodt, and l'Haridon, 2013).

However, the implied range is quite narrow as compared to previous studies, in which discount rates can vary from 5% to more than 1,000%.

Elicited discount rates will be corrected for the effect of diminishing marginal utility, following Andersen et al. (2008), in both the EUT and RDUT framework.

Figure 3: The time-preference task faced by respondents

Choice	Option A (you pay today)	Option B (you pay in 19 years)	Annual Interest Rate in %
1	€377	€415	0.50
2	€344	€415	1.00
3	€285	€415	2.00
4	€237	€415	3.00
5	€197	€415	4.00
6	€137	€415	6.00
7	€96	€415	8.00
8	€81	€415	9.00
9	€68	€415	10.00

4.4. Data collection and sample composition

Data were collected by trained interviewers using the computer-assisted personal interviewed (CAPI) system.[19] The final sample of respondents consists of 797 taxpayers, who reside in the Province of Trento. The sample is split is three groups, each presented with a different version of our best-worst pivot DCE survey. All versions are equally structured, but they differ in the description of the opt-out alternative.[20]

The *consistent-news group* consists of 487 respondents. They are presented with a DCE, in which probabilistic beliefs elicited via the EM are used to generate respondent-specific opt-out

[19] The survey was conducted in the period between January 24th and March 12th, 2012

[20] Survey instructions are presented in the online Appendix 2.

alternatives.

Remaining respondents (310) are presented with DCE, in which the opt-out alternative is designed according to science-based predictions. As described in Figure 2, there are two equally likely states of the worlds: a) the number of contaminated apples in 2030 will be $x_{a,oo} = 65$ and b) the number of contaminated apples in 2030 will be $x_{b,oo} = 75$.

Depending on whether the scenario presented in the opt-out alternative represents good news or bad news relative to each respondent's beliefs about the number of contaminated apples in 2030, each respondent is assigned to the *good-news* or *bad-news group*. Both groups consist of 155 respondents.

In the *bad-news group*, each respondent faces an opt-out alternative, where the number of contaminated apples presented in state of the world a) of the opt-out alternative ($x_{a,oo} = 65$) is higher than the median of her/his subjective belief distribution ($a_{i,1/2}$) and the number of contaminated apples presented in state of the world b) of the opt-out alternative ($x_{b,oo} = 75$) is higher than the maximum end-point of her/his subjective belief distribution ($a_{i,max}$).[21] In our sample, respondents meet both or none of these conditions. In the *good-news group*, respondents face the opposite scenario.

5. Modelling choices

5.1. Modelling DCE-related choices

5.1.1. Random Utility Models

The present paper models choices among policy lotteries by using Fechner models

[21] t-tests are conducted to test whether the distributions of respondents' median and maximum end-point estimates ($a_{i,1/2}$ and $a_{i,max}$) are greater (or lower) than $x_{a,oo}$ and $x_{b,oo}$, respectively, in the *bad-news group* (or *good-news group*). The test rejects the null hypotheses of equality and results are reported in the online Appendix 1d.

(Fechner, 1860). This modelling approach has been extensively used to investigate decision making under risk (e.g., Hey and Orme, 1994; Conte, Hey and Moffat, 2011). The error term of our Fechner models are distributed according to an i.i.d. extreme value distribution and error variances are normalized to $\pi^2/6$.[22] Therefore, our Fechner models are equivalent to random utility models (RUMs) (McFadden, 1974), more specifically to an error component multinomial logit model (Train, 2009: 123ff.). The utility ($U_{i,j}$) that subject i attaches to each alternative j, with $j = j_1,...,J$, is decomposed into two parts, $V_{i,j}$, the indirect utility observed by the researcher plus an error term $\varepsilon_{i,j}$, so that, $U_{i,j} = V_{i,j} + \varepsilon_{i,j}$.

5.1.2. Endogeneity control

Beliefs about the number of contaminated apples ($a_{1/2} = x_{a,oo}$ and $a_{max} = x_{b,oo}$) are potentially endogenous because measurement errors might have occurred during their elicitation via the EM. We control for endogeneity using the two-step control function (CF) approach for discrete choice demand models developed by Villas-Boas and Winer (1999), and more recently, used by Petrin and Train (2010). Lusk, Schroeder and Tonsor (2014) and Malone and Lusk (2017) used this approach to control for endogeneity generated by the incorporation of subjective beliefs into DCEs. The CF approach involves the use of error component models (Villas-Boas and Winer, 1999; Petrin and Train, 2010).

The first step of the CF approach regresses the endogenous variable on observed choice characteristics and an instrument. The endogenous variable is the pooled sample of observations

[22] We did not use the contextual utility normalization (Wilcox, 2011) because the utility associated to each alternative (or lottery) in each choice task depends on the number of contaminated apples and the monetary outcome (i.e., tax to be paid, if any). The multidimensionality of our utility functions make it difficult to identify the maximum and minimum utility over all prizes in our choice tasks (i.e., lottery triples), and hence, the Wilcox's normalizing term in each choice task (or lottery triple).

$a_{i,1/2}$ and $a_{i,max}$, hereafter a_i. Our instrument, q_i, is a dummy variable, which equals 1, if $a_{i,1/2}$ (*or* $a_{i,max}$) is equal to or higher than 63. Otherwise, q_i equals 0. The value of 63 was selected because respondents were informed about the number of contaminated apples in the period 2001-2009 before facing the EM task, and 63 was the number of contaminated apples in 2009 (i.e., the last year for which data were available)[23]. This instrument is inspired by a classic lagged price instrument, which is widely used in choice demand settings (Villas-Boas and Winer, 1999). As our endogenous variable is continuous, we use simple ordinary least squares (OLS) estimation procedure.

In the second step of the CF approach, we transform the estimated residuals μ_i obtained in the first step using bootstrapping procedures and incorporate these into our DCE model. The original error term in the RUM model takes the following form $\tilde{\varepsilon}_{i,j} = \lambda\mu_{i,j} + \sigma\eta_{i,j} + \varepsilon_{i,j}$, where $\varepsilon_{i,j}$ is assumed to be i.i.d. extreme value type I, the error component $\eta_{i,j}$ is assumed to be normally distributed with mean equal to zero and standard deviation σ to be estimated. The error component is always associated with the opt-out alternative. The term $\mu_{i,j}$ is our control function for endogeneity with coefficient λ to be estimated. In this framework, $\mu_{i,j}$ and $\eta_{i,j}$ are assumed to be jointly normal (see Petrin and Train 2010).

5.1.3. Modelling of utility under EUT and RDUT

Our indirect utility function ($V_{i,j}$) is modelled using EUT and RDUT.[24] In our EUT framework, the utility that each subject i gets from choosing alternative j is modelled as

[23] A more exhaustive description of the CF approach is provided in the online Appendix 1e. Additional instrumental variables were tested and used. More details on these variables and estimation results are provided in the online Appendix 1e.
[24] The modelling of our EUT- and RDUT-based indirect utility functions is slightly different from the classic modelling approach used in the DCE literature. We describe our modelling approach and provide an in-depth discussion of strengths and limitations of other possible modelling approaches in the online Appendix 1f.

(Equation 1, Model 1):

$$V_{i,j} = \left\{\left[p(x_{a,j}) * \left(\alpha + \frac{x_{a,j}^{(1-\beta_x)}}{(1-\beta_x)} + \frac{z_{a,j}^{(1-\beta_z)}}{(1-\beta_z)}\right)\right] + \left[[1 - p(x_{a,j})] * \left(\alpha + \frac{x_{a,j}^{(1-\beta_x)}}{(1-\beta_x)} + \frac{z_{a,j}^{(1-\beta_z)}}{(1-\beta_z)}\right)\right]\right\} \quad (1)$$

In Equation 1, $p(x_{a,j})$ and $1\text{-}p(x_{a,j})$ are the probabilities that the number of contaminated apples will be $x_{a,j}$ and $x_{b,j}$ in the year 2030, respectively. The term α indicates the alternative specific constant for the alternative that features the NO R&D program.[25] Note that, each year over the period between 2012 and 2030, the annual tax (t) is taken away from each subject's yearly income (inc_i), so that the variable $z_{i,j} = (inc_i - t_j)$ enters the conditional indirect utility function. The β coefficients, β_x and β_z, measure constant relative risk aversion (CRRA). More specifically, the parameter β_x accounts for risk preference with respect to the number of contaminated apples in 2030, while the parameter β_z accounts for risk preference with respect to net income. The CRRA coefficient's specification used in our model has been extensively implemented in economic experiments and implies risk loving if $\beta < 0$, risk neutrality if $\beta = 0$, and risk aversion if $\beta > 0$ (e.g., Andersen *et al.*, 2012).

In our RDUT framework, the utility that each subject i gets from choosing alternative j is modelled as (Equation 2, Model 2):

$$V_{i,j} = \left\{\left[w[p(x_{a,j})] * \left(\alpha + \frac{x_{a,j}^{(1-\beta_x)}}{(1-\beta_x)} + \frac{z_{a,j}^{(1-\beta_z)}}{(1-\beta_z)}\right)\right] + \left[w[1 - p(x_{a,j})] * \left(\alpha + \frac{x_{a,j}^{(1-\beta_x)}}{(1-\beta_x)} + \frac{z_{a,j}^{(1-\beta_z)}}{(1-\beta_z)}\right)\right]\right\} \quad (2)$$

According to RDUT, people weigh probabilities by using a probability weighting function

[25] The alternative specific constants related to R&D alternatives are normalized to zero (Train, 2009).

$w(.)$ which is strictly increasing in probability and satisfies $w(0)=0$ and $w(1)=1$. Probability weights associated to risky outcomes depend on the complete rank of the outcomes presented in the lottery. Equation 2 can be derived because we have only two outcomes in each lottery and $x_a>x_b$ always.[26]

Many possible parametrizations of the probability weighting functions were proposed in the related literature (Wakker, 2010). Here we rely on the two-parameters Prelec's parametric weighting function (1998):

$$w\left[p\left(x_{a,i,j}\right)\right] = exp\left\{-\tau\left[-p\left(x_{a,i,j}\right)^{\gamma}\right]\right\} \tag{3}$$

This specification enables to relax the EUT's assumption under which probabilities are linearly processed via the estimation of the coefficients γ and τ. The former informs on the curvature of the probability weighting functions, the latter on the inflection point at p.[27] If $\gamma=1$, this specification collapses to the Quiggin's (1982) power probability weighting functions. If $\tau=1$, it collapses to the one parameter Prelec's weighting function (1998).[28]

5.1.4. The good-bad news effect and observed heterogeneity

Building on the baseline specifications of Models 1 (EUT) and 2 (RDUT), we develop two

[26] Derivation of Equation 4 is presented in the online Appendix 1g.

[27] The coefficients γ and τ are allowed to be greater than 1 in all our specifications. This allows the probability weighting function to have a shape that is different from the inverse-S shape. While the widespread opinion is that probability weighting functions have an inverse-S shape, recent work by Wilcox (2015) demonstrates that this is not necessarily the case. An alternative would be the estimation of the one-parameter Prelec's probability weighting function. This is not as flexible as the two-parameter version because implies a fixed inflection point at $p = 1/e = 0.37$.

[28] In this paper, we refer to β_x and β_z as measures of constant relative risk aversion (CRRA) even when we describe RDUT-based models. While we do this to improve the readability of the paper, we acknowledge that this is not appropriate. Wakker (2008) noted that risk attitude is not equivalent to utility curvature in RDUT and Cumulative Prospect Theory (Tversky and Kahneman, 1992) because probability-weighting also contributes to risk preferences.

separate modelling approaches.

The first approach implies the use of parametric equations that allows testing whether preferences for the opt-out alternative (α) as well as risk preferences for apples (β_x) and income (β_z) are affected by the provision of good and bad news. Model 3 (EUT) and 4 (RDUT) imply the estimation of the following parametric equations (Equations 4, 5 and 6)[29]:

$$\alpha = \alpha_0 + \alpha_{good} goodnews + \alpha_{bad} badnews \quad (4)$$

$$\beta_x = \beta_{x,0} + \beta_{x,good} goodnews + \beta_{x,bad} badnews \quad (5)$$

$$\beta_z = \beta_{z,0} + \beta_{z,good} goodnews + \beta_{z,bad} badnews \quad (6)$$

Here the estimated coefficients α_0, $\beta_{x,0}$ and $\beta_{z,0}$ indicate respondents' preferences for risk related to the apple and income outcomes as well as preferences for the opt-out alternative.

The variables *goodnews* and *badnews* are dummy variables which indicates whether respondents belong to the good- and bad-news group, respectively.[30] The estimated coefficients $\alpha_{good\text{-news}}$, $\beta_{x,goodnews}$ and $\beta_{z,goodnews}$ ($\alpha_{bad\text{-news}}$, $\beta_{x,badnews}$ and $\beta_{z,badnews}$) inform on whether preferences of respondents, who receive good news (bad news) differ from those, whose beliefs are consistent with the baseline scenario (*consistent-news*).

Three alternative preference patterns are possible. First, respondents do not react to news that diverge from their beliefs, either good or bad. This behaviour suggests that respondents are insensitive to divergent news. Second, respondents react to divergent news similarly, whether

[29] The good-bad news effect is investigated using the distance between the beliefs and objective measure provided in the opt-out alternative in the good and bad-news groups. More details on the modelling approach and estimation results are provided in the online Appendix 1h.
[30] Summary statistics of these variables are presented in the online Appendix 1i.

this is good or bad. This behaviour suggests no evidence of the good-bad news effect. Third, respondents react to good and bad news differently. This behaviour supports the presence of good and bad news effect.

The investigation of the effect of good or bad news on probability weighting functions in our RDUT framework (Model 4) is examined by introducing the parametric equations below (Equations 7 and 8):

$$\gamma = \gamma_0 + \gamma_{good} goodnews + \gamma_{bad} badnews \tag{7}$$

$$\tau = \tau_0 + \tau_{good} goodnews + \tau_{bad} badnews \tag{8}$$

The second approach implies the investigation of observed heterogeneity. In particular, we explore the effect of gender (*fem*), age (*age*) and weekly apple consumption (*cons*) on all estimated coefficients.[31] Model 5 (EUT) and 6 (RDUT) imply the estimation of the following parametric equations (Equations 9-13):

$$\alpha = \alpha_0 + \alpha_{good} goodnews + \alpha_{bad} badnews + \alpha_{fem} fem + \alpha_{age} age + \alpha_{cons} cons \tag{9}$$

$$\beta_x = \beta_{x,0} + \beta_{x,good} goodnews + \beta_{x,bad} badnews + \beta_{x,fem} fem + \beta_{x,age} age +$$
$$\beta_{x,cons} cons \tag{10}$$

$$\beta_z = \beta_{z,0} + \beta_{z,good} goodnews + \beta_{z,bad} badnews + \beta_{z,fem} fem + \beta_{z,age} age +$$

[31] These variables were selected for the following reasons: i) these are the most important drivers of preferences for food policies aiming to reduce the number of contaminated apples, at least in our view; and ii) the influence of these socio-demographic variables on risk and time preferences is commonly investigated in the related literature (e.g.,Andersen et al., 2012 Harrison et al., 2008; Harrison and Rutström, 2009). Education could have been incorporated as well, but we found this variable to be highly correlated with income, which is already embedded in our econometric framework.

$$\beta_{z,cons}\, cons \quad (11)$$

$$\gamma = \gamma_0 + \gamma_{good} goodnews + \gamma_{bad} badnews + \gamma_{fem}\, fem + \gamma_{age} age + \gamma_{cons}\, cons \quad (12)$$

$$\tau = \tau_0 + \tau_{good} goodnews + \tau_{bad} badnews + \tau_{fem}\, fem + \tau_{age} age + \tau_{cons}\, cons \quad (13)$$

In all modelling approaches presented above, the estimation does not imply random parameters.[32]

5.2. Modelling time preference task-related choices

5.2.1. Random Utility Models

Choices made by respondents in the time-preference elicitation task are modelled using Fechner models, which are equivalent to multinomial logit models here. This approach is consistent with the modelling of DCE-related choices.

The utility of option A is: $V_{i,A} = \frac{(-M_A)^{1-\beta z}}{1-\beta z}$ (14)

where M_A is the amount of money respondents hypothetically pay at the end of the survey, and β_z captures the curvature of the utility function with respect to income.

The discounted utility of option B is: $V_{i,B} = (1 + /(1+\delta)^t \frac{(-M_B)^{1-\beta z}}{1-\beta z}$ (15)

where M_B is the amount of money respondents hypothetically pay in nineteen years' time, and β_z captures the curvature of the utility function with respect to income.

A traditional exponential specification for the discount rate is used.[33]

[32] The estimation of random parameters were attempted using different distributional assumptions. However, there was no presence of unobserved heterogeneity in our sample. More information are provided in the online Appendix 1j.

[33] We acknowledge that other specifications could have been used, for example the popular hyperbolic discounting specifications. However, Andersen et al. (2014) recently found no evidence to support quasi-hyperbolic and hyperbolic discounting, while they find mild support for other specifications such as the Weibull discounting model

5.2.2. Modelling observed heterogeneity

Receiving good or bad news cannot influence choice behaviour in the MPL and, hence time preferences (δ). However, we investigate the effect of gender (*fem*), age (*age*) and weekly apple consumption (*cons*) on time preferences. Model 5 (EUT) and 6 (RDUT) imply the estimation of the following parametric equation (Equation 16)[34,35].

$$\delta = \delta_0 + \delta_{fem}\, fem + \delta_{age} age + \delta_{cons}\, cons \qquad (16)$$

5.3. Estimation procedures

To describe our estimation procedures, we focus on Models 1 (EUT) and 2 (RDUT). All other models are extensions of Model 1 and 2. Coefficients α, β_x, β_z, γ, τ and δ are jointly estimated by using MSL estimations. Our estimation procedures heavily rely on the vast amount of work done by Harrison and Rutström (2008: Appendix F) and Andersen et al. (2008; 2014).

Using choices collected via the DCE task, we estimate rank ordered error component logit models, which are rooted in Luce and Suppes's Ranking Choice Theorem (1965).[36,37] Using

(Read, 2001). However, the magnitude of these discount rates do not substantially differ from the magnitude of the estimated exponential discount rate. Based on this evidence, we limit our analysis to exponential discount rate.

[34] Summary statistics of these variables are presented in the online Appendix 1i.

[35] The estimation of random parameters were attempted in all parameters using different distributional assumptions. However, there was no presence of unobserved heterogeneity in our sample. More information are provided in the online Appendix 1j.

[36] The rank-ordered multinomial logit has been often re-named in different ways in various sub-disciplines. For example, Marley and Louviere (2005) called a re-visitation of the rank-ordered multinomial logit "sequential best-worst choice model"; Marley and Pihlens (2012) refer to the "best-worst multi attribute multinomial logit"; Scarpa *et al.* (2011) refer to "exploded multinomial logit". These are all revisited version of the rank-ordered multinomial logit.

[37] The elicitation of the full weak rank-ordering does not allow respondents to express indifference between alternatives and forces them to make a choice between alternatives they may feel indifferent about. If that occurs, respondents may make less certain choices, or, even choose randomly. Additional models are estimated to control for the potential effect of the full ranking elicitation procedure on the determinism of respondents' choices. Following Scarpa *et a*l. (2011), we introduce and estimate the scale of the Gumbel Error and we allow the scale to

choices observed in the time-preference task, we estimate a standard logit model. The joint likelihood of the DCE and time-preference tasks responses is estimated using STATA13.1 and relying on 1,000 Halton draws.[38]

5.4. Welfare measures

Welfare measure are based on the notion of option price (*OP*) (Graham, 1981). The *OP*, as defined by Graham (1981) and formulated by Cameron (2005b), is equivalent to the definition of expected ex-ante compensating variation (Just, Hueth and Schimtz, 2004).[39] *OP* is the maximum ex-ante payment that equalizes the expected utility of the risk-reducing action, in our application the R&D program, and the business-as-usual scenario, in our application the opt-out alternative (Graham, 1981). Therefore, the expected *OP*, *E*(*OP*), is estimated as the mean ex-ante payments ($t_{,c,max}$) that equalize the utility of the alternative chosen by each subject i in each choice task c ($U_{i,c,max}$) and the utility of the opt-out alternative presented in each choice task ($U_{i,c,oo}$).[40]

Option prices from the EUT-based models, $E(OP_{EUT})$, is the mean $t_{,c,max}$ for which the difference between $U_{i,c,max}$ and $U_{i,c,oo}$ is equal to zero (Equation 17):

$$E(OP_{EUT}) = E\left(t_{i,c,max}\right) = inc - \Bigg[(\beta_z - 1)\Bigg(-\alpha - \frac{inc^{1-\beta_z}}{1-\beta_z} - \frac{x_{b,c,max}^{1-\beta_x}}{1-\beta_x} + \frac{x_{b,c,opt}^{1-\beta_x}}{1-\beta_x} + p\left(x_{a,c,max}\right)\left(\frac{x_{a,c,maz}^{1-\beta_x}}{1-\beta_x} - \frac{x_{b,c,maz}^{1-\beta_x}}{1-\beta_x}\right) + p\left(x_{a,c,opt}\right)\left(\frac{x_{b,c,opt}^{1-\beta_x}}{1-\beta_x} - \frac{x_{a,copt}^{1-\beta_x}}{1-\beta_x}\right)\Bigg)\Bigg]^{\frac{1}{1-\beta_z}} \tag{17}$$

vary between the first and the second ranking stage. The online Appendix 1k provides more details on this modelling and estimation results.

[38] Log-likelihood derivations are presented in the online Appendix 1l.

[39] The estimation of expected ex-post compensating variation (or expected surplus using Graham's terminology) was not attempted because ex post measure would not be appropriate for an ex-ante policy (see discussion in Cameron, (2005b)).

[40] It is assumed that respondents choose the alternative providing the highest utility in each choices situation.

Option prices from RDUT-based models ($E(OP_{RDUT})$) are estimated following the same approach (Equation 18):

$$E(OP_{EUT)} = E(t_{i,c,max}) = inc - \Bigg[(\beta_z - 1)\Bigg(-\alpha - \frac{inc^{1-\beta_z}}{1-\beta_z} - \frac{x_{b,c,max}^{1-\beta_x}}{1-\beta_x} + \frac{x_{b,c,opt}^{1-\beta_x}}{1-\beta_x} +$$

$$w[p(x_{a,c,max})]\left(\frac{x_{a,c,maz}^{1-\beta_x}}{1-\beta_x} - \frac{x_{b,c,maz}^{1-\beta_x}}{1-\beta_x}\right) + w[p(x_{a,c,opt})]\left(\frac{x_{b,c,opt}^{1-\beta_x}}{1-\beta_x} - \frac{x_{a,copt}^{1-\beta_x}}{1-\beta_x}\right)\Bigg)\Bigg]^{\frac{1}{1-\beta_z}} \quad (18)$$

Equations 17 and 18 take a closed form and a simple iterative procedure can be used to calculate $E(OP_{EUT})$ and $E(OP_{RDUT})$.[41]

Poe et al.'s (2005) convolution approach is implemented to test whether welfare measures differ: i) when EUT or RDUT is assumed and ii) when the good-bad news effect is considered or ignored. Using parametric bootstrapping techniques (i.e., Krinsky and Robb, 1986), 20,000 values for each $E(OP)$ measure were generated and 400,000,000 differences between each pair of bootstrapped distributions were calculated.[42]

6. Results

6.1. Econometric estimations of the baseline models

[41] Derivation of $E(OP_{EUT})$ and $E(OP_{RDUT})$ Equations 17 and 18 (respectively) are presented in the online Appendix 1m.

[42] Other approaches to estimate welfare measures are available. In our study policy choices and risk preferences are elicited using the same task. An alternative approach is to elicit choices and preferences using different tasks, following Harrison and Ng (2016). Pros and cons of both approaches are presented in Harrison and Ng (2016).

In this section, we focus on results from the estimation of our baseline error component logit models: Model 1 (EUT) and Model 2 (RDUT) (Table 1). The coefficients αs are negative and statistically significant in both model specifications (p<0.01), showing that respondents prefer R&D programs to the opt-out alternative. The coefficient β_x is statistically greater than 0 in all specifications indicating that respondents are overall risk averse with respect to the number of contaminated apples (p<0.01 in all specifications). The same behavioural pattern applies for the coefficient β_z which is again statistically higher than 0 in all specifications (p<0.01 in all specifications). This result reflects the correction of inferred discount rates for decreasing marginal utility of income, following Andersen et al. (2008). Estimated discount rates δ do not substantially differ across specifications and they range from 2.5% (EUT) to 3% (RDUT), approximately. These estimates are slightly lower than recent experimental evidence (approximately 10%) (e.g., Andersen et *al.,* 2008; Andersen et *al.,* 2013; Andersen et *al.,* 2014).

The coefficient γ in Model 2 is equal to 2.262, while the coefficient τ is equal to 7.396. Both coefficients are statistically different from 1 (p<0.01) and indicate that the sample of respondents does not linearly process probability information. They weigh probability according to a S-shaped probability weighting function. More interestingly, such a shape of the probability weighting function implies that subjects underweigh probabilities lower than or equal to 0.81 and almost ignore probabilities lower than 0.5. They slightly overweigh probabilities greater than 0.81 (Figure 4).

The coefficient of our error component σ is statistically significant at the 10% significance level in Model 1 (EUT), while it is not statistically significant in Model 4 (RDUT). This suggests that the utility variance of R&D and opt-out alternatives are equivalent. Finally, the coefficient λ, which is included in our modelling approach to correct for endogeneity, is positive and statistically significant (p<0.01 in all specifications).

Table 1. Maximum Simulated Likelihood Estimation[a]

Dep. Var.: *CHOICE*	EUT	RDUT
Coefficients	Model 1	Model 2
α	-0.582***	-0.074***
	(0.067)	(0.055)
β_x	0.762***	0.394***
	(0.004)	(0.046)
β_z	0.407***	0.323***
	(0.007)	(0.003)
γ		2.262***
		(0.025)
τ		7.396***
		(0.350)
δ	0.025***	0.030***
	(0.003)	(0.004)
Σ	0.002*	0.001
	(0.001)	(0.001)
Λ	2.638***	1.941***
	(0.098)	(0.074)
H_0: $\gamma = 1$	-	4,540.530***
H_0: $\tau = 1$	-	333.620***
Obs.	26,301	26,301
ID number	797	797
Log.hood	-27,604.932	-25,126.760

***p<0.01, ** p<0.05, *p<0.10
α = opt-out alternative specific constant; β_x = CRRA with respect to apples; β_z = CRRA with respect to income; γ and τ = probability weighting function; δ = discount factor; σ = error component; λ = endogeneity control
[a] Standard errors in parentheses

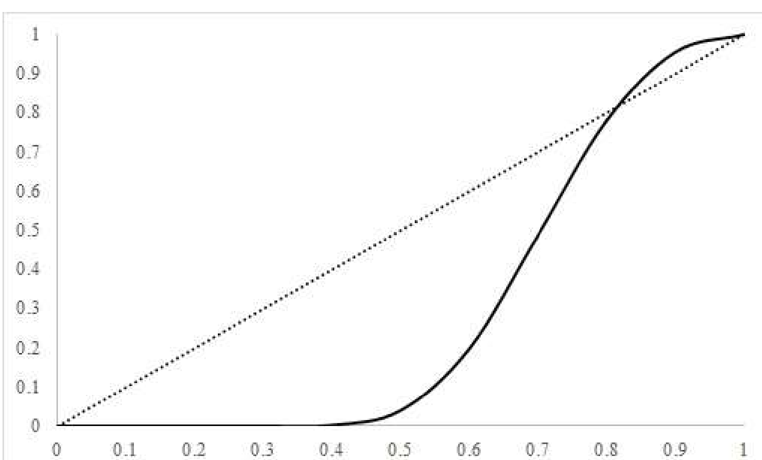

Figure 4: Probability weighting function related to Model 4 (i.e., ignoring the good-bad news effect)

6.2. The good and bad news effect

In this section, we discuss results from Model 3 (EUT) and Model 4 (RDUT), which incorporate control for the good-bad news effect. Results are presented in Table 2. The coefficients α, β_x, β_z, γ, τ, δ, σ and λ are similar to those obtained estimating Model 1 (EUT) and Model 2 (RDUT).

In both Models 3 (EUT) and 4 (RDUT), the coefficient α_{good} is positive and statistically significant (p<0.01). This suggests that respondents, who receive good news (i.e., they are told that the number of contaminated apples will be lower than they believed), prefer the opt-out alternative to the R&D program more than respondents who face an opt-out alternative that is consistent with their beliefs. In contrast, the coefficient α_{bad} is not statistically significant, meaning that bad news does not alter preferences. In fact, respondents remain indifferent between R&D and opt-out alternatives, on average. These results indicate that good news affects preferences for the opt-out alternatives, while bad news does not. We conclude that the good-bad news effect influences attitudes towards the opt-out alternative.

In Model 3 (EUT), the coefficients $\beta_{x,good}$ and $\beta_{x,bad}$ are not statistically significant, indicating that the news, either good or bad, does not affect risk preferences for the apple outcome. In contrast, in Model 4 (RDUT), $\beta_{x,good}$ and $\beta_{x,bad}$ are positive and statistically significant (p<0.01). This indicates that respondents who receive news that diverges from their beliefs, either good or bad, are more risk averse with respect to contaminated apples than the others. Therefore, these subjects are less responsive to decreases (or increases) in the number of contaminated apples. This result does not entirely support the good-bad news effect on risk preferences for the contaminated apple outcome because respondents react similarly to good and bad news.

In both Models 3 (EUT) and 4 (RDUT), the coefficients $\beta_{z,good}$ and $\beta_{z,bad}$ are positive and statistically significant (p<0.01). This indicates that respondents, who receive divergent news, either good or bad, are more risk averse with respect to income than the others. As before, we find that subjects respond similarly to good and bad news. Hence, we conclude that the good-bad news effect does not substantially affect risk preferences related to income.

Interestingly, the good-bad news effect appears to influences respondents' probability weighting in Model 4 (RDUT). The coefficient γ_{good} is equal to 2.913 (p<0.01) and the coefficient τ_{good} is equal to -0.757 (p<0.01). The negative sign of coefficient τ_{good} informs that the inflection point of the probability weighting function of respondents who receive good news is lower than the inflection point of respondents who receive news that is consistent with their beliefs. In addition, the positive sign of the coefficient γ_{good} indicates that respondents who receive good news overweigh high probability outcomes more than respondents who receive news that is consistent with their beliefs. In our DCE, high probabilities (i.e., higher than 0.5) are always related to the bad state of the world, and therefore we conclude that respondents who receive good news are less concerned about the bad outcomes. If we take Figure 4 as a reference point, the coefficient γ_{good} and τ_{good} imply the S-shaped probability weighting function depicted in Figure 5a. In contrast, the coefficient γ_{bad} is equal to 0.136 (p<0.01) and the coefficient τ_{bad} is equal to -0.209 (p<0.01). These coefficients imply a probability weighting functions, which is very similar to that obtained when the good-bad news is ignored (Figure 5b). We conclude that the good-bad news effect strongly influences the way respondents weigh probabilities.

To summarize, our results suggest that the good-bad news effect mainly affects preferences for the opt-out alternative and probability weighting. Risk preferences for contaminated apples and income appear to be affected by divergent news in general. The good or bad nature of the news do not affect risk preferences.

Table 2. Maximum Simulated Likelihood Estimation[a]		
Dep. Var.: *CHOICE*	EUT	RDUT
Coefficients	Model 3	Model 4
α	-0.809***	-0.327***
	(0.085)	(0.068)
α_{good}	0.655***	0.346***
	(0.110)	(0.128)
α_{bad}	-0.262	-0.052
	(0.169)	(0.200)
β_x	0.773***	0.360***
	(0.005)	(0.053)
$\beta_{x,good}$	-0.027	0.583***
	(0.021)	(0.056)
$\beta_{x,bad}$	-0.006	0.455***
	(0.005)	(0.105)
β_z	0.249***	0.199***
	(0.012)	(0.009)
$\beta_{z.good}$	0.202***	0.260***
	(0.032)	(0.029)
$\beta_{z,bad}$	0.499***	0.417***
	(0.019)	(0.026)
γ		2.577***
		(0.022)
γ_{good}		2.913***
		(0.020)
γ_{bad}		0.136***
		(0.044)
T		7.854***
		(0.435)
τ_{good}		-0.757***
		(0.061)
τ_{bad}		-0.209***
		(0.063)
δ	0.023***	0.049***
	(0.003)	(0.005)
σ	0.002*	0.001
	(0.001)	(0.001)
λ	2.789***	2.091***
	(0.103)	(0.081)
$H_{0:}$ $\gamma = 1$	-	4,968.235***
$H_{0:}$ $\tau = 1$	-	246.728***
Obs.	26,301	26,301
ID number	797	797
Log.hood	-27,249.421	-24,841.869

***p<0.01, ** p<0.05, *p<0.10

α = opt-out alternative specific constant; β_x = CRRA with respect to apples; β_z = CRRA with respect to income; γ and τ = probability weighting function; δ = discount factor; σ = error component; λ = endogeneity control

[a] Standard errors in parentheses

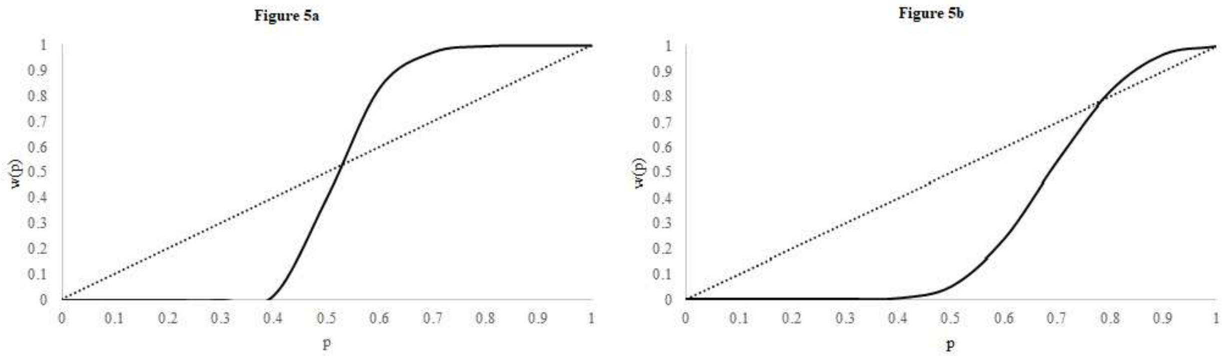

Figure 5: Probability weighting function related to Models 4. Note: Figure 5a, relates to Model 4 when only the good news is taken into account and Figure 5b relates to Model 4 when only the bad news is taken into account

6.3. Observed heterogeneity

In this section, we discuss results from Model 5 (EUT) and Model 6 (RDUT), which investigate the effect of gender (*fem*), age (*age*) and weekly apple consumption (*cons*) (Table 3).

Gender does not affect respondents' preferences. In fact coefficients α_{fem}, $\beta_{x,fem}$, $\beta_{z,fem}$, γ_{fem}, $\tau_{\text{fem and}}$ δ_{fem} are not statistically significant.

The coefficients α_{cons} are negative and statistically significant in both specifications (p<0.01), indicating that respondents who generally consume apples prefer R&D alternatives than the opt-out alternative. The coefficients $\beta_{z,cons}$ are negative and statistically significant in both specifications (p<0.01), indicating that respondents who generally consume apples are less risk averse (with respect to income) than the others. All the other interaction terms involving the apple consumption variable are not statistically significant.

The coefficients $\beta_{z,age}$ is positive and statistically significant in both specifications (p<0.01), suggesting that the older respondents are more risk averse than the others. All the other interaction terms involving age are not statistically significant.

Table 3. Maximum Simulated Likelihood Estimation[a]		
Dep. Var.: *CHOICE*	EUT	RDUT
Coefficients	Model 5	Model 6
α	-0.837***	-0.365***
	(0.100)	(0.087)
α_{good}	0.672***	0.362***
	(0.123)	(0.139)
α_{bad}	-0.273	-0.060
	(0.171)	(0.218)
α_{age}	0.001	0.001
	(0.002)	(0.002)
α_{fem}	0.126	0.130
	(0.098)	(0.112)
α_{cons}	-0.413**	-0.386***
	(0.161)	(0.121)
β_{x}	0.763***	0.369***
	(0.008)	(0.058)
$\beta_{x,good}$	-0.022	0.579***
	(0.022)	(0.055)
$\beta_{x,bad}$	-0.007	0.457***
	(0.007)	(0.105)
$\beta_{x.age}$	0.001	0.000
	(0.001)	(0.000)
$\beta_{x,fem}$	0.010	0.021
	(0.007)	(0.040)
$\beta_{x,cons}$	-0.015	-0.002
	(0.015)	(0.002)
β_{z}	0.294***	0.225***
	(0.017)	(0.013)
$\beta_{z.good}$	0.204***	0.265***
	(0.033)	(0.031)
$\beta_{z,bad}$	0.504***	0.425***
	(0.018)	(0.024)
$\beta_{z.age}$	0.001***	0.001***
	(0.000)	(0.000)
$\beta_{z,fem}$	0.005	0.015
	(0.027)	(0.011)
$\beta_{z,cons}$	-0.065**	-0.042***
	(0.030)	(0.020)
γ		2.572***
		(0.020)
γ_{good}		2.915***
		(0.020)
γ_{bad}		0.138***
		(0.044)
γ_{age}		-0.004
		(0.007)
γ_{fem}		-0.001
		(0.230)
γ_{cons}		0.513
		(0.440)

Table 3. (continued)		
τ		7.866***
		(0.437)
τ_{good}		-0.752***
		(0.058)
τ_{bad}		-0.205***
		(0.059)
τ_{age}		0.007
		(0.007)
τ_{fem}		0.002
		(0.100)
τ_{cons}		0.111
		(0.098)
δ	0.022**	0.047***
	(0.008)	(0.005)
δ_{age}	0.001	0.003
	(0.001)	(0.003)
δ_{fem}	0.005	0.007
	(0.005)	(0.007)
δ_{cons}	0.002	0.002
	(0.009)	(0.008)
σ	0.002*	0.001
	(0.001)	(0.001)
λ	2.806***	2.188***
	(0.105)	(0.090)
H_0: $\gamma = 1$	-	4,956.855***
H_0: $\tau = 1$	-	244.683***
Obs.	26,301	26,301
ID number	797	797
Log.hood	-27,198.592	-24,805.235

***p<0.01, ** p<0.05, *p<0.10

α = opt-out alternative specific constant; β_x = CRRA with respect to apples; β_z = CRRA with respect to income; γ and τ = probability weighting function; δ = discount factor; σ = error component; λ = endogeneity control

[a] Standard errors in parentheses

6.4. Log-likelihood ratio tests

We conduct two sets of log-likelihood ratio tests. Results from the first set are presented in Table 4 and indicate that models controlling for the effect of good-bad news and observed heterogeneity are superior in terms of explanatory power to other models in both the EUT and RDUT framework ($p<0.01$). Results from the second set are presented in Table 5 and show that the RDUT models (Models 2, 4, and 6) outperform the EUT models (Models 1, 3 and 5) ($p<0.01$).[43]

Table 4. Log-likelihood Ratio Test for good-bad news and observed heterogeneity

a. EUT	
H0	**LR statistic**
Model 1 vs Model 3	711.022***
Model 1 vs Model 5	787.060***
Model 3 vs Model 5	60.764***
b. RDUT	
H0	**LR statistic**
Model 2 vs Model 4	569.604***
Model 2 vs Model 6	643.324***
Model 4 vs Model 6	73.720***

***p<0.01; **p<0.05; *p<0.10

Table 5. Log-likelihood Ratio Test for EUT vs RDUT

H0	**LR statistic**
Model 1 - EUT vs Model 2 – RDUT	4,956.256***
Model 3 - EUT vs Model 4 – RDUT	4,815.444***
Model 5 - EUT vs Model 6 – RDUT	4.811.219***

***p<0.01; **p<0.05; *p<0.10

[43] In the related literature, there is contrasting evidence regarding the superiority (in "predicting the facts") of RDUT with respect to EUT. A relatively detailed review of this literature is provided in the online Appendix 1a.

6.5. Welfare measures

Four welfare measures are estimated: i) $E(OP_{Model1})$ assuming EUT and ignoring the good-bad news effect; ii) $E(OP_{Model2})$ assuming RDUT and ignoring the good-bad news effect; iii) $E(OP_{Model5})$ assuming EUT and controlling for the good-bad news effect; and iv) $E(OP_{Model6})$ assuming RDUT and controlling for the good-bad news effect. The yearly tax that respondents are willing to pay, on average, to implement the R&D program ranges from approximately €4.194 to €72.529 per year, depending on the modelling approach (Table 6a).

These $E(OP)$s are slightly lower than those estimated in the only other comparable study that we know of. Smith et al. (2014) estimated an annual marginal *WTP* of about $150 as ex-ante *compensation variation* measure for plans reducing food borne illness.[44]

Results of Poe et al.'s (2005) tests suggest that welfare measures are affected by assumptions on the theory used to model choices (i.e., EUT or RDUT) (Table 6b). Welfare estimated based on RDUT are statistically lower than those obtained by using EUT. In addition, controlling for the good-bad news effect does not affect welfare estimates when choices are modelled using RDUT, while it does when choices are modelled using EUT (Table 6c). These results suggests that the use of EUT-based model without controlling for the good-bad news effect may produce upwardly biased welfare estimates.

[44] Approximately €100 based on the exchange rate in 2007.

Table 6. Average option prices and results from the convolution approach[a]	
a. Mean Option price (€/year)	
$E(OP_{Model1})$	72.52 (40.050; 105.664)
$E(OP_{Model2})$	8.29 (-0.370; 14.338)
$E(OP_{Model5})$	17.53 (10.429; 20.006)
$E(OP_{Model6})$	4.19 (1.741; 7.341)
b. Testing differences between EUT and RDUT models (P-value)	
H_0: $E(OP_{Model1}) = E(OP_{Model2})$	0.000
H_0: $E(OP_{Model5}) = E(OP_{Model6})$	0.000
c. Testing differences between models with control for the good-bad news effect and models with no control (P-value)	
H_0: $E(OP_{Model1}) = E(OP_{Model5})$	0.000
H_0: $E(OP_{Model2}) = E(OP_{Model6})$	0.347

***p<0.01; **p<0.05; *p<0.10
[a] Confidence Intervals (5%;95%)

7. Conclusions

This study investigates preferences and welfare benefits for food-safety policies, which generate long-term and uncertain outcomes. The paper focuses on policies geared to reduce the pesticide residues in apples in the future and explores how the provision of probabilistic information regarding possible policy outcomes affects the public's support for these policies. More interestingly, the present work also aims to shed light on how people respond to probabilistic information depending on whether this is perceived as bad or good news (i.e., the good-bad news effect).

In our survey, we elicit subjective beliefs, risk attitudes and time preferences using different hypothetical tasks. Subjective beliefs about the number of contaminated apples are elicited using the EM. Risk attitudes towards contaminated apples and monetary outcomes are elicited using a novel DCE. In the DCE, each alternative policy scenario is framed as a binary lottery, in which probabilities that a given number of apples will be contaminated are presented to respondents. Time preferences are elicited using a MPL format. A potential limitation of our study is the use of hypothetical elicitation methods that are not as reliable as incentive compatible elicitation procedures.

Using collected data, we estimate EUT- and RDUT- based models using MSL estimation procedure. Risk attitudes and time preferences are estimated, while controlling for the potential effects of receiving good and bad news regarding the number of contaminated apples. To the best of our knowledge, the present study is the first attempt to simultaneously control for probabilistic beliefs, risk attitudes and time preferences in a DCE-based welfare evaluation of a food policy.

Estimation results suggest the provision of news that diverge from respondents' beliefs affects preferences. However, the influence of the good-bad news effect on preferences is limited. In particular, respondents who receive good news are less attracted by the costly policy options than subjects who receive news that is consistent to their beliefs. Bad news does not appear to have an effect on preferences, suggesting that respondents are not willing to process negative information. These results appear to be in line with recent works, suggesting that people are more willing to accept good rather than bad news.

Very interestingly, we find that the good-bad news effect influences probability weighting. Respondents who receive good news tend to attach different weight to low and high probability outcomes, when they are presented with probabilities that diverge from their beliefs. The influence of bad news on probability weighting is much more restricted. In addition, we found that the good-bad news effect does not seem to influence risk preferences for contaminated apples and income. In fact, respondents react to good and bad news very similarly: they become more risk averse.

Our results also suggest that RDUT-based models explain choice-behaviour better than EUT-based models. In addition, we found that the estimation of EUT-based models without controlling for the good-bad news effect produces upwardly biased welfare estimated. The good-bad news effect appears to have a negligible and non-statistically significant influence on welfare measured based on RDUT models.

Our study shows that probabilistic beliefs and the provision of information affect respondents' preferences for long-term and uncertain food policies. Our findings and analyses also highlight new opportunities for further research investigating the extent to which different ways of communicating baseline risks affect information updating tendencies and thereby affect the anticipated benefits of future food policies. Future research that helps identify effective strategies to communicate critical risk information to laypeople and ultimately shapes public support for food policies is critically important.

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