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Bidding behaviour in experimental auctions under risk and uncertainty

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Abstract

This paper explores bidding behaviour under risk and uncertainty using the Becker-DeGroot-Marschak mechanism (BDM) and second price auction (SPA). It investigates whether values elicited via the two mechanisms are consistent and whether bidding behaviour can be influenced by differences in the number and type of sources of risk and uncertainty that people face when exposed to the two mechanisms. In our experiment, subjects are exposed to non-monetary lotteries where they bid for a high-quality seafood product, but there is a chance (known or unknown) that they receive a lower quality seafood product instead. Results indicate that bidding behaviour can be influenced by the number and type of sources of risk and uncertainty that subjects face and subjects' bidding behaviour is only consistent with standard theories of decision making under risk and uncertainty when they bid on a risky product in the SPA. Despite this, BDM and SPA elicit equal values under risk and uncertainty in this study.

Keywords Risk · Uncertainty · Becker-DeGroot-Marschak mechanism · Second price auction · Non-monetary lotteries

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1 Introduction

Even though many decisions by economic agents are made under conditions of risk and uncertainty, the literature investigating bidding behaviour in experimental auctions where the characteristics of the auctioned goods are risky or uncertain is scarce. In this paper, we refer to risk and uncertainty in the Knightian fashion i.e., a situation is risky when the probability of each outcome occurring is known and uncertain when the probability of outcomes occurring is unknown. While experimental auctions are widely used to elicit reservation prices (i.e., certainty equivalents) for monetary lotteries with known and unknown probabilities (Attanasi et al., 2014; Conte & Hey, 2013) there are very few studies eliciting willingness to pay (WTP) for non-monetary lotteries where the quantity and/or the quality of the auctioned good is risky or uncertain (e.g. Sonsino, 2008).

This area of research needs further exploration as many consumer purchasing decisions are made under conditions of risk and uncertainty of this type. For example, consumers may not be completely certain of a product's quality at the time of purchase. This uncertainty is well founded as 6 percent of products entering the European Union (EU) in 2016 were estimated to be counterfeit (European Union Intellectual Property Office, 2019). This figure does not include domestically produced products or those sold online, and so the number of inauthentic products on the market is likely much larger. Regarding online sales, a recent investigation found that 4152 items on Amazon were declared unsafe by federal agencies, deceptively labelled or deceptively branded (Berzon et al., 2019).

Eliciting accurate values is important when experimental auctions are conducted to inform businesses and decision makers. In the literature, the accuracy of elicited values has been investigated by testing empirically whether two or more mechanisms elicit the same WTP for the same private good (Rutström, 1998). Empirical research provides mixed results on whether different auction mechanisms elicit the same WTP for a wide range of private goods that do not display any risk or uncertainty regarding the provision of the auctioned good (Lusk et al., 2004; Lusk & Schroeder, 2006; Caputo et al. 2023). Importantly, there are no studies testing whether different mechanisms elicit the same WTP when the auctioned good displays risk and/or uncertainty in its provision (i.e. product provision risk and uncertainty). This is the first gap in the literature that this paper aims to fill. Our focus is on BDM and SPA as these value elicitation techniques are widely used in many branches of applied economics. A better understanding of accuracy of values elicited via these mechanisms under product provision risk and uncertainty is very important since BDM and SPA results inform business and policy makers in such contexts.

Deviations in values elicited using BDM and SPA can be due to many factors. One stream of research focuses on subjects' misconceptions of the game form (e.g. Cason & Plott, 2014; Bull et al., 2019; Martin and Muñoz-Rodriguez, 2022; Drichoutis and Nayga, 2022).[1] Another stream focuses on potential differences in the expected cost of deviating from the weakly dominant strategy (Noussair, et al.,

[1] Specifically, in the BDM subjects do not recognise the second-price auction's incentive scheme and behave as if they play a first-price auction.

2004; Lusk et al., 2007). This paper focuses on a strand of research which has received little attention: the number and type of sources of uncertainty that subjects face when asked to bid for risky or uncertain goods using BDM and SPA. The focus is driven by a key difference in the design of the two mechanisms which may have consequences on bidding behaviour under risk and uncertainty. This difference relates to the amount of information they convey to subjects about the distribution of market prices. In the BDM, subjects are informed of the distribution of the randomly drawn market prices. In the SPA, the market price is the second highest bid and subjects cannot possibly know other bidders' valuations for the auctioned good.[2] Hence, while subjects face a situation of risk regarding the market price in the BDM (i.e., the market price distribution is known—"market price risk"), they face a situation of uncertainty regarding the market price in the SPA (i.e., the price distribution is unknown—"market price uncertainty").When the auctioned good is a lottery with known or unknown probabilities, these sources of risk and uncertainty produced by design are added to other sources of uncertainty related to the provision of the good.[3] Previous literature suggests that people have difficulties dealing with multiple sources of risk and uncertainty (e.g. Abdellaoui et al., 2011; Baillon, 2008) and that the source of uncertainty matters (e.g. Lange & Ratan, 2010; Li et al., 2018; Rosato & Tymula, 2019). This is likely to generate deviations from standard theories of decision making under risk and uncertainty, which can affect the incentive compatibility of value elicitation mechanisms and hence bidding behaviour.

There exists a niche literature showing that SPA and BDM may no longer be incentive compatible when bidding behaviour deviates from standard theories of decision making under risk and uncertainty, namely, Expected Utility Theory (EUT) (von Neumann and Morgenstern, 1944) and Subjective Expected Utility Theory (SEUT) (Savage, 1954). Horowitz (2006) formally proved that the Becker-DeGroot-Marschak mechanism (BDM) and second price auction (SPA) are not theoretically demand revealing when used to elicit values for certain goods if subjects deviate from standard EUT and behave according to reference-dependent preference models (Kőszegi & Rabin, 2006). Karni and Safra (1986) and Chew (1989) proved that these mechanisms are no longer demand revealing when the provision of the auctioned good is risky or uncertain and subjects behave according to Rank Dependent Expected Utility Theory (RDEUT) (Quiggin, 1982). RDEUT builds upon EUT by introducing non-additive decision weights (i.e. weighing of probabilities) which handles observed violations of EUT (Abdellaoui, 2009). A more detailed overview of this line of research is provided in Appendix B. In the literature, there are no attempts to empirically test whether bidding behaviour departs from standard theories of decision making under risk and uncertainty in SPA and BDM. This is another gap in the literature filled by this paper. Specifically, we investigate whether the presence of different combinations of "product provision" and "market price" risk and uncertainty influence subjects' bidding behaviour and its potential departure

[2] In a multiple round SPA, it is possible to reveal winning or losing bids after each round. We purposely do not use this design so we can explore if the difference in the knowledge of the distribution in the BDM has an effect.

[3] See Figure B1 in Appendix B for an overview of sources of risk and uncertainty present.

from standard theories of decision making under risk and uncertainty. We hypothesize that the departure is more prominent in SPA rather than BDM because subjects will find it more difficult to deal with "market price" uncertainty rather than "market price" risk.

To this end, we conduct an artefactual field experiment that consists of two between-subject treatments: SPA and BDM. Subjects are asked to bid for non-monetary lotteries with known (i.e., risk) and unknown probabilities (i.e., uncertainty). In our empirical application, subjects participate in auctions for a high-quality seafood product, but there is a chance (known or unknown) that they buy a lower quality seafood product instead. This setting resembles a food fraud incident. In addition, deviations from EUT are established by exposing subjects to Tanaka, Camerer, and Nguyen (2010) multi price list (MPL) format, which allows us to investigate subjects' risk preferences and whether they process probabilities linearly (according to EUT) or not (according to REDUT). Deviations from SEUT are explored thanks to the elicitation of ambiguity preferences using Chakravarty and Roy's (2009) MPL. Subjective probabilities regarding the authenticity of fish products are elicited using a quadratic scoring rule (QSR) (Brier, 1950). All behavioural factors are elicited using monetary incentives and incentive compatible elicitation techniques.

Our results suggest that bidding behaviour can be affected by the sources of uncertainty subjects are exposed to in the SPA. Bidding behaviour does not depart from standard theories when subjects face "product provision risk" in the SPA. In contrast, bidding behaviour is not consistent with any theory (EVT, EUT or RDEUT) in the BDM, suggesting that subjects' valuation cannot be aligned with any theoretical frame suggesting that our sample find it difficult to deal with the BDM. When subjects face uncertainty in the provision of the good, bidding behaviour is not consistent with any theories in the SPA or BDM, suggesting that subjects find it difficult to deal with an additional source of uncertainty. This suggest that while SPA is incentive compatible under "product provision risk" it is not under "product provision uncertainty". However, our results also indicate that values elicited by BDM and SPA are equal across mechanisms when the auctioned good is delivered with certainty, under risk and under uncertainty. This indicates that deviations from standard theories of decision making under risk and uncertainty do not affect the consistency of values elicited by BDM and SPA.

The rest of the paper consists of a discussion of the empirical application in Section 2, experimental design is outlined in Section 3, the estimation and results of the empirical studies just described are in Sections 4 and 5, and Section 6 concludes.

2 Empirical application

Consideration of risk and uncertainty is particularly relevant in food purchasing decisions, as such decisions could lead to food safety and human health problems. To examine risk and uncertainty, this study utilises the concept of "food fraud", which involves deliberate or intentional substitution, altering or misrepresentation of the food, its ingredients or packaging for economic gain (HM Government, 2014). We focus on a situation where a product is falsely labelled or sold as a brand or type of product (which it is not) to gain a higher price.[4] This type of fraud occurs in many food products with the highest levels found in animal products and pre-prepared dishes. We focus on fish because it shows one of the higher levels of such fraud among food products globally (Food Standards Agency (FSA) 2013; Warner et al., 2016).

In our study, we re-create in the lab, a possible food fraud incident happening in a supermarket. Consumers purchase what they expect to be (and what is labelled as) a high-quality fish product but there is a chance they may receive a lower-quality fish product due to mislabelling. The high-quality fish is pollan caught in Lough Neagh (Northern Ireland). This product has obtained an EU Protected Designation of Origin (PDO) label which recognises it as a high-quality regional speciality fish in consumers' eyes. A PDO, as with any other EU Geographical Indication (GI) label, enables those who have the right to use the indication to prevent its use by a third party whose product does not meet the designated standards (European Commission, 2013; World Intellectual Property Organization, 2019). These logos were created to protect consumers and producers against imitation and misuse of product names. The low-quality product in our experimental setting is herring fished in United Kingdom (UK) waters. This product has not obtained a GI and is generally seen as an inferior product by UK consumers.

3 Experimental design

3.1 Sample and experiment overview

Our sample consists of 158 consumers randomly recruited from the population living in or near Belfast, Northern Ireland.[5] The study was advertised as a consumer food choice study for fish products. The experiment took place at Queen's University Belfast and received ethical approval from the Ethics Board for the Faculty of Medicine, Health and Life Sciences. Sessions ran at 1 pm or 6 pm to control for possible cofounding effects related to time of day. All sessions were programmed and run using z-Tree (Fischbacher, 2007).

The sample was randomly split across two treatment groups, one for each value elicitation method: 81 subjects were allocated to the BDM treatment and 77 were allocated to the SPA treatment.[6] Each subject is given a show-up fee of £20 which is

[4] There is potential for food fraud to lead to illness or death due to contaminated food or food that is not what it claims to be. It is important to highlight that the type of food fraud used in this experiment does not result in food safety issues but rather food authenticity/quality issues; therefore, there is no possible negative health outcome.

[5] The original sample consisted of 162 consumers. However, data on gender was missing for 3 participants and age was missing for 1 participant hence these observations were dropped.

[6] In the SPA we ran eight sessions: three sessions with eight participants, three with twelve participants, one with sixteen participants and one with four participants. For BDM we ran six sessions: two with eleven participants, one with thirteen, one with fourteen, one with fifteen and one with eighteen participants. Sessions lasted between 1.5 and 2 h. There was a five-minute break after part ii) due to the length of the experiment.

Table 1 Experimental design: sequence of tasks, methods and parameter ranges

Section 1 Questionnaire to ascertain how hungry/full participants are			
Section 2 Behavioural tasks			
No	Task	Method	Parameter range
1	Subjective probability of receiving an authentic fish product (q)	Quadratic scoring rule (Brier, 1950) corrected using Offerman et al. (2009)	{0,..,1}
2	Risk aversion (σ)	MPL (Tanaka, 2010)	{0.05,..,1.50}
3	Probability weighting (γ)		{0.05,..,1.45}
4	Loss aversion (λ)		{0.14,…,9.67}
5	Ambiguity aversion (φ)	MPL (Chakravarty & Roy, 2009)	{0.23,..,1.26}
Section 3 Value elicitation			
Portion of fish		Method	
Pollan		BDM or SPA based on treatment group	
Herring			
Pollan with an unknown probability p to receive herring instead (uncertain)			
Pollan with a known probability p to receive herring instead (risky)			
Section 4 Sociodemographic and shopping habits questionnaire			

paid to them before the experiment started. They complete the following sections in order: (i) questionnaire to ascertain how hungry and full consumers felt before the experiment (ii) behavioural factors elicitation tasks, (iii) value elicitation tasks and (iv) sociodemographic and shopping habits questionnaire.[7] More details of each section are shown in Table 1.

Before each task takes place, the experimenter provides instructions shown on a monitor at the front of the room. Subjects complete the tasks on a private computer screen. Subjects' final payoff depends on their decisions in parts (ii), (iii) and (iv). They are not informed of the outcome of any of the tasks until after the questionnaire is completed. This is to prevent any potential wealth effects in subsequent tasks.

3.2 Value elicitation

Subjects are asked to bid on four different scenarios, all involving portions of frozen fish fillets (250 g). These scenarios are (i) pollan (ii) herring (iii) pollan with an

[7] Experimental instructions are provided in the online supplementary appendix A. Detailed examples were given in the instructions for each task, participants were free to ask questions about the tasks.

unknown probability p that they could receive herring instead (uncertain) and (iv) pollan with a known probability p that they could receive herring instead (risky).[8]

Subjects are told that to resolve the uncertainty in scenario (iii), at the end of the experiment, we will randomly draw a coloured chip from a bag of 100 chips which are blue and purple. They are told that the number of purple chips represents the probability of receiving an inauthentic fish product on the UK market in 2018, based on statistics from FSA (2013) and experts' opinions gathered in a preliminary phase of the project.[9] This is all the information given; hence the probability p is not disclosed. If a blue chip is drawn, they receive pollan; otherwise they receive herring.

Subjects are also informed that to resolve the risk in scenario (iv), we will randomly draw a coloured chip from the same bag. In this case, the probability p is disclosed to them and is equal to 8%; i.e., there is an 8 in 100 chance that they could receive herring (92 blue chips and 8 purple chips). This figure is based on the latest available data (source: Food Standards Agency, 2013). The risky scenario resembles a real-world scenario when an authorised source publishes a new report, and this is widely reported in the news media.

Before subjects bid in the auctions, they are given a description of pollan and herring. Then, they are invited to the experimenter's desk to see the two showcase portions of frozen fish (pollan and herring). These have a similar appearance and packaging and are labelled herring or pollan. The portions of fish were stored in a freezer at the location of the experiment (Queen's University Belfast). Subjects are informed that they can buy only one portion of fish and that this portion will be determined at the end of the experiment with a random draw.[10][11]

3.3 WTP elicitation methods

3.3.1 Second price auction

Subjects are informed that they bid against 3 other bidders (group size = 4) and asked to submit their bids privately (sealed bids) on a computer screen. Subjects could place bids in £0.05 increments. As standard, the highest bidder buys the good at a market price which is equal to the second highest bid. At the end of the experiment, a random draw determines which portion of fish the winners buy. If scenario

[8] The order of (i) pollan and (ii) herring was randomised across sessions. In half of the sessions, subjects bid for pollan first, while in the other half, on herring first. The order of (iii) uncertain and (iv) risky scenarios was always the same in all sessions because the probability of receiving herring cannot be disclosed before subjects bid in the uncertain scenario. The same applies for the BDM setting.

[9] Four food fraud experts, from UK universities and food research organisations, were interviewed in October 2018. As statistics about food fraud in the UK in 2018 were not available, semi structured interviews took place in which experts provided estimates for the probability of this fraud occurring for different products.

[10] Before bidding for the fish products, as a practice and to familiarise themselves with the mechanism participants bid in an induced value task.

[11] We use two proxies to measure if participants perceive pollan as higher quality than herring. Firstly, participants perceive pollan would be tastier than herring on average (see Appendix H) and their willingness to pay for pollan was £0.98 higher than for herring (see Appendix F).

(iii) or (iv) is randomly drawn, the risk (iii) or uncertainty (iv) about the fish is resolved by an additional random draw. The bag with 92 blue chips (corresponding to pollan) and 8 purple chips (corresponding to herring) is used. Instructions follow Lusk and Schroeder (2006) and Cerroni et al., (2019a, b).

3.3.2 BDM mechanism

As standard in the BDM, subjects buy the auctioned good if their bid is higher than the market price which is determined by randomly drawing a price from a uniform distribution with supports [x_{lower}, x_{upper}]. The price at which they buy the portion of fish is equal to the randomly drawn market price. Subjects do not buy the auctioned good if their bid is lower than the market price. The supports are equal across the four scenarios, [£0.05, £8.00] in £0.05 increments. Subjects could place bids in £0.05 increments. Our instructions follow Lusk et al. (2004).

3.4 Eliciting behavioural drivers of willingness to pay

Five different tasks are used to elicit the behavioural factors of interest. All subjects are exposed to these tasks in the same order.[12] Only one of these tasks determines additional earnings for subjects in part (ii) of the experiment. This is randomly drawn at the end of the experiment and is called the binding task. The range of parameters for each task are shown in Table 1.

3.4.1 Eliciting subjective probabilities

In task 1, subjects' subjective beliefs about the probability that a fish product is authentic in the UK market in 2018 (event E) are elicited using the QSR (Brier, 1950). The elicitation of subjective probabilities about event E is needed to model choice behaviour under uncertainty. In the QSR, subjects are asked to select one row among 21 rows. Each row generates two payoffs, one if the fish product will be authentic in the UK market in 2018 (event E) and, the other if the fish product will be inauthentic on the UK market in 2018 (event E_c). Each subject will be paid one payoff or the other depending on whether the fish product will be authentic or inauthentic on the UK market in 2018. To determine subject's payoff, we randomly draw a coloured chip from a bag of 100 chips where purple chips represent inauthentic fish products and blue chips represent authentic fish products. They are told the mix of chips is based on statistics from FSA and experts' opinions.

Each row represents a probability $r \in \{0, 0.05, \ldots, 0.95, 1\}$. Hence, the selected row indirectly informs the researcher regarding the subjective probability r attached to the event E. Our instructions follow those provided in (Trautmann and van de Kuilen 2015). More details regarding the creation of the payoff matrix, the procedure

[12] Tasks were not randomised as tasks 2–4 were kept in order to follow Tanaka et al. (2010). Task 1 and 5 were not randomised as Task 5 was complicated so we did not put it as the first task.

to determine subjects' final payoff from this task and the task shown to the participant is presented in the online supplementary appendix C.

While the QSR overcomes non-incentive compatibility issues of other elicitation methods which do not provide incentives (e.g. Likert scales and direct elicitations), the QSR can be biased if subjects are not risk neutral and they do not process probabilities linearly (Offerman et al., 2009). Potentially biased subjective probabilities are corrected using the Offerman et al.'s approach (2009). We correct potentially biased subjective probability using individual-specific coefficient of relative risk aversion (CRRA) and parameters that indicate the shape of the probability weighting function as estimated in Sect. 4 of the paper using data from Task 2 and 3. However, corrected probabilities may remain biased due to a lack of behavioural incentive compatibility of the QSR (see Danz et al., 2022).[13] More details on this procedure and a further discussion about QSR and alternative methods are provided in the online supplementary appendix C.

3.4.2 Risk preferences and probability weighting

Risk preferences, probability weighting and loss aversion are elicited using three sets of paired lotteries as per the Tanaka, Camerer, and Nguyen (2010).[14] In task 2, subjects are asked to make choices between two binary lotteries in 13 decision problems. They must make a choice for each row. In task 3, subjects face 14 decision problems.,[15][16] In each row subjects are asked to choose between option A and option B. Option A and B are binary lotteries $L[p,x;(1\text{-}p),y]$ with probabilities p and $(1\text{-}p)$, illustrated as a fraction of numbered chips (i.e. chip 1–3 is equal to 3/10), and monetary payoffs x and y.

The lotteries are designed so that any combination of choices in the tasks determine different RDEUT parameter values. The switching points (i.e. the first decision problem where subjects choose option B) in task 2 and 3 jointly determine risk aversion (σ) and probability weighting (γ). Our instructions follow those provided in Tanaka, Camerer, and Nguyen (2010). More details on the parametrisation of subject's utility functions, procedures used to determine subjects' payoff and the task shown the participants are in the online supplementary appendix D.

[13] Behavioural incentive compatibility requires that information on incentives increases truthful revelation and that most participants choose the outcome thought to be uniquely maximizing however Danz et al. (2022) find that the majority of participants fail to select the outcome assumed to be the unique maximiser in the QSR.

[14] A description of strengths and limitation of MPL-based methods to elicit risk preferences, probability weighting function parameters and loss aversion with respect to other approaches is beyond the scope of this paper. A discussion is provided in the online supplementary appendix D.

[15] While the probabilities used in tasks 2 and 3are the same as Tanaka et al.'s the payoffs are different. Payoffs were transformed, for task 2 and 3 dividing by 10 and task 4 dividing by $6^2/_3$, with the transformations the parameters remain the same. Task 3 has the same number of choices as Tanaka et al.'s while task 2 has one less choice due to the size of the payoff for the final choice.

[16] While there was a fourth task with 7 decisions which elicits loss aversion, we do not use the loss aversion parameter in this paper as decisions for the fish products were in the gain domain.

3.4.3 Ambiguity preferences

Ambiguity preferences are elicited in task 5 using Chakravarty and Roy's MPL-based approach (2009).[17] Subjects are asked to make choices in 10 decision problems. Before facing these decision problems, subjects are asked to bet on the occurrence of a blue or yellow token. In each decision problem, they are asked to choose between a risky lottery (option A) in which there is a probability $p = 0.5$ that a yellow chip will be randomly drawn and a probability $(1\text{-}p) = 0.5$ that a blue chip will be randomly drawn and an uncertain lottery (option B) in which there is an unknown probability q that all chips are yellow and a probability $(1\text{-}q)$ that all chips are blue. As before, more details on the parametrisation of subject's utility functions, procedures used to determine subjects' payoff and the task shown to participants are provided in the online supplementary appendix E.

4 Testing consistency across mechanisms

4.1 Testable hypotheses and model specifications

We compare values between BDM and SPA using *marginal willingness to pay* (*mWTP*) of subject *i* for fish portions in three different scenarios *j*:

a) $mWTP_{CERTAINTY} = WTP_{POLLAN} - WTP_{HERRING.}$ This is the difference between subjects' bid for the portion of pollan fillets and their bid for the portion of herring fillets. This ranges from − £3.00 to £8.00.
b) $mWTP_{RISK} = WTP_{POLLAN} - WTP_{RISK.}$ This is the difference between subjects' bid for the portion of pollan fillets and their bid for the portion of pollan fillets under the food fraud risk. This ranges from − £7.35 to £6.50.[18]
c) $mWTP_{UNCERTAINTY} = WTP_{POLLAN} - WTP_{UNCERTAINTY.}$ This is the difference between subjects' bid for the portion of pollan fillets and their bid for the portion of pollan fillets under the food fraud uncertainty. This ranges from − £3.00 to £8.00.[19]

We estimate three different models (Model 1a-1c, one for each scenario) to compare mWTP under certainty, risk and uncertainty. These models are estimated

[17] A description of strengths and limitation of MPL-based methods to elicit ambiguity preferences with respect to other approaches is beyond the scope of this paper. A discussion is provided in the online supplementary appendix E.

[18] -£7.35 is quite a large difference however the next lowest is -£2.50.

[19] Summary statistics of these variables are provided in table F.1 of the online supplementary appendix F. Non-parametric tests show WTP differs across all four portions of fish in both treatments, results are shown in the online appendix (Table F2 and F3).

using an ordinary least squares (OLS) regression.[20] The models have the same formulation:

$$mWTP_{i,j} = \alpha_j + \beta_{BDM,j} BDM + \beta_{Xj} X + \varepsilon_{i,j} \tag{1}$$

where i indicates the subject and j indicates the scenario. The coefficient $\beta_{BDM'j}$ indicates whether values ($mWTP$s) differ across methods (BDM and SPA). Specifically, the BDM and SPA elicit the same values in scenario j, if we fail to reject the null hypotheses that the coefficient $\beta_{BDM'}j$ is equal to 0 (H_0: $\beta_{BDM'}j = 0$, Hypothesis 1). X_i is a vector of variables which may influence willingness to pay. It includes the participants' gender, age, employment status, education level, area of residence, difference in expected taste of pollan and herring, whether they have heard of Lough Neagh Cooperative (the brand of pollan), their knowledge about geographical indications, whether they have eaten fish fillets this week and the importance of authenticity when food shopping.[21] A comparison of observable characteristics across treatments is provided in Table H1 in the online supplementary.

4.2 Results and discussion

Results in Table 2 indicate that values elicited via BDM and SPA are not statistically different. In fact, the coefficient $\beta_{BDM'j}$ is not statistically significant under certainty (Model 1a), risk (Model 1b) nor uncertainty (Model 1c).[22] Standard economic theory predicts bids are equal across the two mechanisms and our results support this hypothesis. This may indicate rational bidding behaviour in our empirical application. Hence, risk and uncertainty regarding the auctioned good do not undermine rationality. Our results may mitigate concerns raised by previous analysis testing if WTP is equal between the BDM and SPA (Lusk et al., 2004; Rutström, 1998).[23] However, our results should be interpreted with caution because based on an ex-post power analysis, our sample size only has enough power to detect an effect larger than the current average in the literature. More specifically, our sample size could detect an effect of a 23% difference in willingness to pay between the two mechanisms (with 80% power) however the average difference in published studies is 17% (see Appendix M for more details). Nevertheless, future studies should test the robustness of our findings with larger sample sizes.

[20] Subjects were informed that the real-world market price for a 250 g portion of frozen fish, similar to pollan and herring, was between £3 and £7 at the time the experiment was conducted. Our modelling approach does not control for bids being censored at these market prices because we found no evidence of bids being concentrated around these prices. Results for censoring can be found in appendix G.

[21] Full details of control variables and their summary statistics can be found in Appendix H.

[22] In the online supplementary appendix G, we provide results obtained via: (i) non-parametric testing procedures, (ii) results from the OLS estimation without controls (iii) results from a tobit estimation. Results from these additional analyses show that our results are very robust across model specification and estimation procedures used.

[23] When model 1a-c is ran with the dependent variable willingness to pay rather than marginal willingness to pay, the results remain the same. We find no difference between the BDM and SPA treatment ($p < 0.05$).

Table 2 Ordinary least square regression for mWTP[a]

Dep. Var:	Model 1a $mWTP_{CERTAINTY}$	Model 1b $mWTP_{RISK}$	Model 1c $mWTP_{UNCERAINTY}$
β_{BDM}	0.223	− 0.006	0.320
	(0.238)	(0.163)	(0.234)
α	− 0.734	− 0.472	− 1.354**
	(0.483)	(0.403)	(0.537)
Obs	158	158	158
R^2	0.188	0.176	0.194
Controls included	Yes	Yes	Yes

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

[a]Standard errors in parentheses

5 Testing for deviations from EUT and SEUT

In this section, we first outline how behavioural parameters are estimated using the data from Part 1 of the experiment and provide the results (Sect. 5.1). Then, we explore whether bidding behaviour deviates from EUT and SEUT using the estimated behavioural parameters and subject's bids (Sect. 5.2).

5.1 Estimating behavioural parameters

5.1.1 Expected utility theory and rank dependent expected utility theory

We assume that participants value lottery payoffs through a power value function (Tversky & Kahneman, 1992):

$$v(x) = x^{\sigma}(1) \quad \text{when x} \geq 0 \tag{2}$$

where x is the lottery payoff and σ is an anti-index of risk aversion.[24] When $r > 1$ this indicates risk seeking (i.e. utility convexity) in contrast when $r < 1$ this indicates risk aversion (i.e. concavity) and $r = 1$ indicates risk neutrality.

In the behavioural tasks, participants are asked to choose between lottery A (x_{A1}, p_{A1}; x_{A2}, p_{A2}) and lottery B (x_{B1}, p_{B1}; x_{B2}, p_{B2}). For each decision in task 1 and 2, the expected utility of participant i for each lottery (A or B) can be written:

$$EU_i^A = p_{A1} \times x_{A1}^{\sigma i} + \left(1 - p_{A1}\right) \times x_{A2}^{\sigma i} \tag{3a}$$

$$EU_i^B = p_{B1} \times x_{B1}^{\sigma i} + \left(1 - p_{B1}\right) \times x_{B2}^{\sigma i} \tag{3b}$$

[24] We only estimate parameters of the utility function for the gain domain as we investigate purchasing decisions in the gain domain.

where x_{A1}, x_{A2} and x_{B1}, x_{B2} are the payoffs of lottery A and B, respectively and p_{A1}, p_{A2} and p_{B1}, p_{B2} are the probabilities of the payoffs.

When a situation is uncertain, subjective expected utility is used instead, resulting in two main changes.[25] Firstly, ambiguity preferences (φ) replace risk preferences. Secondly, subjective probabilities (q) replace objective probabilities. Since in task 5 lottery A is risky and lottery B is uncertain, the expected utility for each lottery is written as follows[26]:

$$EU_i^A = p_{A1} \times x_{A1}^{\sigma i} + \left(1 - p_{A1}\right) \times x_{A2}^{\sigma i} \tag{4a}$$

$$EU_i^B = q_{B1} \times x_{B1}^{\varphi i} + \left(1 - q_{B1}\right) \times x_{B2}^{\varphi i} \tag{4b}$$

An alternative theory for explaining behaviour is rank dependent expected utility theory. In this paper, we focus on the gain domain hence do not investigate loss aversion or risk preferences and probability weighting in the loss domain. Hence, the only difference to expected utility theory and the equations shown above is that decision weights are introduced. Resulting in the utility function as follows:

$$RDEU_i^A = w(p_{A1}) \times x_{A1}^{\sigma i} + \left(1 - w(p_{A1})\right) \times x_{A2}^{\sigma i} \tag{5a}$$

$$RDEU_i^B = w(p_{B1}) \times x_{B1}^{\sigma i} + \left(1 - w(p_{B1})\right) \times x_{B2}^{\sigma i} \tag{5b}$$

$$\mathrm{CPT}_\mathrm{i}^\mathrm{A} = \mathrm{w}(\mathrm{p}_{\mathrm{A1}}) \times \mathrm{x}_{\mathrm{A1}}^{\sigma i} + \left(1 - \mathrm{w}(\mathrm{p}_{\mathrm{A1}})\right) \times \mathrm{x}_{\mathrm{A2}}^{\sigma i}$$

where *w(p)* is the probability weighting function following Prelec's (1998) specification:

$$w(p) = \exp\left[-(-\ln p)^{\gamma}\right] \tag{6}$$

γ indicates the curvature of the probability weighting function. When $\gamma = 1$ this indicates there is no probability distortion. In contrast, when $\gamma < 1$ this implies an overweighting of small probabilities and an underweighting of high probabilities, resulting in an inverse S-shaped function, whereas $\gamma > 1$ implies the opposite, resulting in an S-shaped function. In our case, if $\gamma = 1$ then the utility function is equivalent to expected utility theory.

5.1.2 Estimation strategy

We model the decision as a discrete choice model. Assuming participants follow utility maximising behaviour, observed choices are driven by a latent choice

[25] We follow the second-order model (SOM) developed by Klibanoff et al. (2005) t which allows the separation of risk and ambiguity.

[26] Following Chakravarty and Roy (2009) we assume subjective probabilities q_{B1} and q_{B2} are both 0.5.

index Δ which signifies the difference between the utility of lottery A and B as shown in Eq. 7a for expected utility theory and Eq. 7b for rank dependent expected utility theory.

$$\Delta_i^{EUT} = EU_i^A - EU_i^B \tag{7a}$$

$$\Delta_i^{RDEUT} = RDEU_i^A - RDEU_i^B \tag{7b}$$

Utility can be split into the deterministic part (i.e. Equation 7a and 7b) which include the preference parameters to be estimated (Z_i) plus a random part capturing unobserved heterogeneity (ε_i). In addition, utility parameters may depend on observable individual characteristics (vector Θ):

$$\mathrm{Z_i} = \alpha + \beta\theta_i \tag{8}$$

The choice between lotteries can be described by the following latent regression model where ε_i is a normally distributed error term with a mean of zero and a variance of one:

$$d_i^* = \Delta_i\left(\theta_i\right) + \varepsilon_i, \text{ and } d_i = A \text{ if } d_i^* > 0 \text{ and } B \text{ otherwise,} \tag{9}$$

Based on Eq. 9, we can derive the probability that participant i chooses lottery A, where Φ(.) signifies the standard normal distribution function:

$$\Pr\left(A|\theta_i\right) = \Phi(\Delta_i\left(\theta_i\right)) \tag{10}$$

Our modelling approach relaxes the assumption that participants make deterministic choices (i.e. without random errors). Therefore, a Fechner error (i.e. noise parameter) is included in the analysis. We do this by modifying Eq. 7a and 7b, dividing the difference in utility by μ. If μ tends to zero, then choices are deterministic and as μ gets larger, choices become noisier (Harrsion and Rutström, 2008).

For expected utility theory (Model 2), we estimate four parameters with maximum likelihood: risk aversion (σ_{EUT}), ambiguity aversion (φ_{EUT}) and the Fechner error term for task 2 and 3 (μ_{RISK_EUT}) and for task 4 (μ_{AMBIGK_EUT}). Equation 11 shows the log likelihood function where I(.) is the indicator function and $\mathrm{d_i}$ indicates which lottery participant I chooses in choice j.

$$\begin{aligned} &\ln\left(L(d;\theta;\sigma_{EUT}, \varphi_{EUT}, \mu_{RISK\_EUT}, \mu_{AMBIG\_EUT})\right) \\ &= \sum_i \left\{ \left[\ln\Phi\left(\Delta_j^{EUT}\right)\right].I\left(d_{ij} = A\right) + \left[\ln[1 - \Phi\left(\Delta_j^{EUT}\right)\right].I\left(d_{ij} = B\right) \right\} \end{aligned} \tag{11}$$

A similar empirical strategy is used for rank dependent expected utility theory (Model 3). However, five parameters are estimated: risk aversion (σ_{RDEUT}), ambiguity aversion (φ_{RDEUT}), probability distortion (γ) and the Fechner error term for task 2 and 3 (μ_{RISK_RDEUT}) and for task 4 (μ_{AMBIGK_RDEUT}).

$$Ln\left(L\left(d;\theta;\sigma_{\mathrm{RDEUT}},\varphi_{\mathrm{RDEUT}},\mu_{\mathrm{RISK\_RDEUT}},\mu_{\mathrm{AMBIG\_RDEUT}}\right)\right) = \sum_i \left\{\left[\ln\Phi(\Delta_j^{RDEUT}\right)\right].I\left(d_{ij}=A\right)+\left[\ln[1-\Phi(\Delta_j^{RDEUT})].I\left(d_{ij}=B\right)\right\} \quad (12)$$

Standard errors are clustered to correct for the fact that choices from the same participant may be correlated. The maximum likelihood estimation was completed in Stata following Harrison et al. (2008).

In a first step parameters are estimated under a homogenous model. In a second step, explanatory variables are added to the model Θ (i.e. vector of individual characteristics) in order to estimate parameters for each participant. This is done by jointly estimating the parameters as a linear function of the explanatory variable using maximum likelihood estimates of each parameter. The vector Θ includes gender, age, education level, employment status, area of residence (i.e. if they live in a city or not) and household income (see Appendix H for an overview and summary statistics of explanatory variables). To estimate parameters for each participant based on Model 2 and 3, we use the postestimation function predictnl in Stata.

5.1.3 Results

Table 3 shows the estimates from Model 2 and 3, without controls (column 1 and 3) and with controls (column 2 and 4).[27] The estimated mean value of σ is 0.81 under expected utility theory and 0.56 under rank dependent expected utility theory indicating that participants are risk averse on average. For ambiguity aversion (φ) the estimated mean value is 0.71 under EUT and 0.48 under RDEUT showing that participants are averse to ambiguity on average.[28] Under RDEUT, the probability weighting parameter (γ) is 0.73 on average indicating some evidence of probability distortion in the form of an inverse S-shape. A postestimation Wald test indicates that γ is significantly different to 1, hence on average preference do not collapse to EUT.[29]

Figure 1 shows the distribution of σ and φ as predicted by Model 1. For risk preferences (σ) the majority of predictions are < 1 indicating participants are risk averse. The predictions range from 0.50 which is very risk averse to 1.02 which is risk neutral. For ambiguity preferences, all predictions are < 1 indicating participants are ambiguity averse. This ranges from 0.30 (very ambiguity averse) to 0.93 (close to ambiguity neutral). Figure 2 shows the distribution of σ, φ and γ as predicted by Model 2. Under RDEUT, all participants are predicted to be risk averse (ranging from 0.34 to 0.72) and ambiguity averse (ranging from 0.30 to 0.67). Compared to the predictions under EUT, the distribution is shifted left (i.e. participants are more risk and ambiguity averse). All participants have a predicted value of γ < 1 indicating

27 Full results including coefficients of control variables can be found in Appendix I.

28 Post estimation Wald tests show that risk and ambiguity attitudes differ in both models, see results in Appendix I.

29 Results of all postestimation Wald tests can be found in Appendix I. Additionally, noise parameters (μ_{RISK} and μ_{AMBIG}) are significantly different from zero indicating that choices are not deterministic.

Table 3 Maximum likelihood estimation of behavioural parameters[a]

	EUT		RDEUT	
	(1)	(2)	(3)	(4)
Covariates	Model 2	Model 2	Model 3	Model 3
σ	0.818***	1.104***	0.561***	0.783***
	(0.062)	(0.114)	(0.043)	(0.088)
φ	0.714***	1.012***	0.484***	0.711***
	(0.059)	(0.127)	(0.041)	(0.096)
γ			0.731***	0.795***
			(0.037)	(0.123)
μ_{RISK}	2.550***	2.292***	0.785***	0.706***
	(0.694)	(0.647)	(0.166)	(0.145)
μ_{AMBIG}	0.406***	0.367***	0.240***	0.222***
	(0.062)	(0.060)	(0.032)	(0.030)
Obs	5,846	5,846	5,846	5,846
No. participants	158	158	158	158
Controls (Θ)	No	Yes	No	Yes

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

[a]Robust standard errors in parentheses

overweighting of small probabilities and underweighting large probabilities. However, the strength of this distortion varies across participants (ranging from 0.53 to 0.94).

5.2 Testing deviations

5.2.1 Testable hypotheses and model specifications

We test whether subjects' bidding behaviour is consistent with EVT, EUT or RDEUT when the auctioned good is risky and, similarly, whether subjects' bidding behaviour is consistent with subjective expected value theory (SEVT), SEUT or RDEUT when the good is uncertain.

Specifically, we compare observed bids ($WTP_{RISK,i,j}$) for portions of fish fillets in the risky scenario with bids that we calculate under this scenario assuming that subjects behave according to EVT, EUT and RDEUT in each value elicitation mechanism j (BDM and SPA). To estimate subject i's bids, we use their observed bids (WTP) for fish portions under certainty ($WTP_{POLLAN.i,j}$ and $WTP_{HERRING,i,j}$) elicited in part 3 of the experiment as well as their subject-specific risk preferences (σ_i) and probability weighting parameters (γ_i) from Sect. 5.1 of the paper.[30]

[30] Note that the parameters used to predict willingness to pay under EUT and SEUT come from Model 2 where expected utility theory is assumed and parameters for RDEUT come from Model 3 where cumulative prospect theory is assumed.

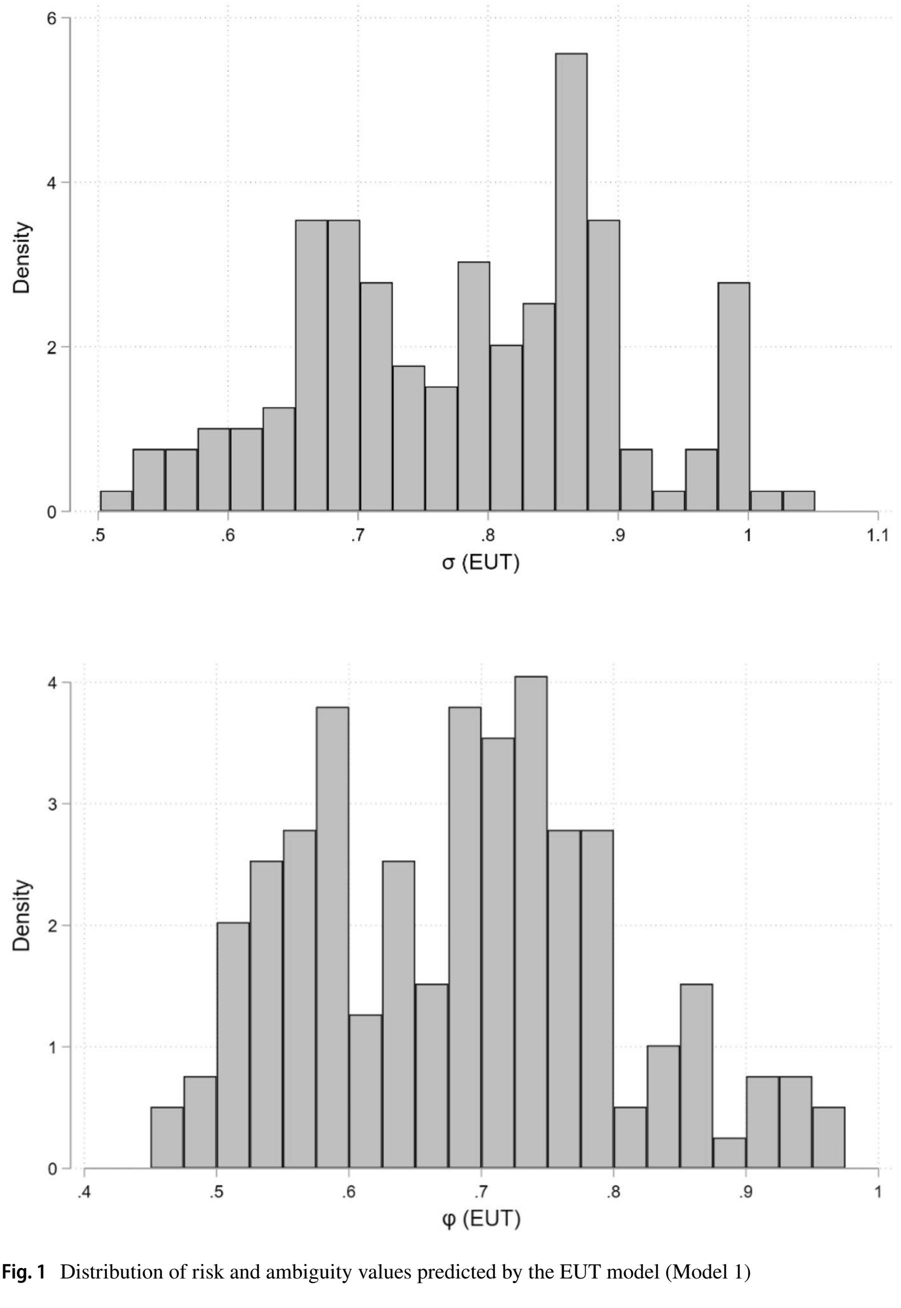

Fig. 1 Distribution of risk and ambiguity values predicted by the EUT model (Model 1)

$$WTP_{EVT,i,j} = WTP_{HERRING,i,j} + p_{POLLAN}\left(WTP_{POLLAN,i,j} - WTP_{HERRING,i,j}\right) \quad (13a)$$

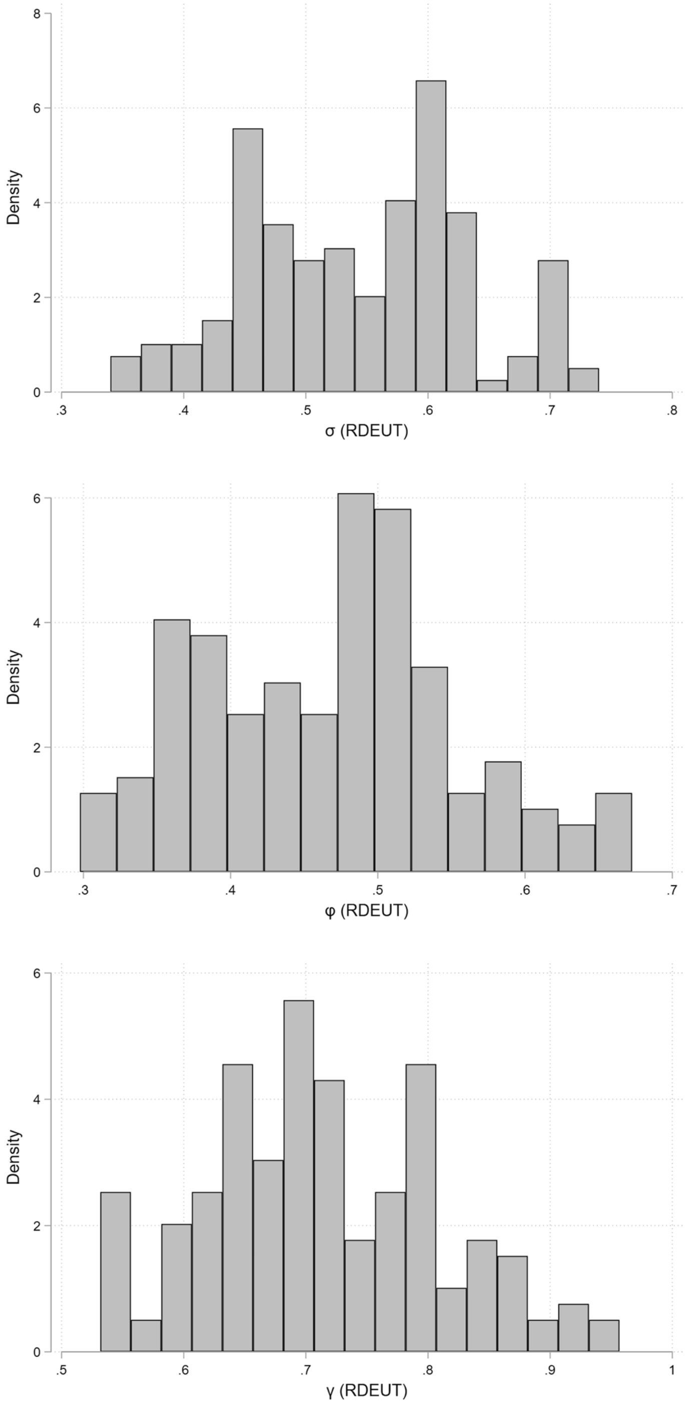

Fig. 2 Distribution of risk, ambiguity and probability weighting values predicted by the RDEUT model (Model 2)

$$WTP_{EUT,i,j} = \left(WTP_{HERRING,i,j}\right)^{\sigma_i} + p_{POLLAN}\left[\left(\left(WTP_{POLLAN,i,j}\right)^{\sigma_i} - \left(WTP_{HERRING,i,j}\right)^{\sigma_i}\right)\right] \tag{13b}$$

$$WTP_{RDEUT,i,j} = \left(WTP_{HERRING,i,j}\right)^{\sigma_i} + \left\{1/\exp\left[\ln\left(1/p_{POLLAN,i}\right)\right]^{\gamma_i}\right\} \left[\left(\left(WTP_{POLLAN,i,j}\right)^{\sigma_i} - \left(WTP_{HERRING,i,j}\right)^{\sigma_i}\right)\right] \tag{13c}$$

To estimate willingness to pay under EUT we use the postestimation function predictnl (using Eq. 13b) in Stata after Model 2. Similarly for willingness to pay under RDEUT we use predictnl (using Eq. 13c) after Model 3.

To test whether subject i's behaviour is consistent with EVT, EUT or RDEUT in elicitation mechanism j (BDM or SPA), we estimate the following models (Model 4a-4c)[31]:

$$WTP_{RISK,i,j} = \alpha + \beta_{EVTj} WTP_{EVT,i,j} + \varepsilon_{i,j} \tag{14a}$$

$$WTP_{RISK,i,j} = \alpha + \beta_{EUTj} WTP_{EUT,i,j} + \varepsilon_{i,j} \tag{14b}$$

$$WTP_{RISK,i,j} = \alpha + \beta_{RDEUTj} WTP_{RDEUT,i,j} + \varepsilon_{i,j} \tag{14c}$$

In Eqs. 14a, 14b and 14c, the dependent variable $WTP_{RISK,i,j}$ ranges from £0 to £8.65. These models are estimated using a Tobit model. A censored model is required as subjects cannot bid less than £0 in our application and we observed a spike of bids at £0.

To test whether subjects' bidding behaviour is consistent with EVT, EUT and RDEUT, we use postestimation Wald tests to test the following null hypotheses:

Hypothesis 2a	Hypothesis 2b	Hypothesis 2c
H_0: $\alpha=0$ and $\beta_{EVT}=1$	H_0: $\alpha=0$ and $\beta_{EUT}=1$	H_0: $\alpha=0$ and $\beta_{RDEUT}=1$
H_1: $\alpha\neq0$ or $\beta_{EVT}\neq1$	H_1: $\alpha\neq0$ or $\beta_{EUT}\neq1$	H_1: $\alpha\neq0$ or $\beta_{RDEUT}\neq1$

Subjects' bidding behaviour is consistent with EVT if we fail to reject the null joint hypothesis in 2a. Similarly, subjects bidding behaviour is consistent with EUT if we fail to reject the null joint hypothesis in 2b and it is consistent with RDEUT if we fail to reject the null joint hypothesis in 2c.

A similar procedure is used to test whether subjects' bidding behaviour is consistent with SEVT, SEUT and RDEUT when subjects are exposed to the uncertain good. However, it is important to note that we estimate bids under uncertainty using subject i's: observed bids (*WTP*) for fish portions under certainty ($WTP_{POLLAN.i}$ and $WTP_{HERRING,i}$) elicited in part 3 of the experiment as well as their subject-specific ambiguity preferences (φ_i), probability weighting parameters (γ_i), and subjective beliefs regarding the number of authentic fish on the UK market in 2018 ($q_{POLLAN,i}$).

[31] As we use this regression to test for if predicted bids equal actual bids we are only interested in correlation. We do not investigate the causal effect of predicted bids on actual bids which would be problematic due to endogeneity caused by simultaneity in the set up.

To test whether subject *i*'s behaviour is consistent with SEVT, SEUT or RDEUT in elicitation mechanism *j* (BDM or SPA), we estimate the following models (Model 5a-5c) using the SCLS estimator:

$$WTP_{UNCERTAINTY,i,j} = \alpha + \beta_{SEVTj} WTP_{SEVT,i,j} + \varepsilon_{i,j} \tag{15a}$$

$$WTP_{UNCERTAINTY,i,j} = \alpha + \beta_{SEUTj} WTP_{SEUT,i,j} + \varepsilon_{i,j} \tag{15b}$$

$$WTP_{UNCERTAINTY,i,j} = \alpha + \beta_{RDEUTj} WTP_{RDEUT,i,j} + \varepsilon_{i,j} \tag{15c}$$

In Eqs. 15a, 15b and 15c, the dependent variable $WTP_{UNCERTAINTY,i,j}$ ranges from £0 to £8.65. Again, these models are estimated using a Tobit regression. To test whether subjects' bidding behaviour is consistent with SEVT, SEUT and RDEUT, we use Wald tests to test the following null hypotheses:

Hypothesis 3a	Hypothesis 3b	Hypothesis 3c
H_0: $\alpha = 0$ and $\beta_{SEVT} = 1$	H_0: $\alpha = 0$ and $\beta_{SEUT} = 1$	H_0: $\alpha = 0$ and $\beta_{RDEUT} = 1$
H_1: $\alpha \neq 0$ or $\beta_{SEVT} \neq 1$	H_1: $\alpha \neq 0$ or $\beta_{SEUT} \neq 1$	H_1: $\alpha \neq 0$ or $\beta_{RDEUT} \neq 1$

Since Models 4 and 5 have generated regressors (i.e. willingness to pay is estimated), a two-step estimation would result in standard errors which are too small in the second-stage regression (Pagan, 1984; Murphy and Topel, 1985). To overcome this, we use a bootstrapping method for computing standard errors. We bootstrap across the entire procedure (i.e. the same random samples are used in both parts of the procedure).[32] The bootstrapping sampling procedure is repeated 1000 times. The bootstrapped standard errors are reported in the results tables for Model 4 and 5.

To test the robustness of our results we complete some additional analysis. Firstly, we estimate Model 4 and 5 using a heteroscedastic Tobit model.[33] Secondly, since bids could only be placed in £0.05 increments, we allow the calculated bid to equal the subject's actual bid if the absolute difference is less than or equal to £0.05.[34]

5.2.2 Results and discussion

Table 4 presents the summary statistics of the differences between observed bids under conditions of risk about the auctioned good ($WTP_{risk,i,j}$) and the corresponding predicted bids under EVT, EUT and RDEUT ($WTP_{EVT,i,j}$, $WTP_{EUT,i,j}$ and $WTP_{RDEUT,i,j}$). The same differences are calculated under conditions of uncertainty

[32] For Model 4a and 5a, we bootstrap across calculating willingness to pay under EVT/SEVT and the Tobit regression. For Model 4b and 5b, we bootstrap across estimating Model 2, the postestimation willingness to pay predictions in Model 2, and the Tobit regression. For Model 4c and 5c, we bootstrap across Model 3, the postestimation willingness to pay predictions in Model 3 and the Tobit regression.

[33] Results regarding normality and homoscedasticity of errors are provided in the online supplementary appendix J.

[34] A description of both models and results can be found in Appendix K.

Table 4 Summary statistics of variables showing absolute difference between observed and predicted bids under risk and uncertainty in the BDM and SPA

	SPA		BDM	
	Mean	St.Dev.	Mean	St.Dev.
$WTP_{risk,i,j} - WTP_{EVT,i,j}$	0.35	0.59	0.58	1.22
$WTP_{risk,i,j} - WTP_{EUTT,i,j}$	0.71	0.91	0.81	1.14
$WTP_{risk,i,j} - WTP_{RDEUT,i,j}$	1.12	1.18	1.09	1.37
$WTP_{uncertainty,i,j} - WTP_{SEVT,i,j}$	0.41	0.65	0.53	1.00
$WTP_{uncertainty,i,j} - WTP_{SEUT,i,j}$	0.64	0.76	0.67	0.79
$WTP_{uncertainty,i,j} - WTP_{RDEUT,i,j}$	0.89	1.02	0.81	1.00

about the auctioned good.[35] It shows that for BDM and SPA, the lowest mean difference between actual and predicted bid is under EVT under risk and SEVT under uncertainty. In both cases, the average difference for SPA is lower than BDM (i.e. 0.35 vs 0.58 for EVT and 0.41 vs 0.53 for SEVT). The share of actual bids equalling calculated bids under each theory can be found in Appendix F.

Results in Table 5 show that we fail to reject the null hypothesis 2b (H_0: $\alpha = 0$ and $\beta_{EUT} = 1$) and 2c (H_0: $\alpha = 0$ and $\beta_{RDEUT} = 1$) in both the BDM and SPA treatments. In contrast, we reject the null hypotheses 2a (H_0: $\alpha = 0$ and $\beta_{EVT} = 1$) in the BDM treatment but fail to reject it in the SPA treatment. These results indicate that, on average, subjects' bidding behaviour is consistent with EVT in the SPA treatments. While no theory is consistent with bidding behaviour under risk in the BDM.

Additionally, our results in Table 6 show that, in the SPA and BDM treatment, we reject the null hypotheses 3a (H_0: $\alpha = 0$ and $\beta_{SEVT} = 1$), 3b (H_0: $\alpha = 0$ and $\beta_{SEUT} = 1$) and 3c (H_0: $\alpha = 0$ and $\beta_{RDEUT} = 1$). This result suggests that, on average bidding behaviour is not consistent with any theory tested under uncertainty in either treatment.

Hence, we conclude that subjects are not likely to behave according to the non-standard expected utility theory of decision making under risk or uncertainty (i.e., RDEUT). While bidding behaviour is consistent with EVT under risk in the SPA treatment and bidding is not consistent with any theory tested in the BDM treatment, this does not seem to affect values elicited via SPA and BDM as they were not statistically different.

For the SPA treatment, bidding behaviour is different under risk (where behaviour is consistent with EVT) and uncertainty (where no theory is consistent with bidding behaviour). Therefore, being exposed to an extra source of uncertainty changes bidding behaviour. This change in bidding behaviour may be due subject's now being exposed to two sources of uncertainty. Since in the SPA treatment, subjects are always exposed to a latent source of uncertainty (i.e. market price uncertainty), which refers to the other bidders' valuations of the auctioned good. They cannot possibly know these valuations. In addition, subjects are exposed to an additional

[35] Results from non-parametric tests of differences between observed and predicted bids and results from the OLS estimations are provided in the online supplementary appendix L.

Table 5 Tobit regression for predicted WTP under risk[a]

	SPA			BDM		
	Model 4a	Model 4b	Model 4c	Model 4a	Model 4b	Model 4c
Dep Var:	WTP_{RISK}	WTP_{RISK}	WTP_{RISK}	WTP_{RISK}	WTP_{RISK}	WTP_{RISK}
β_{EVT}	1.011***			1.026***		
	(0.037)			(0.087)		
β_{EUT}		1.490***			1.418***	
		(0.162)			(0.161)	
β_{RDEUT}			2.450***			2.313***
			(0.211)			(0.229)
α	− 0.184	− 0.466**	− 1.145***	− 0.624**	− 0.758**	− 1.190***
	(0.128)	(0.236)	(0.278)	(0.283)	(0.324)	(0.373)
Obs	77	77	77	81	81	81
Log likelihood	− 81.205	− 99.534	− 96.670	− 122.312	− 123.094	− 122.324
Wald test						
α = 0 & β = 1	2.94	10.28**	69.14***	7.00**	7.22**	40.68***

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

[a]Bootstrap standard errors in parentheses

Table 6 Tobit regression for predicted WTP under uncertainty[a]

	SPA			BDM		
	Model 5a	Model 5b	Model 5c	Model 5a	Model 5b	Model 5c
Dep Var:	WTP_{UNC}	WTP_{UNC}	WTP_{UNC}	WTP_{UNC}	WTP_{UNC}	WTP_{UNC}
β_{SEVT}	0.971***			1.170***		
	(0.054)			(0.107)		
β_{SEUT}		1.623***			1.888***	
		(0.164)			(0.230)	
β_{RDEUT}			2.505***			2.959***
			(0.246)			(0.258)
α	− 0.280**	− 0.633***	− 1.261***	− 1.373***	− 1.556***	− 2.152***
	(0.135)	(0.213)	(0.306)	(0.334)	(0.375)	(0.384)
Obs	77	77	77	81	81	81
Log likelihood	− 86.221	− 88.324	− 89.570	− 98.983	− 89.168	− 83.115
Wald test						
α = 0 & β = 1	9.76**	14.44***	49.42***	16.90***	18.81***	58.07***

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

[a]Bootstrap standard errors in parentheses

source of uncertainty which refers to receiving the lower quality herring instead of pollan fillets.

In the BDM treatment, subjects always face a latent source of risk related to the distribution of prices from which the market price will be randomly drawn (i.e. market price risk). We use the term "source of risk" because subjects know that this distribution is uniform and therefore know the probability that each price will be randomly drawn as the market price. In addition to this source of risk, subjects may be exposed to an additional source of risk or uncertainty about the product. In the BDM, bidding behaviour is not consistent with any theory tested here under risk or uncertainty. Hence, we find no evidence that being exposed to two sources of risk influences bidding behaviour. However, this result also suggests that our sample find it difficult to deal with the BDM. This indicates that previous explanations for deviations in values elicited by SPA and BDM such as misconception of the game form (e.g. Cason & Plott, 2014) or having an exogenously defined market price (i.e. in the BDM) rather than an endogenously defined market price (i.e. SPA) (Lusk and Rousu, 2006) are more important for bidding behaviour rather than the sources of risk and uncertainty present. Further research is needed to establish which theories subjects' bids are consistent with in the BDM under risk and uncertainty and in the SPA under uncertainty to clarify this result.

6 Discussion and conclusion

Many goods have inherent risks and uncertainty in their provision. Hence, establishing how subjects value products under risk and uncertainty is important for providing theoretical insights, policy recommendations and business applications. This paper contributes to the literature by examining bidding behaviour under risk and uncertainty. Two specific value elicitation mechanisms are tested, the BDM and the SPA, which are widely used in the literature and real-world applications. While bidding behaviour has been tested for certain goods, research for risky and uncertain goods is very scarce.

This paper is the first to empirically explore whether values elicited via the BDM and the SPA are consistent when the provision of the auctioned good is risky or uncertain. Standard economic theory predicts that the BDM and SPA should elicit the same WTP; hence values elicited via BDM and SPA should be equal if bidding behaviour is rational. Furthermore, this paper investigates whether bidding behaviour is influenced by the number and type of sources of uncertainty that subjects face during the valuation process. One source of risk and uncertainty is related to the provision of the good in the experiment. The other is intrinsically related to the mechanism used to elicit values, i.e. BDM or SPA. We empirically test whether being exposed to these sources of risk and uncertainty generate deviations from standard theories of decision making under risk and uncertainty, namely from EUT and SEUT.

To this end, we develop non-monetary lotteries with known probabilities (i.e., product risk) and unknown probabilities (i.e., product uncertainty) that imitate food fraud incidents. This is a novelty as the use of non-monetary lotteries are not common in the literature (Cerroni, Notaro, and Raffaelli 2019) and no studies have used them to compare WTP across mechanisms.

Our empirical results support standard economic theory's prediction and therefore rational bidding behaviour. Values elicited under certainty, risk and uncertainty are consistent (i.e. not statistically different) when elicited using the BDM and the SPA. However, due to a potential lack of power based on our sample size, our results should be interpreted with caution. Future research should complete a power analysis before data collection to ensure the sample size is adequate to detect an effect.

Our results show that the sources of uncertainty subjects are exposed to in the SPA can affect bidding behaviour. While bidding behaviour is consistent with EVT when subjects face "product provision risk", bidding behaviour is not consistent with any theory tested (i.e. SEVT, SEUT or RDEUT) when subjects face "product provision uncertainty". This result suggests subjects find it difficult to deal with the extra source of uncertainty. In contrast, in the BDM bidding behaviour is not consistent with any theory tested under risk (i.e. EVT, EUT or RDEUT) or uncertainty. This suggests that subjects in our sample find it difficult to deal with the BDM mechanism. This may be due to previously researched mechanisms such as misconception of the game form (e.g. Cason & Plott, 2014) or the presence of an exogenously determined market price (e.g. Lusk and Rousu, 2006). Even though bidding behaviour differs under SPA and BDM for risky goods, the good news is that this phenomenon does not seem to affect values between the SPA and BDM.

Our results give potential for future research. In order to understand bidding behaviour under risk and uncertainty better, future research could also investigate if bidding behaviour is consistent with different theories of decision making. Recently, there has been a focus on cognitive ability and demand revelation in experimental auctions (e.g. Drichoutis & Nayga, 2019; Lee et al., 2020). The robustness of our results could be tested for low vs high cognitive ability subjects to investigate if deviations from standard theories and demand revelation are related to cognitive ability. Additionally, future research could test the robustness of our results by establishing if the group size in the SPA affects equality of WTP between SPA and BDM, given that larger group size could produce some behavioural concerns such as the joy of winning (Cooper & Fang, 2008).

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Data and code availability Data and code used in the manuscript are available at https://pure.qub.ac.uk/en/persons/chloemccallum-2/datasets/.

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