EXPERIMENTAL AUCTIONS VS REAL CHOICE EXPERIMENT: AN EMPIRICAL APPLICATION ON CONSUMER VALUATION FOR FOOD QUALITY ATTRIBUTES

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A THESIS

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Agricultural, Food and Resource Economics – Master of Science

2019

ABSTRACT

EXPERIMENTAL AUCTIONS VS REAL CHOICE EXPERIMENT:
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Real choice experiments (RCEs) and experimental auctions (EAs) are two non-market valuation methods which have increasingly been used to elicit consumers' preferences and willingness to pay (WTP) for food products. This paper aims to determine whether EAs and RCEs derive different welfare estimates or not and examines their incentive compatibility using data from a U.S. consumer study. We compare the bidding behavior of consumers in three different incentive compatible EAs to the behavior of consumers who made non-hypothetical discrete choices for egg products. We find that the valuations elicited from EAs differ significantly from those obtained from RCEs. Nonetheless, for the goods evaluated, individuals' preference orderings were consistent across elicitation methods. These findings hold relevant implications for the design of real choice experiments and experimental auctions. The practical implications for food retailers are also discussed.

To my Grandmother Rena

ACKNOWLEDGEMENTS

Throughout the writing of this thesis, I have received a great deal of support and assistance. I would first like to thank my thesis advisor Dr. Caputo Vincenzina, Assistant Professor of the Department of Agricultural, Food, and Resource Economics at Michigan State University. The door to Prof. Caputo's office was always open whenever I ran into trouble or had a question about my research or writing. She consistently steered me in the right direction throughout the process of designing, implementing and writing this thesis.

Furthermore, I would like to thank Dr. Caputo and Dr. Robert Shupp, Associate Professor of the Department of Agricultural, Food, and Resource Economics at Michigan State University for funding the data collection used for this research project. Dr. Shupp also assisted me throughout the design, the implementation, and the review of this research paper with his valuable comments, edits, and additions. Also, I would like to thank the participants in my survey, who have willingly shared their precious time during the whole process.

I am also grateful to the other two members of my committee (in addition to Dr. Caputo and Dr. Shupp) who were involved in the review process of this paper: Dr. Robert Myers, Associate Chairperson, Graduate Program Director, and University Distinguished Professor of the Department of Agricultural, Food, and Resource Economics at Michigan State University and Dr. Eduardo Nakasone, Assistant Professor of the Department of Agricultural, Food, and Resource Economics and the Department of Media and Information at Michigan State University. Without their passionate participation and input, the master's thesis could not have been successfully completed.

I also wish to thank Dr. Andreas Drichoutis, Assistant Professor of the Department of Agricultural Economics and Rural Development at the Agricultural University of Athens, for his advice during the initial steps of this research project. Moreover, Dr. Drichoutis has always been a role model for me and he was the one who ignited my interest in pursuing an academic career.

Thanks should also go to Dr. Christos Papadas, Associate Professor of the Department of Agricultural Economics and Rural Development at the Agricultural University of Athens, who was instrumental in guiding me during my application process for graduate programs in the United States. I would not have made it that far without him.

I would also like to extend my deepest gratitude to my colleague Danielle Kaminski for her assistance and support throughout the design and the implementation of the data collection. Her unwavering support helped me through good and bad times in the last couple of years.

I would like to express my sincere thanks to April Athnos and Christine Sauer, very good friends and Ph.D. candidates of the Department of Agricultural, Food, and Resource Economics at Michigan State University, as the second readers of this thesis, and I am gratefully indebted to them for their valuable comments and friendship.

The completion of my thesis would not have been possible without the support and nurturing of my colleagues and beloved friends within the department of Agricultural, Food, and Resource Economics. Brian Bartle, Dan Ochs, Sarah Chase-Walsh, Tanner Connors, Ari Kornelis, Sean Posey, Sarah Kopper, Danielle Ufer, Kelsey Hopkins, Simone Faas, Ben DeMuth, Maria-Elena Marescotti, Petjon Balco and Carolina Vargas are only a few from the people who never wavered in their support.

I cannot begin to express my thanks to my family, who has always been the most important pillar of my life. My grandparents, my parents, my siblings and my brothers in life Elias and Kostas, who have always been there for me and supported me in the hardest decision I have ever made; to leave Greece and follow my dreams abroad. I would specifically like to thank my mother for keeping me harmonious and reminding me who I am when myself or other people tended to forget. I will be grateful forever for your love.

Finally, I must express my very profound gratitude to my wife for providing me with unfailing support, love and continuous encouragement throughout the last year of my study and through the process of researching and writing this thesis. This accomplishment would not have been possible without her. Thank you.

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1. INTRODUCTION

Real choice experiments (RCEs) and experimental auctions (EAs) are two of the most popular non-hypothetical non-market valuation methods used to elicit consumers' preferences and willingness to pay (WTP) for food attributes and products. In RCEs respondents are faced with multiple choice scenarios and are asked to make decisions between different product alternatives. The alternatives are defined by different attributes and attribute levels. Once a respondent completes the experiment one of these choice questions is randomly selected as binding; the respondent has to buy the chosen alternative in the binding choice question and pay the price indicated in the chosen alternative. In EAs consumers place their bids for a specific product characterized by different attributes and attribute levels. Once the experiment is completed, the highest bidder(s) buys the product, paying the market price which is defined from the auction mechanism. The vast majority of the research implementing these valuation methods (i.e.: EAs and RCEs) elicit homegrown values, defined as the subjective valuations of participants for a good (Murphy et al., 2010).

From a theoretical perspective, the RCE and EA methods are both incentive compatible because every participant is incentivized to truly reveal their preferences.[1] Hence, if participants truly reveal their preferences, then welfare estimates such as the marginal and total WTP should not differ across the two methods. However, data from a number of studies suggest that WTP estimates for food attributes differ across RCEs and EAs. For instance, Gracia et al. (2011), using a random *n*th price auction mechanism and a RCE to elicit WTP for cured-ham products, observed that the estimates derived from the two elicitation methods differ in

[1] Not all EAs are considered incentive compatible. For example, the English auction is not considered incentive compatible while the second price and the random *n*th price auctions are. In our comparison we only use incentive compatible EA methods. However, previous studies have raised some concerns regarding the incentive compatibility of the BDM auction (Horowitz, 2006). One of the goals of this paper is to reach a conclusion on whether the BDM auction is incentive compatible or not.

magnitudes and are inconsistent across different product profiles. Similarly, Lusk and Schroeder (2006) find that auction bids for beef steaks, under a second price auction mechanism, are significantly lower than the valuations obtained from their RCE.

The previously mentioned studies compare RCEs with only one type of incentive compatible auction mechanism (nth price auction or second price auction). Hence, it is still not known whether results between RCEs and EAs differ consistently across alternative auction mechanisms commonly used in food choice literature (second price, random *n*th price, and Becker–DeGroot–Marschak (BDM)).

There are two primary goals of this study: First, we investigate whether homegrown RCEs and EAs produce different marginal WTP for food attributes. Unlike previous studies, this study compares a RCE with three different popular auction mechanisms; specifically, the second price (Vickrey, 1961), the random *n*th price (Shogren et al., 2001), and the BDM (Becker, DeGroot, and Marschak, 1964) auction mechanisms. Second, we compare valuation estimates across the aforementioned EAs. Additionally, while research has been carried out on comparing welfare estimates derived from different EA mechanisms, only a few studies have compared the auction institutions as elicitation mechanisms for food attributes (Lusk et al. 2004, Rutström, 1998), with some of the most prominent previous studies focusing on collectible trading cards (Lucking- Reiley, 1999; List, 2003). This is important because consumers routinely purchase food products in a typical posted-price market such as grocery stores.

To achieve the research objectives, we used a between-subjects approach and conducted a RCE and three EAs: (i) second price, (ii) BDM, and (iii) random *n*th price. In total, 271 consumers participated in our study. In all experiments, the participants were asked to indicate their preferences for a dozen large, grade A, brown eggs produced either with the conventional method, the cage free system or the USDA organic production requirements. Our results indicate that the WTP estimates differ across RCE and one of the EAs. Specifically, the BDM auction yields higher estimates than the other mechanisms. The second price auction, the random *n*th price auction and the RCE do not generate statistically different estimates from each other. This suggests that the implementation of a different EA mechanism affects consumers' behavior and induces individuals to make choices which might not necessarily represent their true preferences.

This study advances the experimental economics literature in three important ways. First, to the best of our knowledge, this is the first study to provide comprehensive results from a comparison of RCE and EAs. Comparisons of RCE and EA choice mechanisms are essential to establish whether the mechanisms are incentive compatible and whether they induce different estimates of WTP. Our study informs the mechanism selection in future studies and has important implications for economists' understanding of consumer preferences. For example, due to their convenience, RCEs could potentially replace the use of BDM auctions in developing countries. RCEs present similar benefits with the BDM auction (no need to form groups of people to run the experiments, individual decision-making) and they have the advantage of replicating an actual market scenario, which is very familiar to consumers. Additionally, several concerns have been raised for the incentive compatibility of the BDM (Horowitz, 2006).

Second, while numerous studies comparing auctions focus on collectible trading cards (Lucking-Reiley, 1999; List, 2003), only a few applications of EAs have been implemented in the food choice literature (Rutström, 1998; Lusk et al., 2004). Hence, this study adds to this research area by providing a deeper understanding of whether valuations are equivalent across theoretically incentive compatible auctions when used to evaluate food products' attributes.

Third, this study offers a detailed overview of prior research implementing RCEs in food economics, EA studies comparing multiple auction mechanisms, and prior literature comparing RCEs to EAs.

This article is structured as follows: first, we provide a brief description of the previous studies comparing EAs with one another and with RCEs. This is followed by the experimental procedures and the econometric analyses that were implemented in the RCE and EAs. The final section discusses the results and presents the conclusions.

2. BACKGROUND AND PREVIOUS STUDIES

In contrast with most widely used available elicitation mechanisms, which ask consumers hypothetical questions, EAs and RCEs induce people to participate in an "active market" scenario where they pay real money in exchange for real goods. In the following paragraphs we describe the EAs and the RCE mechanisms in more detail and review the existing literature.

2.1 Experimental Auctions (EAs)

EAs constitute one of the most widely used elicitation methods in recent literature (Corrigan and Rousu, 2006; Lusk et al., 2004). The main advantage of EAs is that the bids constitute a direct measure of auction participants' WTP for a product with specific attributes. Researchers increasingly use EAs because the environment of the experiment is real (real products and real money are used) and hence participants have an incentive to reveal their true preferences for the products being examined (Fox et al., 1996).

When implementing EAs in a laboratory setting, external factors should be held constant. This protects participants' bidding patterns from being influenced by unobservable external forces (other people's opinion, marketing, etc.). Thus, researchers must have the ability to control for the effects of external factors (location of study, instructions, etc.) in order to isolate the effect of changes in our variables of interest (Lusk and Shogren, 2007).

There are several EA mechanisms that have been widely used in market research and decision making during the last decade. Lusk and Shogren (2007), in their seminal study, describe the most significant EA mechanisms, which are summarized in Table 1.

Table 1: Experimental Auctions

Elicitation Mechanisms	Participant Procedure	Market Price	Rule	Number of Winners
English	Sequentially offer ascending bids	Last offered bid	Highest bidder pays market price	1
Second Price	Simultaneously submit sealed bids	Second Highest bid	Highest bidder pays market price	1
Nth Price	Simultaneously submit sealed bids	Nth highest bid	n-1 highest bidders pay market price	n-1
BDM (Becker-De-Groot-Marschak)	Simultaneously submit sealed bids	Randomly drawn price (random number generator)	People pay market price if bid exceeds randomly drawn price	Individually determined
Random Nth price	Simultaneously submit sealed bids	Randomly drawn (nth) bid	n-1 highest bidders pay market price	n-1
Collective Auction	Simultaneously submit sealed bids	Mean bid	Each individual pays market price (subject to unanimity rule) if sum of bids exceeds sum of costs	None or all

Source: Lusk and Shogren (2007)

Past research has established that the selection of the EA mechanism depends on a number of factors. First, several lines of evidence suggest that when selecting the appropriate mechanism, bidder affiliation should be avoided (Milgrom and Weber, 2006; Lusk et al., 2004).

That is, for strategic equivalence across auctions, independent valuations from the rivals are required (i.e. nonaffiliated participants and/or non-collaborative bids). Second, each auction mechanism implies a different experimental setting which might affect consumers' choice behavior (Noussair et al., 2004). This is evident in second price auction where participants submit their bids together with other participants. In contrast, in BDM auction, participants make decisions individually, as experiments are conducted one-to-one. As such, if one of the primary goals of the researcher is to observe how participants interact during an EA, then the second price auction would be preferred over the BDM auction. Moreover, every auction has a different training factor included which depends on how familiar participants are with the mechanism (Noussair et al., 2004). For example, the English auction is very well known to participants and hence, it requires only a short training. On the other hand, the BDM auction is unfamiliar to most participants and requires a longer training. Additionally, several studies suggest that convenience is an another important for selection of the auction mechanism. This is certainly true in the case of the BDM auction. Although the BDM mechanism is not necessarily incentive compatible (Horowitz, 2006), its use is widespread because it can be administered to one individual at a time. This is especially important in experimental design in international development settings (De Groote et al., 2001). According to Wertenbroch and Skiera, 2003, the benefit of implementing BDM with one individual at a time is that it allows for the experimenter to do the experiment at real points of purchase under the specific conditions he/she desires.[2]

Another factor to consider when selecting an auction mechanism is whether the researcher is interested in more accurately estimating the upper or lower end of the demand curve. High value bidders help researchers estimate the upper end of the demand curve, while

[2] For example, the experimenter can implement the BDM auction next to an outdoors market with participants who just shopped from the market.

low value bidders aid in estimation of the lower end of the demand curve (Lusk and Shogren, 2007). To illustrate, Knetsch et al. (2005) examined bidding behavior in a second price auction and concluded that the auction might not engage low-value bidders who have the perception that they will never win (i.e.: second price auction might fail to engage off-margin bidders). According to Lusk and Shogren (2007), it is also essential to consider how participants' personal characteristics inform demand for the products up for auction.

The selection of one type of auction instead of another has important implications in terms of welfare estimates, too. In this regard, there exists a plethora of studies comparing different incentive compatible EA mechanisms to elicit WTPs using homegrown experiments (Shogren et al., 2004; Rutström, 1998; Lucking-Reiley, 1999; List, 2003; Lusk et al., 2004). With a few exceptions (Shogren et al., 1994), results from most of these studies suggest that different EA mechanisms may lead to different welfare estimates (Rutström, 1998; List, 2003; Lusk et al., 2004). Table 2 summarizes studies which have compared EAs using homegrown experiments.

Table 2: Comparison of EAs using homegrown experiments

Authors	**Country/Year**	**Subject**	**Experimental Auctions Compared**	**Results**
Shogren et al.	USA/1994	Irradiation to control the food borne pathogen Trichinella (Food Economics)	Second price auction (2PR), random *n*th price auction (RNP), and combinatorial private-collective (PC) auction	$WTP^{2PR} = WTP^{RNP} = WTP^{PC}$
Rutström	USA/1998	Gourmet chocolate truffles (Food Economics)	English auction (EN); second price auction, and BDM auction	$WTP^{EN} < WTP^{2PR}$ $WTP^{BDM} < WTP^{2PR}$

Table 2 (cont'd)

Lusk et al.	USA/2004	Beef ribeye steaks (Food Economics)	Second price auction, random nth price auction, BDM auction, and English auction	$WTP^{2PR} > WTP^{BDM}$ $WTP^{2PR} > WTP^{RNP}$ $WTP^{2PR} > WTP^{EN}$ $WTP^{RNP} < WTP^{EN}$ $WTP^{RNP} < WTP^{BDM}$
Lucking-Riley	USA/1999 (Internet)	Collectible trading cards	English auction, Dutch auction, first price auction (1ST), and second price auction	$WTP^{EN}=WTP^{2PR}$ $WTP^{DUTCH}>WTP^{1ST}$
List	USA/2003 (field experiment)	Sports cards	Second price auction and random nth price auction	$WTP^{RNP} > WTP^{2PR}$

To illustrate, in their longitudinal study, Shogren et al. (1994) compared a second-price auction, a random nth-price auction and a combinatorial private-collective auction. The combinatorial auction was created by combining a second price auction with a collective auction. Participants were provided a sandwich and a $25 endowment. Then, another sandwich was auctioned with the difference being that it had been treated with irradiation to control the food borne pathogen Trichinella. Participants were told that a sandwich must be eaten to receive their take-home income. Results from this study indicate no statistically significant difference between the second price and random nth price auctions; as well as between the second price and the combinatorial private-collective auctions.[3]

Rutström (1998) compared the bids from English, second price, and BDM auctions. The experiment design implemented conducted comparisons across different sub-samples of the participants varying the auction mechanism. The product was a box of gourmet chocolate truffles. Results from the study indicate that, on average, English and BDM auction bids are lower than the second price auction bids.

Lusk et al. (2004) compared the results from the following incentive compatible auction mechanisms: second price, English, BDM, and random nth price. To conduct such a comparison, they asked consumers to evaluate several different types of beef ribeye steaks. Results indicated that consumers bid higher in the second price auction compared to the English, BDM, and random *n*th price auctions. This result was magnified in the bidding rounds of the random *nth* price auctions. Furthermore, the authors found that random *n*th price auctions generate lower valuations than English and BDM auctions, on average.

In contrast, Lucking-Reiley (1999) found that estimates of WTP generated from an English auction and a second price auction are not statistically different. Comparing results from internet auctions (English, Dutch, first price sealed bid, and second price) using collectible trading cards as the product for sale, the author created two pairs of auctions and auctioned a copy of the same card in each institution. The two pairs were Dutch vs. first price auction and English vs. second price auction.[4] Lucking-Reiley concluded that Dutch auctions

[3] Specifically, using the overall averages for the second-price auction and the random nth price auction, Shogren et al. were not able to reject the hypothesis that the average bids in trial 1 and in trial 10 (the first and the last of 10 trials) were equal.

[4] In the Dutch auction, the price is continuously reduced until a buyer is found. Both in the Dutch and in the English auction, there is "real-time" bidding process. In the first price sealed bid auction, each participant submits a bid and the highest bidder wins the good, paying his/her bid.

earn approximately 30 percent more revenue than first price auctions and that English and second-price auctions exhibited revenue equivalence.

Similar to Lucking-Reiley (1999), List (2003) auctioned sports cards and compared the mean bids between a second price and a random *n*th price auction. Results from this study indicate that mean bids from the two types of auction are significantly different with the second price auction yielding lower WTPs than the random *n*th price auction when actual auctions were implemented.

Taken together, results from these studies suggest that different auction mechanisms generate different welfare estimates. Our study adds to this existing literature by exploring whether three widely used EA mechanisms (i.e., second price auction, BDM auction, and random *n*th price auction) produce equivalent welfare estimates using a generic commodity, eggs. A generic commodity is important because consumers routinely buy it, and eggs can be purchased in a traditional posted-price market such as grocery stores, convenience stores and on internet auction sites like E-bay. In addition, our study contributes to the literature by adding another piece of evidence against the equivalence of valuations derived under different EA mechanisms; showing that one auction mechanism (BDM) derives statistically different results from the other EAs. Our ultimate purpose is to investigate whether an EA (second price/BDM/random *n*th price) method should be preferred over the other two methods (BDM-random *n*th price/second price-random *n*th price/second price-BDM) or not and explore the reasons for potential differences across EAs.

2.2 Real Choice Experiment (RCE)

The choice experiment approach has its foundation in Lancastrian consumer theory (Lancaster, 1966) and random utility theory (see McFadden, 1974; Hanemann and Kanninen, 2001). Lancaster (1966) suggested that the total utility for a specific product can be broken down into sub-utilities for each attribute of the product. Random utility theory is based on the classical economic assumption that individual agents act rationally and always select the option that maximizes their derived utility. Therefore, the higher the utility each alternative provides (among the different alternatives), the higher the probability for the consumer to select that alternative. McFadden (McFadden 1986; McFadden and Train 2000; McFadden 1974) has worked heavily on discrete choice theory and methods, extending Thurstone's (1927) original theory of paired comparisons. As for their practical applications, discrete choice experiments were originally used in the fields of transportation and marketing with the ultimate purpose of predicting demand for new products. The first discrete choice experiment (as we know it today) is widely considered to have been created from Louviere and Hensher (1982) in the field of transportation.

Since then, discrete choice experiments have become one of the most popular non-market valuation methods employed in different fields of applied economics including food economics (Chang et al., 2009; Lusk and Schroeder, 2004, 2006; Alfnes et al., 2006; van Loo et al., 2011, 2014; Van Wezemael et al., 2014; Lusk and Tonsor, 2016; Ortega et al., 2011; Caputo et al., 2013, 2018a, 2018b; Hu et al., 2006), marketing (Ashok et al., 2003), development (Ortega and Ward, 2016; Otieno, 2011), transportation (Hess et al., 2008; Rose and Bliemer, 2009), and environmental economics (Ferrini and Scarpa, 2007; Scarpa et al., 2012). The popularity of discrete choice experiments has increased due to its advantages compared to other preference elicitation methods. Lusk and Schroeder (2004) summarize these advantages as follows. First, discrete choice experiments are more flexible than EAs because the evaluation of product alternatives or food attributes occurs simultaneously. To illustrate, in EAs, the number of attributes is usually minimized to facilitate operations and the products are usually evaluated one-by-one. On the other hand, in DCEs, product profiles are described by multiple attributes that can be simultaneously valued by the participants. Second, they are consistent with Lancaster's theory of consumer demand and Random Utility Theory.[5] Third, choice tasks (i.e., choice questions) are designed in a way that closely mirrors actual shopping situations (e.g., making a choice among multiple products offered at different prices).

Most of the choice experiments implemented in the field of agricultural and food economics are hypothetical (e.g., van Loo et al. (2011, 2014), Van Wezemael et al. (2014), Lusk & Tonsor (2016), Ortega et al. (2011), Caputo et al. (2013, 2018a, 2018b). However, due to the existence of hypothetical bias, an increasing number of studies are now implementing RCEs (Chang et al., 2009; Lusk & Schroeder 2004, 2006; Alfnes et al., 2006; Bazzani et al., 2017).[6] For instance, Chang et al. (2009) compared RCE and hypothetical choices concerning ground beef, wheat flour, and dishwashing liquid. Lusk and Schroeder (2004, 2006) elicited willingness to pay from RCEs regarding beef products. Alfnes et al. (2006) derived consumers' willingness to pay for the color of salmon and Bazzani et al. (2017) examined consumers' valuation for local versus organic food. Our study contributes to the growing body of RCE research by eliciting consumers WTP for a generic commodity (eggs) and most importantly, by comparing RCEs and three commonly used EAs.[7]

[5]According to Lancaster's theory, the total utility for a specific product consists of the sub-utilities for each attribute of the product, while following the classical economic assumption on which random utility theory is based, individual agents act rationally and always select the option that maximizes their derived utility.

[6] Hypothetical bias occurs when participants do not have to support their choices with real monetary commitment (i.e., buy the binding product) (Lusk and Schroeder, 2004; De-Magistris et al., 2013).

[7] Related to the monetary commitment is the participants' WTP, which plays a key role in the success of a RCE. WTP, which is elicited with the use of experimental methods (EAs, RCE, Contingent Valuation), is often used as an input or surrogate for demand measurement in welfare analyses of food policies (Gao and Schroeder, 2009). In addition, WTP normally provides feedback for various food labeling programs (Lusk and Anderson, 2004; Lubben, 2005). Hence, determining consumers' WTP for food quality attributes accurately has far reaching implications as it influences the decision makers of the market (i.e., policy makers, producers, intermediaries). The ability to determine which attributes are important to consumers has become more and more important over the last decade for two reasons: first, the use of labeling has drastically increased in food markets over the past ten years and second, product differentiation is essential in the effort to create "added value" for food products. Identifying which attributes are important to consumers can also lead to more directed marketing and could enhance the branding and labeling of food products.

2.3 Experimental Auctions versus Real Choice Experiments

Whether hypothetical or real, choice experiments and EAs are now the most widely used experimental methods in valuing goods and attributes. RCEs and EAs are considered to have similar design features, to be incentive compatible and hence to yield equivalent outcomes (Lusk and Schroeder, 2006). Notably, only a few studies have compared RCEs and EAs with each other. Results from those studies have revealed that RCE and EA result in different welfare estimates (WTPs). Table 3 summarizes the studies which have compared a RCE with an EA.

Table 3: Real choice experiment versus experimental auctions literature table

Authors	**Country/ Year**	**Subject**	**Experimental Auction**		**Real Choice Experiment**		**Results**
			Mechanism (Sample Size)	*Rounds*	*Attributes*	*Choice Tasks (Sample Size)*	
Gracia et al.	Spain/2011	Cured-Ham Products	Random *n*th price (N=62)	1	4 price levels; 4 animal welfare levels	16 (N=107)	$WTP^{RCE} \neq WTP^{EA}$
Lusk and Schroeder	USA/2006	Beef Steaks	Second price (N=35)	5	4 price levels; 5 beef steak types	17 (N=67)	$WTP^{RCE} > WTP^{EA}$
Shi et al.	China/2018	Orange Juice Products	BDM (N=107)	1	4 price levels; 3 types of orange juice	10 (N=76)	$WTP^{RCE} > WTP^{BDM}$

Gracia et al. (2011), using a between sample approach, compared RCE and EA by means of cured-ham products, differentiated by four different levels of an animal welfare label: (a) standard animal welfare; (b) improved animal housing; (c) improved transport conditions; and (d) comprehensive animal welfare (comprising the last two improvements). In the RCE, respondents were presented with 16 choice questions, each represented by two cured-ham products and a no-purchase option. In the EA, respondents submitted bids for each product using a random *n*th price auction mechanism. Both experiments were conducted in Spain (Zaragoza) with actual consumers. Their results indicate that the WTP estimates under both elicitation procedures have the same sign (positive) but of different magnitudes. Statistically significant differences were also found between the elicitation methods for most demographic profiles in the case of the comprehensive animal welfare label.[8] The authors concluded that WTP estimates vary across elicitation methods. This could be due to the more direct approach of RCEs compared to EAs, the familiarity consumers feel with the RCE, the existence of peer pressure in EAs, and the different price settings between RCE and EA (Gracia et al., 2011).

In the same vein, Lusk and Schroeder (2006) investigated whether WTPs for steak attributes differ between a second price auction and a RCE. Using a between-sample approach, consumers were asked to participate either in an auction market (second price auction) or in a choice task including five beef ribeye steaks: (a) a generic steak; (b) a guaranteed tender steak; (c) a "natural" steak; (d) a USDA choice steak and (e) a certified Angus beef steak.[9] In the RCE, respondents were faced with 17 choice questions, while in the EA people were asked to place bids. Findings from this study can be summarized as follows: a) auction bids were significantly lower as compared to WTPs from the RCE, b) own-price elasticities of demand for higher quality products were notably higher when derived from the auction data than when

[8] Their hypothesis ($WTP^{RCE} = WTP^{EA}$) was rejected in most cases.
[9] In a between sample approach, every participant in the sample participates only in one experiment.

derived from the RCE data, and c) the consumers' preference orderings were similar across the two elicitation methods.

Recent research by Shi et al. (2018) found that BDM auction bids for three different types of orange juice were significantly lower than WTP estimates derived from the RCE experiment. By controlling for participants' deal-proneness, the authors also found that higher levels of deal-proneness lead to lower bids in BDM auctions, while it did not affect WTP estimates from the real double-bounded dichotomous contingent valuation (RCVM) and the RCE.[10] In addition, lower level of deal-proneness led to smaller differences in WTP estimates across BDM auction and RCE. These results suggest that the "gambling behavior" of deal-prone people may be influenced by the BDM auction mechanism and hence, the bids derived from this mechanism may be understated.

Although these studies provide evidence about bidding behavior across experiments, all of them only compared one type of EA with the RCE rather than comparing a RCE with multiple EA mechanisms. Hence, it is still unclear whether the documented differences in WTP estimates between RCE and EAs are a result of the type of auction mechanism selected for the EA. This study adds to the existing literature by comparing a RCE with multiple EAs (i.e., second price auction, BDM auction, random *n*th price auction). Moreover, our study will provide more recent evidence to the pre-existing research in this area; the studies from Gracia et al. (2011) and Lusk and Schroeder (2006) are 8 and 13 years old respectively. As those elicitation methods have been increasingly used during the last decade, newest research might provide more relevant evidence given that consumers are on average more familiar with EAs and RCEs today than they used to be 10 years ago. Finally, this research is the second study to be implemented in the U.S., after the one from Lusk and Schroeder (2006).

[10] Deal-proneness in the context of this study means: "the aggressiveness in obtaining low prices"

3. EXPERIMENTAL PROCEDURES AND SURVEY DESIGN

Data Collection

In order to assess consumers' WTP across EAs and a RCE, participants were recruited from the general population of the college town of East Lansing and the neighboring capital city of Lansing, Michigan, during Spring 2018. Participants were recruited through the "Community Paid Participant Pool" recruitment system offered by the College of Communication and Arts and Science at Michigan State University.[11]

The experiments were conducted at Michigan State University. Selected participants were older than 18 years, responsible for grocery shopping, had purchased eggs during the last three months, were not lactose intolerant and did not follow a vegan diet. They all received $13 cash to participate in the study. Sessions were scheduled Monday through Sunday during morning, afternoon and evening hours to avoid timing effects (Lusk and Shogren, 2007). The duration of each session was approximately 45 minutes.[12]

The products used in the experiment were three different types of eggs: (i) Conventional, (ii) Cage free, and (iii) USDA organic. All eggs were provided by the dozen and were of similar size (large), grade (A), color (brown) and packaging. Eggs were selected in this study because they are a generic commodity; that is: widely available in various food outlets including grocery stores, convenience stores, and farmers markets all over the United States.[13] Although several brands exist for eggs, non-branded products were used to avoid branding-effects.

[11] Participants were notified through email for the availability of the study.
[12] The cost of each of the four treatments we implemented was approximately $1,135 (not including the labor cost of the experimenters involved in the data collection).
[13] Unlike items used in previous studies such as tickets, mugs, and coupons, consumers frequently purchase eggs, and eggs can be found in every typical posted-price market.

Upon arriving at the lab for a session, participants were randomly assigned to one of the four following treatments: a second price auction, a random *n*th price auction, a BDM auction, or a RCE. That is, we conducted between-subject comparisons across elicitation methods. We used the between-subject approach to avoid bias introduced by the participation in multiple experiments (Lusk and Schroeder, 2006), fatigue effects (Charness et al., 2012) and the potential demand reduction when consumers purchase more than one product (Lusk and Schroeder, 2006).The second price and the random nth price auctions were conducted in groups of five people, whereas the BDM auction and the choice experiment were conducted in a private interview setting (one-on-one).[14] After assigning participants to one of the treatments, they received the participation fee in cash and were asked to read and sign the consent form (see Appendix F). Subsequently, they were asked to complete a questionnaire, which included questions about the participant's demographics, prior knowledge, consumption habits, and other behavioral questions. Next, the experiment started, and participants had the chance to examine the different products (conventional, USDA organic, cage free) featured on a display table. In addition, a captioned picture describing each of the egg types was read aloud and shown to participants (see Figure 1). After that, bid or choices were made depending on the treatment participants were assigned to.

[14] We randomly assigned participants to groups upon arrival in the research area. Small group size helps to avoid the disengagement of off-margin bidders from the auction procedure (Shogren et al., 2001). In addition, there is evidence from recent theoretical (Banerji and Gupta, 2014) and empirical studies (Rosato and Tymula, 2016) that the equilibrium bid is lower when the number of bidders is larger and that can potentially lead to a confounding bidding effect. Moreover, the number of participants in each group was kept constant to keep everyone equally engaged (Drichoutis et al., 2017).

Figure 1: Labels used in our study

Eggs labeled "cage-free" are laid by hens that are allowed to roam in a room or open area, which is typically a barn or poultry house.

Eggs marked with the USDA's National Organic Program (NOP) label come from uncaged hens that are allowed free range of their houses & access to outdoor spaces. They are fed an organic diet produced according to NOP standards [USDA organic regulations (7 CFR §205)].

Sources: Priscilla (2013), United States Code of Federal Regulations, 7 C.F.R. § 205.239 (2002), Hurst (2016)

After the completion of the experimental part of the study, participants completed a second questionnaire including questions concerning animal welfare and environmental attitudes, risk preferences, involvement, and competitiveness. Both the questionnaires were implemented using tablets (iPad), while the auctions and the choice experiment were conducted on paper.

In what follows, we describe the experimental procedures for each of the elicitation methods.

Experimental Auctions

Participants that were randomly selected to participate in an EA, were first subjected to a hypothetical auction for four different candy bars to familiarize themselves with the procedure of each type of auction. Following the candy bar auction, consumers participated in an auction for each of the dozens of eggs. The following subparagraphs illustrate the experimental procedures and steps followed to implement the three EAs: second price, random *n*th price, and BDM.

Second Price Auction

The basic procedure for the implementation of the second price auction was as follows:

- Step 1: A total of three rounds with 5 participants were conducted, one for each product: a) the conventional eggs, b) the USDA organic eggs, and c) the cage free eggs. At the beginning of each round, the participants received a bid sheet and were asked to simultaneously bid for the product up for auction in that round. The bidding sheets for each type of eggs were collected before the next ones were handed out.
- Step 2: The experimenter rolled a four-sided die to determine which egg auction was binding. Importantly, all the auctions had an equally likely chance of being binding.
- Step 3: The bids in the chosen auction were confidentially ranked from highest to lowest. The person with the highest bid for the eggs purchased the eggs but, he/she paid the 2^{nd} highest bid for the eggs.
- Step 4: For the chosen egg auction, the experimenter wrote the winning bidder(s) number and the price paid (second highest bid) on the board for everyone to see.
- Step 5: The winning bidder(s) came forward after the completion of the second questionnaire, paid the second highest bid and obtained the eggs. All other participants paid nothing and received nothing.

Random n*th price auction*

The basic procedure for the random nth price auction was as follows:

- Step 1 and Step 2 for the random *n*th price auction were the same with the first two steps for the second price auction (mentioned above).
- Step 3: The bids in the chosen auction were then ranked from highest to lowest. Next, a random number (N) was drawn by rolling a die to determine how many participants will win the eggs. The random number (N) was somewhere between 2 and 5 (number of

participants). The N-1 highest bidders in the binding egg auction purchased the eggs and paid the nth highest bid.

- Step 4: For the chosen egg auction, the experimenter wrote the winning bidder(s) number and the price paid (nth highest bid) on the board for everyone to see.
- Step 5: The winning bidder(s) came forward after the completion of the second questionnaire, paid the nth highest bid and obtained the eggs. All other participants paid nothing and received nothing.

Becker-DeGroot-Marschak (BDM) auction

The basic procedure for the BDM auction which was implemented on a 1-1 interview setting was as follows:

- Step 1 and Step 2 for the BDM auction were exactly the same with the other two auctions, except from the fact that the BDM auction was implemented on a 1-1 private interview setting and not in groups of 5 people.
- Step 3: The experimenter then rolled a 10-sided die two times (one for the second decimal and one for the first decimal) and a 7-sided die one time to determine a randomly drawn price between \$0.00 and \$6.00. If the bid for the binding eggs was greater than or equal to the randomly drawn price, the participant purchased the eggs and paid the randomly drawn price. If the bid for the binding eggs was less than the randomly drawn price, the participant paid nothing and received nothing.
- Step 4: For the chosen eggs auction, the experimenter wrote the randomly drawn price (between \$0.00 and \$6.00) on the board.
- Step 5: The winning bidder came forward after the completion of the second questionnaire, paid the randomly drawn price and obtained the eggs. [15]

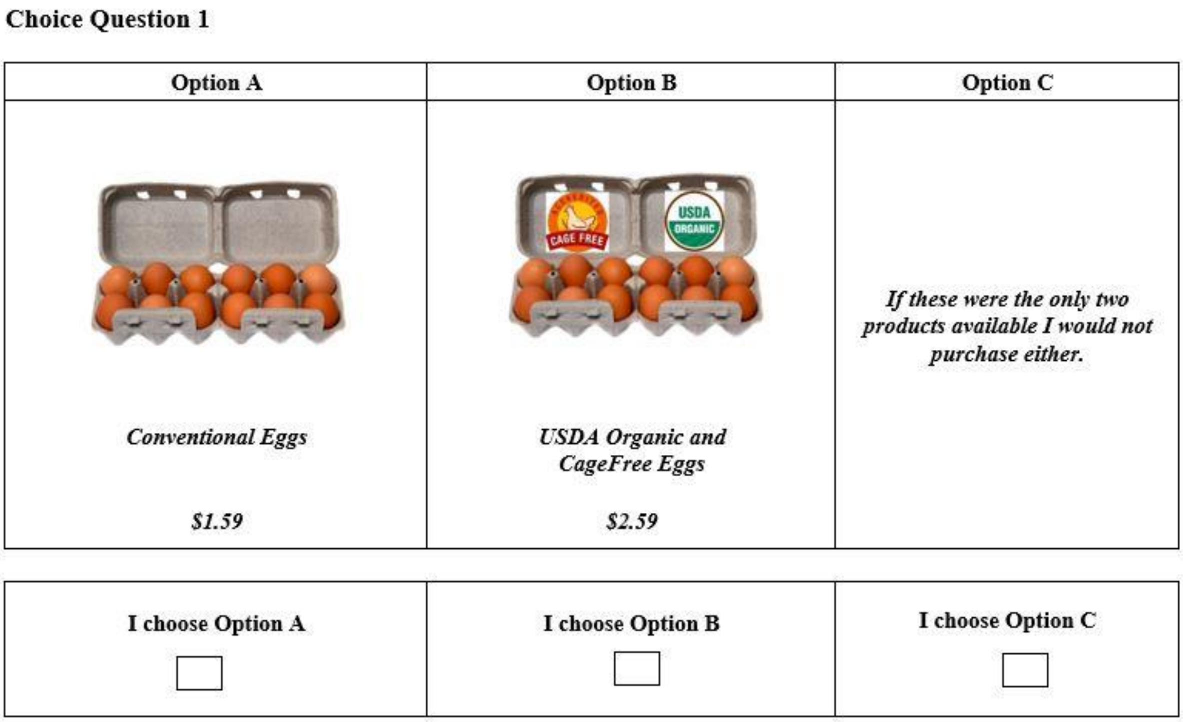
[15] The bidder won the auction if his/her bid was higher than or equal to the randomly drawn price. In any other case the bidder paid nothing and didn't receive any eggs.

Real Choice Experiment

Participants who were randomly selected to participate in a RCE, were first subjected to a hypothetical choice experiment over a selection of four candy bars in order to familiarize themselves with the procedure. After that consumers participated in the egg RCE.

The RCE closely followed protocols used in related studies (Lusk and Schroeder, 2006; Gracia et al., 2011; Bazzani et al., 2017). During the experiment, our participants were faced with repeated choice questions, each represented by three alternatives: two types of eggs and a no-buy ("none of these") option, which was included to mirror what people experience in real shopping situations.[16] For each choice question, they were then asked to select their preferred one. Figure 2 provides a sample (CE) question.

Figure 2: Example of Choice Experiment Question



The eggs (dozen large, grade A, brown eggs) were described by three attributes and their respective levels: price ($1.59, $2.59, $3.59, and $4.59), USDA-organic label

[16] Adamowicz et al. (1998) introduced the no-choice option to such frameworks given the fact that a no-buy option is a fundamental element of shopping/choice behavior.

(present/absent), and cage free label (present/absent). Egg price levels were chosen to reflect the prices in local grocery stores and retail prices reported by the U.S. Department of Agriculture - Agricultural Marketing Service and the USDA's National Retail Reports at the time of the experiment.

The number of the choice questions that were presented to the participants was determined by an optimal orthogonal in the differences (OOD) design developed by Street et al. (2001).[17] Given the number of attributes and levels and using the generator (1, 1, 1), the design resulted in 8 choice questions, with a D-Optimality of 96.6% (Table 4). The 8 choice questions were then randomly divided in two blocks of 4 choice questions each. To alleviate any ordering effects, the order in which the choice tasks were presented was randomized.

Table 4: Prices in Discrete Choice Tasks

	Alternative 1			Alternative 2		
Choice Set	Price	Cage Free	USDA Organic	Price	Cage Free	USDA Organic
Block 1						
1	$1.59	-	-	$2.59	√	√
2	$3.59	-	√	$4.59	√	-
3	$2.59	√	-	$3.59	-	√
4	$4.59	√	√	$1.59	-	-
Block 2						
5	$2.59		√	$3.59	√	
6	$4.59			$1.59	√	√
7	$1.59	√	√	$2.59	-	-
8	$3.59	√	-	$4.59	-	√

The basic procedure for the RCE was as follows:

[17] The OOD is a special type of a sequential orthogonal design. The orthogonality of the design allows us to determine the independent influence each attribute has on each participant's choices. In addition to orthogonality, an optimal (D-optimal) design ensures that attributes common across alternatives never take the same level during the experiment (Burgers and Street, 2005; Street and Burgess, 2004; Street et al., 2001, 2005). In general, D-optimal designs are intended to maximize the attribute level differences.

- Step 1: The RCE was conducted with one participant at a time. Each participant received a choice sheet and he/she was faced with four choice questions, one at a time. For each choice question, the participant was asked to select their preferred egg product at the listed price or the no-purchase option and record the choice on the choice sheet.
- Step 2: After the participant had finished responding to all four choice sets, the experimenter collected the choice sheet.
- Step 3: The experimenter rolled a four-sided die to determine which choice question was binding. That is, if a 1 is rolled, and the participant had chosen one of the two types of eggs in the first-choice question, he/she was given the product he/she selected and was asked to pay the price listed in the choice. If the participant had chosen the "no-purchase" option, then he/she was not given any type of eggs and paid nothing.

4. EMPIRICAL MODELS AND SPECIFICATION

Experimental auction model and specification

In the EAs, participants simultaneously submitted bids for each one of the three types of eggs (i.e., conventional eggs; cage free eggs; and USDA organic eggs). Using the bids collected from each auction mechanism (i.e., second price auction; BDM auction; random *n*th price auction) we calculated both the marginal and total WTP estimates. The marginal WTP was calculated by subtracting the elicited participants' bids for the conventional eggs from the bids for the other corresponding types of eggs. The total WTP coincides with the participants' actual bids for each of the auctioned types of eggs.

Using the total and marginal WTPs, we then explore whether there exists a statistically significant difference in WTP elicited from the three different EA mechanisms:

$$H_0 = WTP^{2PR} = WTP^{BDM} = WTP^{RNP}$$

Failing to reject this hypothesis, we would conclude that there is statistical equality among the WTPs elicited from the three auction mechanisms. In order to test this hypothesis, we compared the total WTP and the marginal WTP for each egg type auctioned, from all auction mechanisms, by carrying out two traditional F-Tests (one-way Anova), respectively. Our goal was to compare the means (i.e., mean total and mean marginal WTPs) of all auctions. Subsequently, we estimated post-hoc pairwise comparisons which are described in detail later in this section.

Consequently, we estimated three Tobit models (one for each type of auction). In EAs, bids are greater than or equal to zero for all of the auctioned goods (Gracia et al., 2011; Lusk and Schroeder, 2006). As a result, the Tobit model is one of the most widely used econometric models to analyze the WTPs elicited through EAs. Accordingly, to determine whether the auction mechanism influenced participants' bids significantly, we estimated three random effects Tobit models[18]. The Tobit model, incorporating random effects can be expressed as follows:

$$bid_{it} = \alpha' \boldsymbol{x}_{it} + u_i + \upsilon_{it} \quad (1)$$

where bid_{it} is the (auction) bid for the *i*th participant and the *t*th eggs type (conventional, cage free, USDA organic), which is detected only at non-negative values; $\boldsymbol{x}_{it}$ is a vector of independent variables including dummy variables identifying egg-type and sociodemographic characteristics; α is the (conformable) vector of coefficients; u_i is an individual specific disturbance for participant *i;* and υ_{it} is the overall error term (Lusk et al., 2004).[19]

Finally, to check the robustness of the results from the three separate Tobit models, we estimated three pooled Tobit models. In the first pooled Tobit model (Pooled Tobit 1), we included the auction mechanisms and the products as independent (factor) variables and the marginal WTP as the dependent variable. The second model (Pooled Tobit 2) adds to the first one by also including interaction terms between the auction mechanisms and the type of eggs. Finally, the third pooled Tobit model (Pooled Tobit 3) includes additional interaction terms between the demographic variables and the auction mechanisms. Following the method used by Rutström (1998), one of the elicitation mechanisms (the second price auction in our case) and one of the types of the eggs (the conventional in our case) were treated as baseline.

Real Choice Experiment (RCE)

In RCEs, consumers make a discrete choice from a set of presented product alternatives, each represented by a number of attributes with different levels, combined within choice sets. According to random utility theory, a given alternative within each choice set will be selected

[18] We incorporated random effects into the Tobit models in order to account for the panel nature of the data (i.e., each participant submitted multiple bids for different types of eggs).

[19] In our analysis, we estimated two models based on equation (1): a reduced one, which only includes the two labelled attributes indicator variables in the marginal WTP regression (model 1) and an extended one, which also includes the set of interaction terms between the type of the eggs and the selected sociodemographic variables (model 2).

if the perceived utility provided by such alternative is the highest among the alternative ones. The researcher is not able to observe and measure the respondent's perceived utility; he/she can only observe the characteristics of the alternatives and the choice made by the individual.

As previously mentioned, RCEs are consistent with the Random Utility Theory. The utility that individual n derives from alternative j at choice situation t can be defined by a deterministic component V_{njt} and a stochastic component ε_{njt}:

$$U_{njt} = V_{njt} + \varepsilon_{njt} \tag{2}$$

Different discrete choice models can be specified depending on the assumptions regarding the joint distribution of the vector of random error terms as well as the functional form of the deterministic portion of the utility function. As shown by Train (2009), assuming ε_{njt} are distributed iid type I extreme value, the multinomial logit (MNL) specification results in:

$$P_{nit} = \frac{exp(V_{nit})}{\sum_j \ exp(V_{njt})} \tag{3}$$

where P_{nit} is the probability to choose alternative i in the choice occasion t by person n.

In addition to the independence from irrelevant alternatives (IIA) property (Ben-Akiva and Lerman, 1985; McFadden, 1986), the MNL imposes the restrictive assumption that the representative utility is deterministic, and the random terms are independently and identically distributed (iid, i.e., uncorrelated over alternatives). Importantly, it also assumes preference homogeneity in the sample, implying that all coefficients of the utility expression in equation (2) are the same across individuals (i.e., parameters of V_{njt} are fixed). Thus, if some heterogeneity is expected, the MNL specification is not sufficient for the purposes of our analysis. Hence, we estimated a mixed logit model (MXL) (Train 2009).

Unlike the MNL, the MXL model allows for random state variation, unrestricted substitution patterns, and correlation in unobserved factors over time. In our RCE, participants provided a sequence of four choice responses. Hence, a panel data approach is used to allow for correlation among individual preferences in a series of choice decisions (four choice sets per participant in our case). According to Train (2003), consider a sequence of observed choices $\mathbf{i}$ by individual *n*, one for each time period (i.e.: choice task), conditional on $\boldsymbol{\beta}$, the probability that individual *n* makes this sequence of choices is represented by the following joint probability:

$$L_{ni}(\boldsymbol{\beta}) = \prod_{\boldsymbol{t=1}}^{\boldsymbol{T}} \left[\frac{exp(\beta'_n x_{njt})}{\sum_j \; exp(\beta'_n x_{njt})}\right] \tag{4}$$

The unconditional probability is the integral of this product over all values of $\boldsymbol{\beta}$ in the space of the distribution:

$$P_{ni} = \int L_{ni}(\boldsymbol{\beta}_n)\, f(\boldsymbol{\beta}) d\beta \tag{5}$$

Following Train (2003), the parameters of the model are estimated by simulated maximum likelihood estimation techniques.

In this application, the utility in (2) was specified in WTP space (see Train and Weeks 2005; Scarpa, Thiene, and Train 2008) rather than in preference-space to allow for heterogeneity in the price coefficient (Scarpa, Thiene, and Train 2008; Daly, Hess and Train 2012).[20] In addition, utility in willingness to pay space provides directly the WTP for each attribute in the design (i.e.: cage free and USDA organic) (Scarpa and Willis, 2010). Following the analysis from Train and Weeks (2005), Scarpa et al. (2008) and Bazzani et al. (2019), assuming the utility is linear in the parameters, the utility that individual *n* obtains from alternative *j* at choice situation *t* is specified as follows:

$$U_{njt} = \lambda_n(\beta_{n1} CFREE_{njt} + \beta_{n2} USDA_{njt} - p_{njt}) + \varepsilon_{njt} \tag{6}$$

[20] To test the robustness of our results, we implemented utility specifications in preference space, too. The results from the estimation in preference space are presented in the Appendix C.

where λ_n is a random positive scalar representing the price/scale parameter; p_{njt} is the price (continuous) variable generated by the price levels in our experimental design; $CFREE_{njt}$ and $USDA_{njt}$ are dummy variables for the cage free and the USDA organic attributes. They take a value of 1 when the label is present in the product, and 0 otherwise; β_{n1} and β_{n2} are the random coefficients of the estimated WTP values; and ε_{njt} is the (random) error term which follows a Type I Extreme Value distribution. The coefficients for the USDA organic and the cage free labels are assumed to be random following a normal distribution.[21]

Comparison of Experimental Auction Data and Real Choice Experiment Data

In an effort to compare the auction data with the RCE data, it must be highlighted that EA data are continuous in nature while the RCE data are discrete. In order to compare the two types of data, either auction data must be converted to simulated choice data or vice versa. Following Lusk and Schroeder (2006), in this application we compared the individuals' WTP derived from the RPL model with our auction bids.

Using the individual WTPs, we then explore whether there exists a statistically significant difference in WTP elicited from the RCE and the three different EA mechanisms:

$$H_0: WTP^{RCE} = WTP^{2PR} = WTP^{BDM} = WTP^{RNP}$$

Failing to reject this hypothesis, we would conclude that there is statistical equality among the WTPs elicited from these four methods. In order to test this hypothesis, we first needed to estimate the marginal WTP for each label (i.e.: cage free and USDA organic) in the RCE and for each participant (i.e.: individuals' WTP). As previously discussed, while in the EAs the

[21] We used NLOGIT 6.0 for the calculation of the WTP space model by setting the price coefficient to 1 and its standard deviation to 0. For our estimation, we used 500 Halton draws. We used Halton draws (Train, 2003) instead of random draws since the Halton draws provide a more efficient simulation procedure for the RPL (Train, 1999).

marginal WTPs can be simply derived by subtracting the bids for the conventional eggs from the other type of eggs, in the RCE, individuals' WTP is derived by implementing conditional inference.

To illustrate, following the methods described by Train (2003), we have two (probabilistic) events: choice y_n and taste β_n. Let $h(\beta|y,x,\theta)$ be the conditional distribution of taste for the participants who chose y, when faced with scenario x, and let θ denote the population parameters. β is drawn from the population distribution $g(\beta|x,\theta)$. The distribution of h has a lower variance than the distribution of g, since the latter includes all the distributions for all possible choices. Hence, its use is preferable for statistical inference and comparisons like the one we are trying to implement. By Baye's rule:

$$h(\beta|y,x,\theta) = \frac{P(y|x,\beta)g(\beta|\theta)}{P(y|x,\theta)} \quad (7)$$

Using this formula, we have the ability to derive various statistics conditional on the choices of the participants y (e.g.: mean, variance, and predicted choice probabilities). In our case, we derived the individual specific WTP conditional on choice. For each individual $\boldsymbol{i}$, we calculated their WTP for label $\boldsymbol{j}$. As we explained earlier, the derivation of WTP differs across preference space and WTP space.[22]

After deriving the individuals' WTP for each attribute (USDA organic and Cage Free), we compared them with the respective auction marginal bids from all auction mechanisms. We did so by performing a traditional F-test (one-way Anova).[23] Subsequently, we estimated post-hoc pairwise comparisons.[24] We implemented pairwise comparisons based upon the

[22] NLOGIT 6.0 derived the distinctive individuals' WTP matrices for both our attributes.
[23] We estimated the comparisons in Stata 14.0 statistical software.
[24] Post-hoc pairwise comparisons are commonly used when there are three or more levels of a factor (4 treatments in our case) (UCLA, 2019). The statistical software we used (Stata) has three built-ins pairwise methods (Sidak, Bonferroni and Scheffe) in the F-test command. Although these comparisons are easy to implement, these methods are considered to be too conservative for pairwise comparisons (UCLA, 2019; Hedayat and Kirk, 2006). Scheffe is the most conservative method of the three, followed, in order by Bonferroni and Sidak.

Studentized Range distribution.[25] Finally, to check the robustness of our results we estimated a pooled Tobit model applying the same procedures followed in the comparison of the EAs. In the model, the elicitation mechanisms and the products were entered as independent (factor) variables, while the marginal WTP was the dependent variable. In the estimation, the second price auction was treated as baseline.

[25] The IDRE Statistical Consulting Group (UCLA, 2019) has developed three different programs for the use of the three following methods: (1) the Tukey HSD, (2) the Tukey-Kramer and (3) the Fisher-Hayter respectively (Gleason, 2019). The three methods perform the same test statistic when the cell sizes (sample size of each treatment in our case) are equal but will differ when cell sizes are unequal. The Tukey-Kramer or the Fisher-Hayter tests are usually preferred when the cell sizes are unequal (UCLA, 2019; Hedayat and Kirk, 2006).

5. RESULTS

Sample Characteristics

For our experiments, we recruited consumers from the local community, rather than university students, in an effort to ensure that participants were the primary shoppers of their households (Chang et al., 2009, Gracia et al., 2011). Table 5 shows the sociodemographic characteristics of the four samples used in the EAs and RCE. Most participants in our study were women; in general, women have a higher participation rate in research studies and traditionally also make the food shopping decisions for their household. The participants' age ranged from 18 to 78 years and the average household was comprised of two to three people. Around 34% of the participants declared that they had a university degree and 26% indicated to have either completed a graduate degree or were a graduate student at the time of the research. Approximately 58% of our participants had an annual household net income lower than $50,000. The sociodemographic characteristics for all four samples are similar. Specifically, the reciprocal tests (chi-square test or ANOVA) of equality between the sociodemographic variables in our four samples (EAs and RCE) were not rejected at the 5% significance level.

Table 5: Sample Characteristics (%, unless stated)

Variable Definition	Real Choice Experiment	Second Price Auction	BDM Auction	Random *n*th Price Auction	*p*-Value
Gender					0.899
0=male	29.0	33.3	28.6	32.9	
1=female	71.0	66.7	71.4	67.1	
Age	31.8	33.4	30.6	28.4	0.171
Household size	2.7	2.3	2.4	2.3	0.201
Education					0.257
High school	40.3	26.1	31.4	27.1	
College	25.8	37.7	37.1	35.7	
Postgraduate studies	22.6	30.4	22.9	28.6	
Average household income					0.803
Low income = less than $49,999	51.6	62.3	58.6	57.1	
Medium income = between $49,999 and 99,999	25.8	17.4	20	14.3	

Table 5 (cont'd)

High income = more than $100,000	14.5	11.6	12.9	15.7

Note: We conducted analysis of variance to test the equality between the sociodemographic variables within the 4 treatments; our null hypothesis was not rejected at the 5% significance level for the sociodemographic characteristics. In addition, to check the robustness of those tests, a non-parametric test such as the Kruskal–Wallis test by ranks was implemented. Results from the test indicate our null hypothesis was not rejected at the 5% significance level for all sociodemographic characteristics.

Bids from Experimental Auctions

Auction bids segregated by auction treatment and egg type are reported in Table 6.

Table 6: WTP Bids by Auction Mechanism and Egg Type

Egg Type	Second Price Auction	BDM Auction	Random *n*th Price Auction	*p*- Value
Conventional Eggs				0.363
Mean	0.867	1.064	0.926	
Standard Deviation	0.831	0.718	0.945	
Cage Free Eggs				0.004
Mean	1.148	1.726	1.304	
Standard Deviation	1.031	1.032	1.081	
USDA Organic Eggs				0.080
Mean	1.592	2.042	1.634	
Standard Deviation	1.360	1.155	1.366	

Note: We conducted a chi-square test or analysis of variance to test the equality between the auction bids within the three auction mechanisms; our null hypothesis was not rejected at the 5% significance level for the conventional and the USDA Organic Eggs. Our null hypothesis was rejected at the 10% significance level for the USDA organic eggs.

Results indicate that participants were willing to pay on average $0.87 for a dozen of conventional eggs and $1.59 for a dozen USDA organic eggs in the second price auction. These values increased to $1.06 and $2.04 respectively, in the BDM auction. A simple comparison of bids across the auction mechanisms shows that the second price auction bids are similar to random *n*th price auction bids, but lower than bids in the BDM auction.

Implementing the Tukey-Kramer and the Fisher-Hayter post-hoc tests, we conclude that the BDM auction generates differences in means for the cage free eggs and the USDA organic eggs and that the second price and the random *n*th price auctions are not statistically different.

In an effort to implement a robust comparison of the auction bids from the three EA mechanisms, the entire distribution of WTPs may be of interest (Lusk and Schroeder, 2006). Figures A1 through A3 in Appendix A display the inverse cumulative density functions of WTP for the conventional, Cage Free, and USDA organic eggs, respectively.

The marginal WTP bids (presented in Table 7) are derived by subtracting the bids for the conventional eggs from the bids for the cage free eggs and the USDA organic eggs for each participant, respectively. The results from the mean marginal WTP bids are consistent with the results from the mean total WTP bids.

Table 7: Marginal WTP Bids by Auction Mechanism and Egg Type

Egg Type	Second Price Auction	BDM Auction	Random *n*th Price Auction	*p*- Value
Cage Free Eggs				0.006
Mean	0.281	0.662	0.378	
Standard Deviation	0.718	0.795	0.640	
USDA Organic Eggs				0.257
Mean	0.725	0.978	0.708	
Standard Deviation	1.194	1.048	0.991	

Note: We conducted a chi-square test or analysis of variance to test the equality between the auction bids within the three auction mechanisms; our null hypothesis was not rejected at the 5% significance level for the USDA Organic Eggs. In addition, to check the robustness of those tests, a non-parametric test such as the Kruskal–Wallis test by ranks was implemented. Results from the test indicate our null hypothesis was not rejected at the 5% significance level for all sociodemographic characteristics.

To determine whether the three auction mechanisms provide differences that are statistically significant, we estimated a random effects tobit model for each auction mechanism. Two models were specified: Model 1, in which the dependent variable is represented by the marginal WTPs from the different auctions and the independent variable is defined by the type of the eggs (i.e., cage free eggs, USDA organic eggs); and Model 2, which adds to Model 1 by also including the demographic variables as independent variables. Table 8 describes the variables used in our auction data analysis, while Table 9 provides the estimates from models 1 and 2.[26]

Table 8: Variables used in auction data analysis (Tobit model for each auction type and pooled Tobit models)

Variables	Description
Dependent Variable	
Marginal WTP	The marginal auction bids for all types of eggs
Independent Variables	
Product	2=cage free eggs; 3=USDA Organic eggs
Gender	1=female; 0=male
Age	Age in years
Household size	Total number of people leaving in the same house with the participant (including himself/herself)
Education	Years of education
Household income	Total household annual income in dollars/10000

Table 9: Tobit results for marginal WTP per auction mechanism

	Second Price Auction		BDM Auction		Random *n*th Price Auction	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Cage Free Eggs (CF)	0.281** (0.115)	0.265** (0.119)	0.662** (0.104)	0.667** (0.113)	0.378** (0.102)	0.368** (0.114)
USDA Organic Eggs (USDA)	0.725** (0.115)	0.687** (0.119)	0.978** (0.104)	0.973** (0.113)	0.708** (0.102)	0.721** (0.114)
Female		0.152 (0.150)		0.237 (0.157)		0.019 (0.125)
Age		0.013** (0.005)		0.010* (0.006)		-0.010* (0.006)
Education		0.067** (0.029)		0.023 (0.031)		0.049* (0.025)
Household income		-0.050** (0.018)		0.034** (0.019)		0.016 (0.014)
Household Size		0.071 (0.059)		0.003 (0.062)		-0.006 (0.053)
Log likelihood	-239.29	-211.77	-228.29	-210.84	-211.69	-187.33
N	69	63	70	64	70	61

Note: Standard errors are in the parentheses. * denotes statistically significant variables at the 10% level and ** denotes statistically significant variables at the 5%.

[26] We did not use any censoring for the models estimating the marginal WTP since we had negative values created when we calculated the marginal bids.

The marginal WTP estimates from Model 1 are reported in the second, fourth and sixth columns of Table 9. Results generally indicate that consumers are willing to pay a price premium for both egg types, although the marginal WTP for the USDA organic eggs is higher than the one for cage free eggs in all EAs. Most notably, differences across EAs were found. More specifically, consistent with previous studies (Shogren et al. 1994), bids for both products from the BDM auction are higher than the bids from the second price auction and random *n*th price auctions. In addition, differences are also found between the second price and random *n*th price auction. To illustrate, the orderings of bids for the various egg products are not consistent; the second price auction yields higher bids for the USDA organic eggs but lower bids for the cage free eggs as compared to the random *n*th price auction counterpart bids. This finding is consistent with Lusk et al. (2004), who also found inconsistencies across bidding rounds and products.

Turning to the marginal WTPs from Model 2 (third, fifth and seventh column of Table 9), it can be seen that adding socio-demographics characteristics to Model 1 results in small changes in the magnitude of the coefficients of the Cage Free and the USDA organic eggs. In addition, as it can be seen from the table (above), age was the only demographic characteristic found to have a statistically significant effect on the marginal WTPs for Cage Free and USDA organic eggs in all type of auctions. Furthermore, Table 9 illustrates that education had a statistically significant effect on the marginal WTPs for Cage Free and USDA organic eggs in the second price and the random *n*th price auction, while household income had a statistically significant effect on the marginal WTPs (for Cage Free and USDA organic eggs) in the second price and the BDM auction. To illustrate, for each additional year of age, consumers are willing to pay on average 1 more cent for eggs (independently of the attributed characteristics of the eggs). Moreover, for each additional year of education, participants are willing to pay 7 more cents in the second price auction and 5 more cents in the random *n*th price auction, ceteris paribus. Regarding the household income, an additional annual revenue of $10,000 would make participants to pay, ceteris paribus, 3 more cents for eggs in the BDM auction and 5 less cents in the second price auction.

Subsequently, we estimated three pooled Tobit models (Pooled Model 1, Pooled Model 2, and Pooled Model 3) to determine the effect of auction institution on bids. Pooled Model 1 uses the Model 1 specification (from Table 9) to explore the effect of EA on bids, ceteris paribus. Pooled Model 2 adds to Pooled Model 1 by also including the set of interaction terms between the type of the eggs and the type of the EAs as independent variables. Finally, Pooled Model 3 adds to Pooled Model 2 by also including interaction terms between the type of the auction and the demographic variables as independent variables. Table 10 summarizes the results.

Table 10: The effect of Auction Institution on marginal WTP: Random Effects Pooled Tobit Estimates

Independent Variables		*Marginal WTP*	
	Pooled Model 1	Pooled Model 2	Pooled Model 3
Cage Free Eggs (CF)	0.441** (0.062)	0.281** (0.107)	0.265** (0.115)
USDA Organic Eggs (USDA)	0.804** (0.062)	0.725** (0.107)	0.687** (0.115)
BDM Auction (BDM)	0.211** (0.091)	0.000 (0.126)	0.430 (0.676)
Random *n*th price auction (RNP)	0.026 (0.091)	0.000 (0.126)	0.938 (0.673)
CF*BDM		0.381** (0.151)	0.401** (0.162)
USDA*BDM		0.253* (0.151)	0.286* (0.162)
CF*BDM		0.097 (0.151)	0.103 (0.164)
USDA*RNP		-0.018 (0.151)	0.034 (0.164)
Female			0.152 (0.143)
BDM*Female			0.085 (0.206)
RNP*Female			-0.134 (0.202)
Age			0.013** (0.005)

Table 10 (cont'd)

BDM*Age			-0.003 (0.007)
RNP*Age			-0.023** (0.008)
Education			0.067** (0.028)
BDM*Education			-0.044 (0.041)
RNP*Education			-0.018 (0.040)
Household income			-0.050** (0.018)
BDM*Household income			0.088** (0.025)
RNP*Household income			0.065** (0.024)
Household size			0.071 (0.056)
BDM*Household size			-0.068 (0.081)
RNP*Household size			-0.077 (0.082)
Log likelihood	-686.022	-682.15	-611.39
N	209	209	188

Note: Standard errors are in the parentheses. * denotes statistically significant variables at the 10% level and ** denotes statistically significant variables at the 5%.

It is apparent from this table that when it comes to the type of eggs, in all models (Pooled Model 1, Pooled Model 2, Pooled Model 3), the coefficients of the Cage Free and the USDA organic eggs are of positive magnitude and statistically significant. Further, the coefficient for the USDA organic eggs is higher than the coefficient of the Cage Free eggs in every case. This indicates that consumers are always willing to pay higher for the USDA organic eggs compared to the Cage Free eggs.

However, differences were found across auction mechanisms. To illustrate, the results of Pooled Model 1 indicate that the coefficient of the BDM auction variable is positive and statistically significant (0.211), while the coefficient of the random *n*th price auction, although positive, is not statistically significant. This evidence suggests that, on average, marginal WTPs from BDM are higher than the second price auction bids, while the second price and random *n*th price auctions produce similar marginal WTP. This result is consistent with Shogren et al. (1994), who also found no statistically significant differences in mean (total) WTP estimates between second price and random *n*th price auctions. A potential explanation for this equivalence could be the similarities in design those two elicitation methods have (see section 2.1, Table 1).

In Pooled Model 2 we also included the interaction terms between auction mechanisms and type of eggs. When we include an interaction term, the coefficients of the original variables can be tricky to interpret (Wooldridge, 2016). For example, in the Pooled Model 2, the coefficients of the auction mechanisms are now interpreted as the effect of auction mechanism on marginal WTP when the product is zero. This effect is not of interest at any case.[27] Turning to the effects on consumer valuation for eggs across EAs, it can be seen that the coefficients of the interaction terms of the BDM auction with both types of eggs (USDA organic and Cage Free) are positive and statistically significant suggesting that the marginal WTP for both types of eggs is higher when the auction mechanism implemented is the BDM. On the other hand, the coefficients of the interaction terms of the random *n*th price auction with both types of eggs are not statistically significant. Hence, we can conclude that the random *n*th price auction does not have a differential effect on the marginal WTP compared to the second price auction (for either type of eggs). Differences between BDM auction and the other two EA mechanisms (second price and random *n*th price) might be explained by the lack of peer pressure or competition during the BDM auction.[28] For instance, recent study by Rosato and Tymula (2019) suggests that in homegrown value auctions bids decline with increased competition.[29]

[27] We are interested in the value of the coefficients when the product=2 (Cage Free eggs) and when the product=3 (USDA organic eggs). Hence, the fact that the coefficients of the auction mechanisms in Pooled Model 2 take value of zero is not of interest for our analysis.

[28] To illustrate, while participants in the BDM auction bid individually, in the second and the random nth price auction they submit bids in groups of five people.

[29] The authors conducted an experiment where participants bided in multiple second price auctions for real objects and induced value items, with each auction having a different number of bidders.

The authors argued that this finding is consistent with loss aversion behavior; with an increase in the number of bidders, participants perception is that there is a lower chance of winning and they interpret that as a loss, and hence their willingness to pay gets reduced.[30]

In Pooled Model 3, when additional to the interaction terms included in Pooled Model 2, we included interaction terms between the type of auction mechanisms and the demographic characteristics, we observed that age, education and household income have a statistically significant effect on marginal WTPs, ceteris paribus.[31] In addition, our results reveal that the random *n*th price auction has differential effect on age and household income while the BDM auction has a differential effect on income (i.e.: all three coefficients are positive and statistically significant).

Real Choice Experiment

The estimation results from the mixed logit model specified in WTP space are reported in Table 11.[32]

Table 11: Estimates for the Mixed Logit Model in WTP space

Parameters	Estimates
Cage Free Eggs (CF)	0.270 (0.376)
USDA Organic Eggs (USDA)	0.693** (0.344)
Price	1.0
No Buy	-2.453** (0.454)
Standard deviations of parameter distributions	

[30] The study by Rosato and Tymula (2019) suggests that while in real-object auctions bids decrease with the increase of competition, in induced-value auctions, bids do not vary with the magnitude of competition. The authors conclude that participants may behave differently in homegrown auctions than in induced-value ones.
[31] For every additional year of age, participants were willing to pay on average 1.3 more cents for eggs; for every additional year of education, participants were willing to pay on average 6.7 more cents for eggs; and for every additional household income of $10,000, participants were willing to pay on average 5 less cents for eggs.
[32] Other econometric models were estimated, all leading to a lower predictive performance. The results of the basic Multinomial specification are reported in Appendix B. The results of the Random Parameter Logit model with fixed price coefficient (RPL (FPC)) and the Random Parameter Logit model with price following a triangular distribution (RPL (RPC)) are reported in Appendix C.

Table 11 (cont'd)

Cage Free Eggs (CF)	0.891** (0.356)
USDA Organic Eggs (USDA)	1.485** (0.396)
Price	0.0
N	248
Log likelihood	-192.97
χ^2	158.96
Pseudo-R^2	0.29

Note: Standard errors are in the parentheses. * denotes statistically significant variables at the 10% level and ** denotes statistically significant variables at the 5%.

Results indicate that, on average, respondents are willing to pay a price premium of $0.693 for USDA organic eggs (dozen), while the WTP premium for cage free ($0.270) is not statistically significant. The standard deviation of cage free is significant at the 5% significance level. This indicates that although participants, on average, are not willing to pay a price premium for cage free, a sub-group of consumers has a significant price premium for the product with the cage-free label.

These results are consistent with the current status of the egg market in the US, where, according to (Lusk, 2018), "choices imply that half of consumers are willing to pay no more than a 30 cents/doz. premium for cage-free eggs". In addition, Lusk (2018), examining the marginal effects of egg attributes in changing market shares (for the control group), concluded that the existence of the USDA organic label would have higher impact than the addition of the cage free label. Our data also indicate that the USDA organic label produces a higher WTP estimate.[33]

[33] In addition, as noted by Train and Weeks (2005), the specification we used in WTP space provided lower and more realistic estimates for our two attributes compared with the specifications in preference space (see Appendix C).

Comparing Real Choice and Experimental Auctions Willingness to Pay

To compare the results from the RCE and EAs, we derived marginal WTP estimates from both the RCE and EAs institutions for all labelled characteristics analyzed. We derived the marginal WTP for each labelled characteristic in the EAs by subtracting the bids for the conventional eggs from the bids for the cage free and USDA organic eggs. Furthermore, in order to implement our comparison, we derived the individuals' WTPs from the RCE (as described in Section 4).[34] Table 12 shows the results from the F-test we implemented for the comparison of the mean marginal WTPs from all four treatments.

Table 12: Mean marginal WTP per elicitation mechanism

Elicitation Mechanism	**Marginal Estimated WTP**
WTP Cage Free	
Real Choice Experiment	0.265 (0.503)
Second Price Auction	0.281 (0.718)
BDM Auction	0.662 (0.795)
Random *n*th Price Auction	0.378 (0.640)
F-Test	5.05
p-value	0.002**
WTP USDA Organic	
Real Choice Experiment	0.702 (1.157)
Second Price Auction	0.725 (1.194)
BDM Auction	0.978 (1.048)
Random *n*th Price Auction	0.708 (0.991)
F-Test	1.02
p-value	0.385

Note: H_0: WTP(RCE) = WTP(2PR) = WTP(BDM) = WTP(RNP), H_1: WTP(RCE) ≠ WTP(2PR) ≠ WTP(BDM) ≠ WTP(RNP). Standard deviations of mean marginal WTPs are reported in the parentheses. * denotes statistically different WTP at the 10% level and ** denotes statistically different WTP at the 5%. In addition, to check the robustness of those tests, a non-parametric test such as the Kruskal–Wallis test by ranks was implemented. Results from the test indicate our null hypothesis of equality of the means was rejected at the 5% significance level for the Cage Free eggs. This finding confirms the results of the F-Tests implemented.

[34] In Appendix D, we report the number of zero bids for all products per EA and the number of no-buys for all choice sets (per participant) in the RCE.

The WTPs (mean parameter) for the RCE are 0.265 for the cage free attribute, and 0.702 for the USDA organic attribute. As demonstrated in Table 12, mean marginal WTPs under the four different elicitation procedures are positive but of different magnitudes. WTPs for the USDA organic eggs are almost the same for the second price auction, the random *n*th price auction and the RCE. WTPs for the cage free eggs are similar for the RCE and the second price auction and the WTP derived from the random *n*th price auction is slightly higher. In contrast, the BDM auction derives significantly higher WTPs than all other mechanisms for both attributes. Overall, the mean marginal WTPs do not differ when equality F-Tests (ANOVA) are conducted for the USDA organic attribute but do differ for the cage free attribute. It is worth to note that while the marginal WTPs for USDA organic eggs are not statistically different across elicitation methods, results are useful for illustrative purposes and could provide insights when used alongside the overall statistical analysis we implemented (Lusk, 2003).

Taken together these results, alongside with the results from the post-hoc tests, indicate that the BDM auction is the only mechanism that generates differences in means and, only for the cage free attribute. Furthermore, the second price auction, the random *n*th price auction and the RCE do not provide statistically different means at the 5% level for either of the two attributes; USDA organic and cage free. Hence, our null hypothesis ($WTP^{RCE} = WTP^{EAs}$) is rejected for the cage free eggs but not for the USDA organic eggs.

Subsequently, to check the robustness of the results from the F-Test and to determine the effect of elicitation mechanism on marginal WTP we estimated a pooled Tobit model. Similar to the comparison of the EAs, we used the products (i.e. cage free and USDA organic) and the treatments (i.e. all EAs and the RCE) as independent variables and the marginal WTP as the dependent variable. The results of the pooled Tobit model for all elicitation methods are summarized in Table 13.

Table 13: The effect of institution on marginal WTP: Random Effects Pooled Tobit Estimates

Independent Variables	*Marginal WTP*
Cage Free Eggs (CF)	0.401** (0.055)
USDA Organic Eggs (USDA)	0.781** (0.055)
BDM Auction	0.211** (0.089)
Random *n*th price auction	0.026 (0.089)
Real Choice Experiment	-0.013 (0.092)
Log likelihood	-887.643
N	271

Note: Standard errors are in the parentheses. * denotes statistically significant variables at the 10% level and ** denotes statistically significant variables at the 5%.

Consistent with the results from the EAs, holding the type of eggs constant, the BDM coefficient is positive and statistically significant (0.211). On the other hand, the coefficient of the random *n*th price auction is not statistically significant. Moreover, the results indicate that the marginal WTP from the RCE is lower than the second price auction bids on average, ceteris paribus. These findings are consistent with some of the findings of Gracia et al. (2011), where for some of the attributes the RCE yielded lower estimates than the EA. In general, we can conclude that BDM bids are higher than the second price auction bids on average. Furthermore, estimates from the second price auction, the random *n*th price auction and the RCE were found to be statistically equivalent.

Interestingly, these results contradict our earlier finding from the implementation of F-tests, where the mean marginal WTPs did not differ across the four elicitation methods for the USDA organic attribute but did differ for the cage free attribute. This inconsistency in results derived from the two different tests (i.e.: F-Test and Pooled Tobit Models) could be associated with the reduction in sample size that occurs when splitting the data by egg type.

Overall, cage free eggs are found to be valued \$0.40 more than the conventional eggs, on average, while the USDA organic eggs have a \$0.80 WTP premium when compared with conventional eggs, ceteris paribus.

6. DISCUSSION AND CONCLUSIONS

In recent years, there has been a growing interest in utilizing non-hypothetical elicitation methods such as EAs and RCEs for economic research. However, it is still unclear whether these experimental methods provide consistent welfare estimates such as WTP values. To the best of our knowledge, only three studies have compared valuations from EAs with those from RCEs (Lusk and Schroeder, 2006; Shi et al., 2018; Gracia et al., 2011). However, the authors compare RCEs with only one type of incentive compatible auction mechanism (second price auction, BDM auction, and random *n*th price auction respectively). Our study contributes to the existing literature by examining whether and how valuations from RCEs differ from three different EAs commonly used in food choice literature: second price, Becker–DeGroot–Marschak (BDM), and random *n*th price. In addition, in contrast with the previous studies where the RCE was consisted of a large number of choice tasks while the EA was conducted in a small number of rounds, in our study we implemented 4 choice tasks for the RCE and 3 rounds (one for each type of eggs) for each EA (see Table 3). This could make our comparison across elicitation methods more robust.

Overall, our findings indicate that the USDA organic label is valued more highly than the Cage Free label and that preference rankings across these egg types remain consistent across elicitation methods. Our results also suggest that the WTP values derived from the BDM auction are statistically different and higher than those derived from the other EAs (second price and random *n*th price) and the RCE when holding the type of eggs constant (Pooled Tobit Models). When testing for equivalence of the elicitation methods within the egg types (through separate F-Tests), we found that the BDM marginal WTPs are statistically different from the other elicitation methods for the cage free eggs; in contrast, we found that all elicitation methods provide statistically equivalent marginal WTPs for USDA organic eggs.

Comparisons across the three auction mechanisms suggest that the BDM auction tends to produce higher bids when comparing the three EAs holding the egg type constant, while the second price auction and the random *n*th price auction yield equivalent marginal WTPs. This finding could be attributed to the fact that the BDM auction has been found not to be incentive compatible (Horowitz, 2006). In addition, the observed increase in WTPs could be attributed to the fact that participants individually revealed their preferences in the BDM auction, while they were in groups of five in the second and the random *n*th price auction. Hence, peer pressure or competition might have influenced their decisions in the second price and the random *n*th price auctions (Rosato and Tymula, 2019). Moreover, results from our models reveal that age, education, and household income have a statistically significant effect on marginal WTPs (in all three EAs), ceteris paribus.

When comparing WTPs across EAs and RCE, our results reveal that these methods derive equivalent WTPs for USDA organic eggs; while the BDM auction derives higher (and statistically significant) WTPs for the Cage Free eggs. Focusing on the WTP estimates from the BDM auction and the RCE, our findings indicate that RCE yields lower WTPs, which are also consistent with the other two EAs (second price and random *n*th price). This evidence provides further support for the hypothesis that the RCE better simulates a market scenario with participants making purchasing decisions rather than submitting bids. It may be the case therefore that subjects might be less familiar with bidding and this might create a barrier in their efforts to reveal their true preferences.

Findings from this study are of interest for researchers who utilize EAs and/or RCE methods. In this regard, our findings question the extended use of BDM auctions (especially in developing countries). RCEs could potentially provide estimates of WTP that are consistent with second price and random *n*th price auction mechanisms, while preserving the same logistic advantages of a BDM auction (no need to form groups of people to run the experiments, individual decision-making). Furthermore, RCEs have the advantage of simulating an actual market scenario (with posted prices), which is very familiar to consumers (in contrast with the BDM auction setting which is new to most participants). However, with a small sample size, caution must be applied, as the findings might not be extrapolated to all studies implementing BDM auctions. Our findings are also relevant for marketing teams in food production, retail companies, and policy makers. Specifically, we found that consumers are willing to pay a higher premium for USDA organic eggs, which indicates that the use of the production methods underlined by the USDA is welcomed by consumers.

The generalizability of our results is subject to certain limitations. For instance, we had a relatively small sample size (similar limitation with the previous studies comparing RCEs with EAs). To illustrate, all four elicitation methods had a sub-sample of equal to or less than 70 participants each. Having a larger sample size might provide more accurate mean values, easier identification of outliers that could skew the data and a smaller margin of error. Sample size limitations are especially evident when we make comparisons of the elicitation methods over the data that are split by egg type.

Finally, further research should be undertaken to check the robustness of the results by using scanner data and/or induced value experiments. This would be a necessary step to reach a concrete conclusion on whether welfare estimates from EAs are different from those elicited from RCE.

APPENDICES

Appendix A: Inverse Cumulative Density Functions (CDFs) of WTP for the eggs

Figure A1: Distribution of Willingness-to-Pay for Conventional Eggs

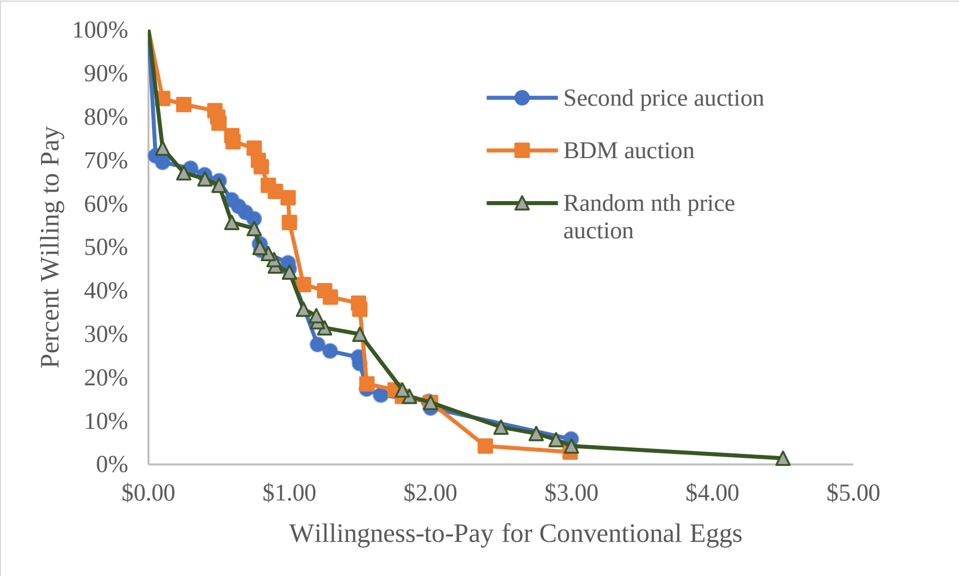


Figure A2: Distribution of Willingness-to-Pay for Cage Free Eggs

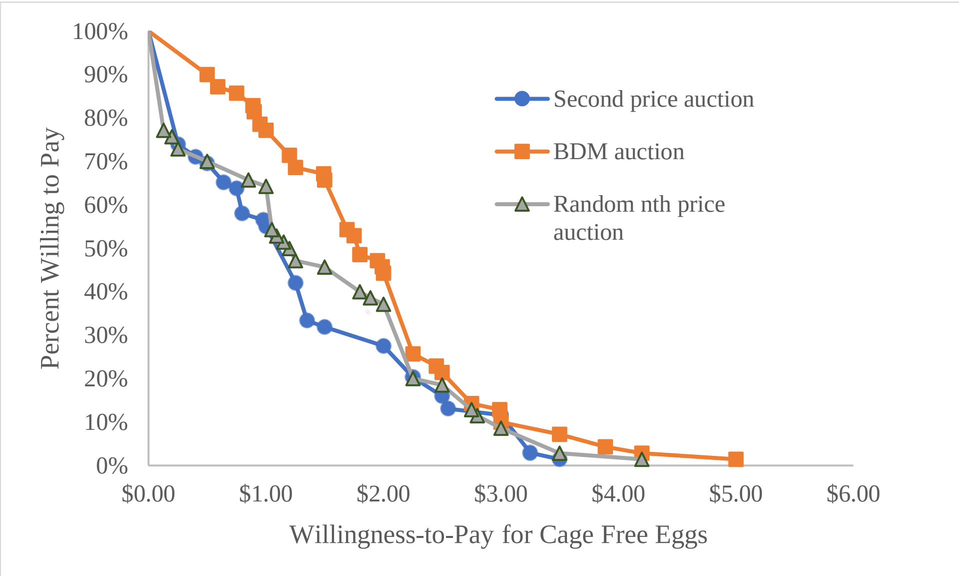
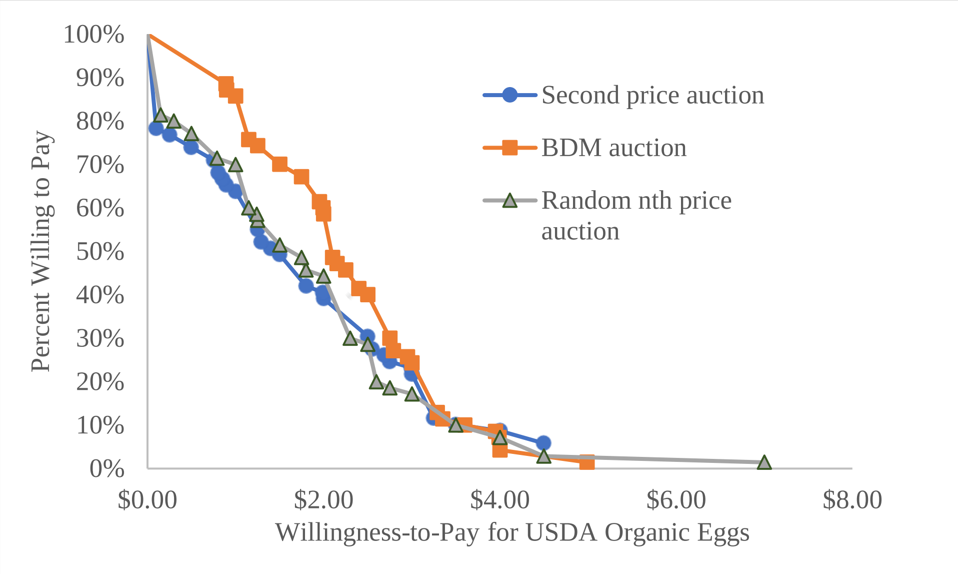


Figure A3: Distribution of Willingness-to-Pay for USDA Organic Eggs



The figures above (CDFs) can be interpreted as demand curves as long as we assume that each participant only purchases (consumes) one dozen of eggs and, for each figure, no other egg alternative exists in the market (Lusk and Schroeder, 2006). For all three types of eggs, the distributions of WTP implied from the BDM auction tends to lie above the WTP distributions implied from the second price and the random *n*th price auctions (see Figures A1 to A3). However, for the conventional eggs, and for price levels higher than $2.00, the inverse CDF from the BDM auction lies exclusively to the left of the inverse CDFs from the second price and the random *n*th price auction (see Figure A1). In addition, Figures A1 and A3 show that the inverse CDFs for the conventional and the USDA organic eggs from the second price and the random *n*th price auctions are virtually indistinguishable for all price levels. Nevertheless, as shown in Figure A2, the inverse CDF from the random *n*th price auction for Cage Free eggs, lies on the right of the inverse CDF from the second price auction.

Overall, these results indicate that the BDM auction derives on average, a higher WTP than the second price and the random *n*th price auctions for all types of eggs. In addition, we can conclude that the second price and the random *n*th price auctions derive similar WTPs, except from the case of the Cage Free eggs, where the random *n*th price auction derives slightly higher WTPs than the second price auction.

As noted by Lusk and Schroeder (2006), following the inverse CDFs, we could calculate optimal prices that would maximize profit given an assumed fixed marginal cost. In this case the profit is calculated by multiplying the number of participants with WTP greater than the price charged and the difference in the price and the (assumed) marginal cost.

Appendix B: Empirical Estimates for the MNL specification in the RCE

Table B1: Empirical Estimates for the RCE

Parameters	MNL
Cage Free Eggs (CF)	0.169
	(0.208)
USDA Organic Eggs (USDA)	0.698**
	(0.216)
Price	-0.973**
	(0.119)
No Buy	-1.587**
	(0.355)
N	248
Log likelihood	-210.557

Note: Standard errors are in the parentheses. * denotes statistically significant variables at the 10% level and ** denotes statistically significant variables at the 5%.

Table B1 provides the multinomial logit results, which were rejected in favor of a random parameters logit (RPL) for the reasons we specified in chapter 4. The RPL models (Table C1) uses the panel data structure of our data to take into account the fact that each individual made four choices (Gracia et al., 2011; Train 2003).

Appendix C: Empirical Estimates for the RCE in preference space

Table C1: Empirical Estimates for the RCE in preference space

Parameters	RPL (FPC)	RPL (RPC)
Cage Free Eggs (CF)	0.391 (0.365)	0.407 (0.321)
USDA Organic Eggs (USDA)	1.001** (0.436)	1.245** (0.412)
Price	-1.428** (0.204)	-2.077** (0.355)
No Buy	-2.454** (0.487)	-3.657** (0.681)
Standard deviations of parameter distributions		
Cage Free Eggs (CF)	1.267** (0.496)	0.768 (0.640)
USDA Organic Eggs (USDA)	2.129** (0.509)	1.629** (0.561)
Price		2.077** (0.355)
N	248	248
Log likelihood	-192.95	-183.39
χ^2	159.02	178.13
Pseudo-R^2	0.29	0.33

Note: Standard errors are in the parentheses. * denotes statistically significant variables at the 10% level and ** denotes statistically significant variables at the 5%.

In the second column of the results presented in table C1, we assumed that the coefficients for the two labelled characteristics' variables are random following a normal distribution and that the price coefficient is fixed. In the third column, we assumed that the coefficients for the two labelled characteristics' variables are random following a normal distribution and that the price coefficient is random (RPC) following a triangular distribution. The two labelled characteristics were cage free and USDA organic.

Appendix D: Number of all zero bids and all no buy options

Table D1: Participants with all zero bids/all no-buys

Experimental treatment	*Number of zero bids/all no-buys*	*Total number of participants*	*Percentage of zero bids/no buys*
Second Price Auction	8	69	12%
BDM Auction	5	70	7%
Random *n*th Price Auction	7	70	10%
Real Choice Experiment	15	62[35]	24%

[35] Originally, 69 people participated in our RCE treatment. In the beginning of our analysis we dropped 7 observations due to the fact that they followed an irrational pattern during the course of their choices and hence they were considered to not engage with the experiment.

Appendix E: Instructions for the elicitation methods

Instructions to Participants: Treatment 1, Homegrown Value Second Price Auction

Introduction

Today you will be participating in an auction in which you will bid to potentially purchase a product (eggs). You will be shown four different types of eggs. These eggs will differ in terms of labelled characteristics. In order to purchase the eggs, you will have to bid for them. How you bid will be explained soon.

First, a quick overview of what follows. (i) We will describe the auction and implement a **practice round with four candy bars** to help you better understand the mechanism (this round will not count for payment purposes). (ii) We'll introduce the 4 different types of eggs you will be bidding for. (iii) You'll fill in your **real auction bids** on the bidding sheets which will be given to you later. (iv) The outcomes of the auction will be determined.

As you may have noticed, there are five participants in this room. You will be competing with these participants when participating in the egg auctions. In the end, only one of the four egg auctions will be randomly selected to count or be binding. If you are the winning bidder in the binding auction you will purchase the eggs.

You will bid for each type of eggs. Once you enter bids for all four egg auctions, one of them will be randomly selected as binding. The person with the highest bid in the binding eggs auction will purchase the eggs BUT, he/she will NOT pay what they bid, but will pay the 2^{nd} highest bid.

Practice Round

Step 1: First, each of you will receive a bid sheet for the practice round with the candy bars. The practice bid sheet includes places to enter your four bids, one for each candy bar. On the bid sheet, you will enter the **most** you are willing to pay for each of the candy bars you see in the pictures in the center of the room. Note: You will write four bids, one for each candy bar. Your bids are private information and should not be shared with anyone.

[I will show them **one by one** the 4 candy bars; they will write their bids in the practice sheet.]

Step 2: After you have finished writing your bids, I will go around the room and collect your bid sheets.

Step 3: We will then roll a four-sided die to determine which candy bar auction is binding. For example, if a 1 is rolled, only the auction with candy bar No 1 will count and all other auctions and bids will be ignored. Importantly, all the auctions have an equally likely chance of being binding.

Note: since this is the hypothetical example, the highest bidder will not pay and will not receive the candy bar.

Step 4: The bids in the chosen auction will then be ranked from highest to lowest. The person with the *highest* bid for the candy bar will purchase the candy bar BUT, he/she will pay the *2nd highest bid* for the candy bar.

[I will do the ranking privately.]

Step 5: For the chosen practice auction, we will write the winning bidder(s) number and the price paid (second highest bid) on the board for everyone to see.

***Step 6*:** If this practice auction was real, the highest bidder would come forward and pay the 2nd highest bid and obtain the candy bar. All other participants will pay nothing and receive nothing.

Real Auctions

Now that we are done with the practice, we will begin the real auctions. Here in the front of the room, we have four types of eggs: Conventional, USDA Organic, Cage Free and USDA Organic & Cage Free. Other than differences in these characteristics, the eggs are of similar size, color, etc.

We will now conduct an auction for each type of egg. The auction mechanism will be the same as in the practice round, except that you will write bids one at a time and we will collect the bid after each auction. Recall that for each bid, you should indicate the **most** you are willing to pay for one dozen of that type of egg.

To refresh your memory as to how the auction works, I will go through the instructions again.

Step 1: You will receive a bid sheet (for one of the types of eggs). On the bid sheet you will enter the ***most*** you are willing to pay for one dozen of that type of egg. You will bid for each of the following: a) the *conventional* eggs, b) the *USDA Organic* eggs, c) the *Cage Free* eggs and d) the *USDA Organic & Cage Free* eggs. You will get one bidding sheet at a time, they will be collected before the next one is handed out. Your bids are private information and should not be shared with anyone.

Important Notes

- Because we randomly choose only one auction to be binding, you *cannot* purchase more than one type of eggs. That is, under no bidding scenario will you take home more than one dozen eggs.
- If there is a **tie** (more than one participant bids the same highest bid), then all of the highest bidders will pay the next (or 2nd) highest bid and purchase the eggs.
- The highest bidder(s) ***will actually pay money*** for the eggs. This set of auctions is **not** hypothetical, and you cannot make changes.
- In this type of auction, the best strategy is to bid ***exactly*** what each dozen of eggs is worth to you. Consider the following: if you bid *more* than the eggs are worth to you, you may end up having to buy eggs for more than you really want to pay. Conversely, if you bid *less* than the eggs are really worth to you, you may end up not winning the auction even though you could have bought a dozen of eggs at a price you were actually willing to pay. Thus, your best strategy is to bid *exactly* what the dozen eggs is worth to you.

- It is acceptable to bid $0.00 for any type of eggs.

Step 2: After you have finished writing your bids for the first type of eggs, I will go around the room and collect your bid sheet. This procedure will be repeated 4 times; once for each type of eggs.

[Here I will give them one-by-one the bidding sheets and they will bid for each type of eggs.]

Step 3: We will then roll a four-sided die to determine which egg auction is binding (either the Conventional, USDA Organic, Cage Free, USDA Organic and Cage Free). For example, if a 1 is rolled, only the first auction (conventional in our case) will count and all other auctions and bids will be ignored. Importantly, all the auctions have an equally likely chance of being binding.

Step 4: The bids in the chosen auction will then be ranked from highest to lowest. The person with the *highest* bid for the eggs will purchase the eggs BUT, he/she will pay the *2nd highest bid* for the eggs.

[I will do the ranking privately.]

Step 5: For the chosen egg auction, we will write the winning bidder(s) number and the price paid (second highest bid) on the board for everyone to see.

Step 6: The winning bidder will come forward and pay the 2nd highest bid and obtain the eggs. All other participants will pay nothing and receive nothing.

Instructions to Participants: Treatment 2, Homegrown Value BDM Auction

[Participants will read the instructions and implement the experiment step-by-step with me]

Introduction

Today you will be participating in an auction in which you will bid to potentially purchase a product (eggs). You will be shown four different types of eggs. These eggs will differ in terms of labelled characteristics. In order to purchase the eggs, you will have to bid for them. How you bid will be explained soon.

First, a quick overview of what follows. (i) We will describe the auction and implement a **practice round with four candy bars** to help you better understand the mechanism (this round will not count for payment purposes). (ii) We'll introduce the 4 different types of eggs you will be bidding for. (iii) You'll fill in your **real auction bids** on the bidding sheets which will be given to you later. (iv) The outcomes of the auction will be determined.

For each of you, this is a decision-making situation. In the auction, you don't compete against other people. You will bid against a randomly chosen price from a uniform distribution on the interval from $0.00 to $6.00. You will bid for each type of egg. In the end, only one of the four egg auctions will be randomly selected to count or be binding. If you win the binding auction you will purchase the eggs.

Once you enter bids for all four egg auctions, one of them will be randomly selected as binding. I will then randomly draw a price (from the uniform distribution between $0.00 and $6.00) for the binding auction. If your bid ***is equal to or greater than*** the randomly drawn price you will purchase the eggs BUT, you will NOT pay what you bided, but will pay the randomly drawn price. (If your bid is less than the randomly drawn price you will not purchase the eggs and you will pay nothing.)

Practice Round

Step 1: First, each of you will receive a bid sheet for the practice round with the candy bars. The practice bid sheet includes places to enter your four bids, one for each candy bar. On the bid sheet, you will enter the **most** you are willing to pay for each of the candy bars you see in the pictures in the center of the room. Note: You will write four bids, one for each candy bar. Your bids are private information and should not be shared with anyone.

[I will show them **one by one** the 4 candy bars; they will write their bids in the practice sheet.]

Step 2: After you have finished writing your bids, I will go around the room and collect your bid sheets.

Step 3: We will then roll a four-sided die to determine which candy bar auction is binding. For example, if a 1 is rolled, only the auction with candy bar No 1 will count and all other auctions and bids will be ignored. Importantly, all the auctions have an equally likely chance of being binding.

Note: since this is the hypothetical example, you will not pay anything and will not receive any candy bar.

Step 4: Then, we will roll a 10-sided die two times (one for the second decimal and one for the first decimal) and a "7-sided" die one time to determine the randomly drawn price between $0.00 and $4.00. If your bid for the candy bar is ***greater than or equal to*** the randomly drawn price, you will win the candy bar practice auction BUT, you will pay the randomly drawn price, not your bid (unless they are the same) for the candy bar.

Step 5: For the chosen practice auction, we will write the randomly drawn price (between $0.00 and $4.00) on the board.

***Step 6*:** If this practice auction was real, the winning bidder would come forward and pay the randomly drawn price and obtain the candy bar. All other participants will pay nothing and receive nothing.

Note: since this is the hypothetical example, the highest bidder will not pay and will not purchase the candy bar.

Real Auctions

Now that we are done with the practice, we will begin the real auctions. Here in the front of the room, we have four types of eggs: Conventional, USDA Organic, Cage Free and USDA Organic & Cage Free. Other than differences in these characteristics, the eggs are of similar size, color, etc.

We will now conduct an auction for each type of egg. The auction mechanism will be the same as in the practice round, except that you will write bids one at a time and we will collect the bid after each auction. Recall that for each bid, you should indicate the **most** you are willing to pay for one dozen of that type of egg.

To refresh your memory as to how the auction works, I will go through the instructions again.

Step 1: You will receive a bid sheet (for one of the types of eggs). On the bid sheet you will enter and the ***most*** you are willing to pay for one dozen of that type of egg. You will bid for each of the following: a) the *conventional* eggs, b) the *USDA Organic* eggs, c) the *Cage Free* eggs and d) the *USDA Organic & Cage Free* eggs. You will get one bidding sheet at a time, they will be collected before the next one is handed out. Your bids are private information and should not be shared with anyone.

Important Notes

- Because we randomly choose only one auction to be binding, you *cannot* purchase more than one type of eggs. That is, under no bidding scenario will you take home more than one dozen eggs.
- If your bid is greater or equal than the randomly drawn price ***will actually pay money*** for the eggs. This set of auctions is **not** hypothetical, and you cannot make changes.
- In this type of auction, the best strategy is to bid ***exactly*** what each dozen of eggs is worth to you. Consider the following: if you bid *more* than the eggs are worth to you, you may end up having to buy eggs for more than you really want to pay. Conversely, if you bid *less* than the eggs are really worth to you, you may end up not winning the auction even though you could have bought a dozen of eggs at a price you were actually willing to pay. Thus, your best strategy is to bid *exactly* what the dozen eggs is worth to you.
- It is acceptable to bid $0.00 for any type of eggs.

Step 2: After you have finished writing your bids for the first type of eggs, I will go around the room and collect your bid sheet. This procedure will be repeated 4 times; once for each type of eggs.

[Here I will give them one-by-one the bidding sheets and they will bid for each type of eggs]

Step 3: We will then roll a four-sided die to determine which type of eggs auction is binding (either the Conventional, USDA Organic, Cage Free, USDA Organic and Cage Free). For example, if a 1 is rolled, only the first auction (conventional in our case) will count and all other auctions and bids will be ignored. Importantly, all the auctions have an equally likely chance of being binding.

Step 4: We will then roll a 10-sided die two times (one for the second decimal and one for the first decimal) and a "7-sided" die one time to determine the randomly drawn price between $0.00 and $6.00. If your bid for the binding eggs is ***greater than or equal to*** the randomly drawn price, you will purchase the eggs BUT, you will pay the randomly drawn price, not your bid (unless they are the same) for the eggs.

Step 5: For the chosen eggs auction, we will write the randomly drawn price (between $0.00 and $6.00) on the board.

Step 6: The winning bidder will come forward and pay the randomly drawn price and obtain the binding eggs.

*Instructions to Participants: Treatment 3, Homegrown Value Random n*th *Price Auction*

[Participants will read the instructions and implement the experiment step-by-step with me]

Introduction

Today you will be participating in an auction in which you will bid to potentially purchase a product (eggs). You will be shown four different types of eggs. These eggs will differ in terms of labelled characteristics. In order to purchase the eggs, you will have to bid for them. How you bid will be explained soon.

First, a quick overview of what follows. (i) We will describe the auction and implement a **practice round with four candy bars** to help you better understand the mechanism (this round will not count for payment purposes). (ii) We'll introduce the 4 different types of eggs you will be bidding for. (iii) You'll fill in your **real auction bids** on the bidding sheets which will be given to you later. (iv) The outcomes of the auction will be determined.

As you may have noticed, there are five participants in this room. You will be competing with these participants when participating in the egg auctions. In the end, only one of the four egg auctions will be randomly selected to count or be binding. If you are the winning bidder in the binding auction you will purchase the eggs.

You will bid for each type of eggs. Once you enter bids for all four eggs auctions, one of them will be randomly selected as binding. The bids for the binding type of eggs will be ranked from highest to lowest. Next, a random number will be drawn to determine how many participants will win the binding egg auction. The random number will be between 2 and 5 (the number of participants). Call this random number N. The N-1 highest bidders in the binding egg auction will purchase the eggs BUT, they will NOT pay what they bid, but will pay the Nth highest bid. For example, if the random number is a 3, then the 2 highest bidders would each purchase the eggs BUT pay the 3rd highest bid for them.

Practice Round

Step 1: First, each of you will receive a bid sheet for the practice round with the candy bars. On the bid sheet, you will enter your ID number and the **most** you are willing to pay for each of the candy bars you see in the pictures in the center of the room. Note: You will write four bids, one for each candy bar. Your bids are private information and should not be shared with anyone.

[I will show them **one by one** the 4 candy bars; they will write their bids in the practice sheet.]

Step 2: After you have finished writing your bids, I will go around the room and collect your bid sheets.

Step 3: We will then roll a four-sided die to determine which candy bar auction is binding. For example, if a 1 is rolled, only the auction with candy bar No 1 will count and all other auctions and bids will be ignored. Importantly, all the auctions have an equally likely chance of being binding.

Note: since this is the hypothetical example, the highest bidder will not pay and will not receive the candy bar.

Step 4: The bids in the chosen auction will then be ranked from highest to lowest. Next, the random number will be drawn by rolling a 6-sided die to determine how many participants will win the candy bar. As noted above, the random number (N) will be somewhere between 2 and 5 (number of participants), so if a one or six is rolled, we will roll again. The N-1 highest bidders in the binding practice candy bar auction will purchase the candy bar BUT, they will NOT pay what they bid (except in the unlikely event of a special tie as explained later) but will pay the Nth highest bid.

[I will do the ranking privately. I will announce what is the N number (e.g.: 4 or 5).]

Step 5: For the chosen practice auction, we will write the winning bidder(s) number and the price paid (Nth highest bid) on the board for everyone to see.

Step 6**:** If this practice auction was real, the N-1 highest bidders would come forward and pay the Nth highest bid and obtain the candy bar. All other participants will pay nothing and receive nothing.

Real Auctions

Now that we are done with the practice, we will begin the real auctions. Here in the front of the room, we have four types of eggs: Conventional, USDA Organic, Cage Free and USDA Organic & Cage Free. Other than differences in these characteristics, the eggs are of similar size, color, etc.

We will now conduct an auction for each type of egg. The auction mechanism will be the same as in the practice round, except that you will write bids one at a time and we will collect the bid after each auction. Recall that for each bid, you should indicate the **most** you are willing to pay for one dozen of that type of egg.

To refresh your memory as to how the auction works, I will go through the instructions again.

Step 1: You will receive a bid sheet (for one of the types of eggs). On the bid sheet you will enter your ID number and the ***most*** you are willing to pay for one dozen of that type of egg. You will bid for each of the following: a) the *conventional* eggs, b) the *USDA Organic* eggs, c) the *Cage Free* eggs and d) the *USDA Organic & Cage Free* eggs. You will get one bidding sheet at a time, they will be collected before the next one is handed out. Your bids are private information and should not be shared with anyone.

Important Notes

- Because we randomly choose only one auction to be binding, you *cannot* purchase more than one type of eggs. That is, under no bidding scenario will you take home more than one dozen eggs.
- If there is a **tie** (more than one participant bids the same N-1th highest bid), then all the N-1th highest bidders will pay the Nth highest bid and purchase the eggs. The only exception to this is if the tie is between the 4th and 5th highest bidders AND a 5 was rolled. In this case, everyone would buy and pay the tied bid, meaning that the 4th and 5th highest bidders would pay what they bid.
- The highest bidder(s) ***will actually pay money*** for the eggs. This set of auctions is **not** hypothetical, and you cannot make changes.
- In this type of auction, the best strategy is to bid ***exactly*** what each dozen of eggs is worth to you. Consider the following: if you bid *more* than the eggs are worth to you, you may end up having to buy eggs for more than you really want to pay. Conversely, if you bid *less* than the eggs are really worth to you, you may end up not winning the auction even though you could have bought a dozen of eggs at a price you were actually willing to pay. Thus, your best strategy is to bid *exactly* what the dozen eggs is worth to you.
- It is acceptable to bid $0.00 for any type of eggs.

Step 2: After you have finished writing your bids for the first type of eggs, I will go around the room and collect your bid sheet. This procedure will be repeated 4 times; once for each type of eggs.

[Here I will give them one-by-one the bidding sheets and they will bid for each type of eggs]

Step 3: We will then roll a four-sided dice to determine which type of eggs auction is binding (either the Conventional, USDA Organic, Cage Free, USDA Organic and Cage Free). For example, if a 1 is rolled, only the first auction (conventional in our case) will count and all other auctions and bids will be ignored. Importantly, all the auctions have an equally likely chance of being binding.

Step 4: The bids in the chosen auction will then be ranked from highest to lowest. Next, the random number will be drawn by rolling a 6-sided die to determine how many participants will win the eggs. The random number (N) will be somewhere between 2 and 5 (number of participants), so if a one or six is rolled, we will roll again. The N-1 highest bidders in the binding eggs auction will purchase the eggs BUT, they will NOT pay what they bid (except in the unlikely event of a special tie) but will pay the Nth highest bid.

[I will do the ranking privately. I will announce what is the N number (e.g.: 4 or 5).]

Step 5: For the chosen egg auction, we will write the winning bidder(s) number and the price paid (Nth highest bid) on the board for everyone to see.

Step 6: The winning bidder(s) will come forward and pay the Nth highest bid and obtain the eggs. All other participants will pay nothing and receive nothing.

Instructions to Participants: Treatment 4, Homegrown Value Real Choice Experiment

[Participants will read the instructions and implement the experiment step-by-step with me]

Introduction

Today you will be participating in a choice experiment in which you will have a chance to purchase a product (eggs). You will be shown four different choice sets. Every choice set involves two different types of eggs and a no-purchase option. The eggs will differ in terms of labelled characteristics. In order to purchase the eggs, you will have to choose them. How you choose will be explained soon.

First, a quick overview of what follows. (i) We will describe the shopping scenario task and implement a **practice round with candy bars** to help you better understand the mechanism (this round will not count for payment purposes). (ii) You'll fill in your **real choices** on your choice sheet which will be given to you later. (iii) The outcomes of the task will be determined.

You will make a choice for each of those four different shopping scenarios. In the end, only one of the shopping scenarios will be randomly selected, and this will be the one which will determine if you purchase eggs or not.

Practice Round

Step 1: First, you will receive a practice choice sheet. On the choice sheet, write your ID number. The practice choice sheet includes places to make four different shopping choices (Choice Question 1, etc.) based on four different sopping scenarios. Every choice scenario involves two different candy bars and a no-purchase option. In each of those you will choose the candy bar you prefer to purchase given the listed prices. Alternatively, you may choose not to purchase either product. Please carefully examine each option before you make a decision and choose the product that you prefer most.
[Note: your choices are private information and should not be shared with anyone.
Given that the RCE practice round will be implemented with multiple participants.]

Step 2: After you have finished responding to the four choice sets, I will collect your choice sheet.

Step 3: After reviewing your choices, we will roll a four-sided die to determine which choice task is binding. For example, if a 1 is rolled, then the first-choice question will be binding, etc. That is, if a 1 is rolled, and **if you chose one of the two candy bars** in that choice question, **you will be given the product you selected** and be asked to **pay the price listed in the choice**. If you **chose the "no-purchase" option**, then **you will not be given any candy bar** and **you will pay nothing.** It is important to understand that all 4 questions have the same chance of being selected as binding.

Note: since this is the hypothetical example, you will not pay and will not purchase the candy bar.

Real Choice Tasks

Now that we are done with the practice, we will begin the real choice tasks. Here in the front of the room, we have four types of eggs: Conventional, USDA Organic, Cage Free and USDA Organic & Cage Free. Other than differences in these characteristics, the eggs are of similar size, color, etc.

For the real choices, you will be presented with 4 shopping scenarios. Each scenario involves two of the different types of eggs and a no-purchase option. The procedures for making choices in this task are exactly the same as the candy bar practice round.

To refresh your memory as to how the choice task works, I will go through the instructions again.

Step 1: You will receive a choice sheet. On the choice sheet, write your ID number. For each shopping scenario, please choose the type of eggs you would prefer to purchase given the listed prices. Alternatively, you may choose NOT to purchase any product. Please carefully examine each option before you make a decision and choose the product that you prefer most and indicate your choice on the choice sheet.

It is important to understand that all 4 choice tasks have the same chance of being selected as binding in the end. Thus, you should consider each choice question as if it is the real chosen choice. Because of this, it is important that you answer the choice questions truthfully. If you do not, you might end up buying a product at a higher price than what you are willing to pay, or you might end up not being able to get the product when you would have actually been willing to buy it.

Important Notes

- CHOOSE only one option for each scenario: one of the two types of eggs or not to purchase
- ASSUME that the options we will show you are the only ones available
- Once you have made your choice and moved to the next question you cannot go back
- The choices are all separate, so you do not and should not try to remember previous choices when making any particular new choice. In other words, we are asking you to treat each round of questions as separate from the previous one
- At the end of the experiment, we will choose a binding scenario and if you did not select not to purchase, you will be ASKED TO BUY one dozen of the eggs you picked in that scenario.

Step 2: After you have finished responding to the four choice sets, I will collect your choice sheet.

Step 3: After reviewing your choices to check they are completed correctly; I will roll a four-sided dice to determine which scenario will be binding. If a 1 is rolled, then the first-choice question will be binding, etc. That is, if a 1 is rolled, and **if you chose one of the two types of eggs** in that choice question, **you will be given the product you selected** and be asked to **pay the price listed in the choice**. If you **chose the "no-purchase" option**, then **you will not be given any type of eggs** and **you will pay nothing.**

Appendix F: Consent form for participation in the study

Consent Form

This study is aimed at assessing your preferences for eggs and milk. You will be asked to complete a questionnaire about consumption habits, behavior and demographics, participate in an auction or a real choice experiment, and then complete an additional survey. This study will take about 30-45 minutes to complete.

Risk and Benefits: There are no anticipated risks in participating in this study. Your participation will assist in the advancement of knowledge of consumer choice behavior. In addition, you will be given $13 for your participation. During the experiment you will have the option to buy eggs. All the products offered are approved by the Food and Drug Administration. There are no additional risks to consumption of the eggs above those associated with similar purchases from traditional retailers.

Voluntary Participation: Your participation in this research is completely voluntary.

Confidentiality: All information will be kept confidential to the extent allowed by applicable State and Federal law. ID#'s of participants will be distributed at random at the onset of the experiment and records with identifiable, personal data will not be kept except to record whether participants appeared for their assigned time slot and received their compensation.

Right to Withdraw: You are free to withdraw from the study at any time or refuse to answer any questions.

Questions, Concerns and Complaints: If you have any questions or concerns about this study, you may contact Dr. Vincenzina Caputo (vcaputo@msu.edu). For questions or concerns about your rights as a research participant, please contact irb@msu.edu or +1 (517) 355-2180.

Consent: I have read this consent form and my questions have been answered. I hereby give my voluntary consent to participate in this study.

SIGNATURE ______________________________ DATE ____________________

REFERENCES

REFERENCES

Adamowicz, W., Louviere, J., and Swait, J. 1998. "Introduction to attribute-based stated choice methods." NOAA-National Oceanic Atmospheric Administration, Washington, 7-31 January.

Alfnes, F., Guttormsen, A. G., Steine, G., and Kolstad, K. 2006. "Consumers' willingness to pay for the color of salmon: a choice experiment with real economic incentives." American Journal of Agricultural Economics 88(4):1050-1061.

Ashok, K., Dillon, W. R., and Yuan, S. 2002. "Extending discrete choice models to incorporate attitudinal and other latent variables." Journal of marketing research 39(1):31-46.

Banerji, A., and Gupta, N. 2014. "Detection, identification, and estimation of loss aversion: Evidence from an auction experiment." American Economic Journal: Microeconomics 6(1):91-133.

Bazzani, C., Caputo, V., Nayga Jr, R. M., and Canavari, M. 2017. "Revisiting consumers' valuation for local versus organic food using a non-hypothetical choice experiment: Does personality matter?" Food Quality and Preference 62:144-154.

Becker, G. M., DeGroot, M. H., and Marschak, J. 1964. "Measuring utility by a single-response sequential method." Behavioral science 9(3):226-232.

Ben-Akiva, M. E., Lerman, S. R., and Lerman, S. R. 1985. "Discrete choice analysis: theory and application to travel demand" (Vol. 9). MIT press.

Burgess, L., and Street, D. J. 2005. "Optimal designs for choice experiments with asymmetric attributes." Journal of Statistical Planning and Inference 134(1):288-301.

Caputo, V., Lusk, J. L., and Nayga Jr, R. M. 2018a. "Choice experiments are not conducted in a vacuum: The effects of external price information on choice behavior." Journal of Economic Behavior & Organization 145:335-351.

Caputo, V., Van Loo, E. J., Scarpa, R., Nayga Jr, R. M., and Verbeke, W. 2018b. "Comparing serial, and choice task stated and inferred attribute non-attendance methods in food choice experiments." Journal of agricultural economics 69(1):35-57.

Caputo, V., Nayga Jr, R. M., and Scarpa, R. 2013. "Food miles or carbon emissions? Exploring labelling preference for food transport footprint with a stated choice study." Australian Journal of Agricultural and Resource Economics 57(4):465-482.

Chang, J. B., Lusk, J. L., and Norwood, F. B. 2009. "How closely do hypothetical surveys and laboratory experiments predict field behavior?" American Journal of Agricultural Economics 91(2):518-534.

Charness, G., Gneezy, U., and Kuhn, M. A. 2012. "Experimental methods: Between-subject and within-subject design." Journal of Economic Behavior & Organization 81(1):1-8.

Corrigan, J. R., and Rousu, M. C. 2006. "The effect of initial endowments in experimental auctions." American Journal of Agricultural Economics 88(2):448-457.

De Groote, H., Kimenju, S. C., and Morawetz, U. B. 2011. "Estimating consumer willingness to pay for food quality with experimental auctions: the case of yellow versus fortified maize meal in Kenya." Agricultural Economics 42(1):1-16.

De-Magistris, T., Gracia, A., and Nayga Jr, R. M. 2013. "On the use of honesty priming tasks to mitigate hypothetical bias in choice experiments." American Journal of Agricultural Economics 95(5):1136-1154.

Drichoutis, A. C., Klonaris, S., and Papoutsi, G. S. 2017. "Do good things come in small packages? Bottle size effects on willingness to pay for pomegranate wine and grape wine." Journal of Wine Economics 12(1):84-104.

Ferrini, S., and Scarpa, R. 2007. "Designs with a priori information for nonmarket valuation with choice experiments: A Monte Carlo study." Journal of environmental economics and management 53(3):342-363.

Fiebig, D. G., Keane, M. P., Louviere, J., and Wasi, N. 2010. "The generalized multinomial logit model: accounting for scale and coefficient heterogeneity." Marketing Science 29(3):393-421.

Fox, J. A., Hayes, D. J., Shogren, J. F., and Kliebenstein, J. B. 1996. "Experimental methods in consumer preference studies." Journal of food distribution research 27(856-2016-57133):1-7.

Gao, Z., and Schroeder, T. C. 2009. "Effects of label information on consumer willingness-to-pay for food attributes." American Journal of Agricultural Economics 91(3):795-809.

Gleason, R. J. 2019. tukeyhsd, tkcomp, fhcomp: test statistics. UCLA: Statistical Consulting Group. Retrieved from https://stats.idre.ucla.edu/stata/ado/analysis/.

Gracia, A., Loureiro, M. L., and Nayga Jr, R. M. 2011. “Are valuations from nonhypothetical choice experiments different from those of experimental auctions?” American Journal of Agricultural Economics 93(5):1358-1373.

Hanemann, M., and Kanninen, B. 2001. “The Statistical Analysis of Discrete-Response CV Data.” In Valuing environmental preferences: theory and practice of the contingent valuation method in the US, EU, and developing countries. Oxford University Press, pp. 302–441.

Hedayat, A., and Kirk, R. E. 2006. “Experimental Design: Procedures for the Behavioral Sciences.” Biometrics 26(3):590.

Hess, S., Rose, J. M., and Hensher, D. A. 2008. “Asymmetric preference formation in willingness to pay estimates in discrete choice models.” Transportation Research Part E: Logistics and Transportation Review 44(5):847-863.

Horowitz, J. K. 2006. “The Becker-DeGroot-Marschak mechanism is not necessarily incentive compatible, even for non-random goods.” Economics Letter 93(1):6-11.

HOW CAN I DO POST-HOC PAIRWISE COMPARISONS USING STATA? 2019. Retrieved August 7, 2018, from https://stats.idre.ucla.edu/other/mult-pkg/faq/general/faq-how-do-i-cite-web-pages-and-programs-from-the-ucla-statistical-consulting-group/

Hu, W., Adamowicz, W. L., and Veeman, M. M. 2006. “Labeling context and reference point effects in models of food attribute demand.” American Journal of Agricultural Economics 88(4):1034-1049.

Hurst, D. L. 2016. Let The Hens Out! Cage Free Eggs. Retrieved January 2, 2018, from https://www.dirt-to-dinner.com/let-the-hens-out-cage-free-eggs/

Knetsch, J. L., Tang, F. F., and Thaler, R. H. 2001. “The endowment effect and repeated market trials: Is the Vickrey auction demand revealing?” Experimental Economics 4(3):257-269.

Lancaster, K. J. 1966. “A New Approach to Consumer Theory.” Journal of Political Economy 74(2):132–157.

Lin, W., Ortega, D. L., Caputo, V., and Lusk, J. L. 2019. “Personality traits and consumer acceptance of controversial food technology: A cross-country investigation of genetically modified animal products.” Food Quality and Preference 76:10-19.

List, J. A. 2003. "Using random nth price auctions to value non-market goods and services." Journal of Regulatory Economics 23(2):193-205.

Louviere, J., and Hensher, D. 1982. "Design and Analysis of Simulated Choice or Allocation Experiments in Travel Choice Modelling." Transportation Research Board 890:11-17.

Lubben, B. D. 2005. A welfare analysis of country-of-origin labeling and alternative policy choices for beef. Kansas State University.

Lucking-Reiley, D. 1999. "Using Field Experiments to Test Equivalence Between Auction Formats: Magic on the Internet." American Economic Review 89(5):1063–1080.

Lusk, J. L. 2003. "Effects of cheap talk on consumer willingness-to-pay for golden rice." American Journal of Agricultural Economics 85(4):840-856.

Lusk, J. L. 2018. Market Potential for Cage Free Eggs. Retrieved February 21, 2019, from http://jaysonlusk.com/blog/2018/1/1/market-potential-for-cage-free-eggs

Lusk, J. L., and Schroeder, T. C. 2004. "Are choice experiments incentive compatible? A test with quality differentiated beef steaks." American Journal of Agricultural Economics 86(2):467-482.

Lusk, J. L., and Schroeder, T. C. 2006. "Auction bids and shopping choices." Advances in Economic Analysis & Policy 6(1).

Lusk, J. L., and Anderson, J. D. 2004. "Effects of country-of-origin labeling on meat producers and consumers." Journal of Agricultural and Resource Economics 185-205.

Lusk, J. L., Feldkamp, T., and Schroeder, T. C. 2004. "Experimental auction procedure: impact on valuation of quality differentiated goods." American Journal of Agricultural Economics 86(2):389-405.

Lusk, J. L., and Shogren, J. F. 2007. Experimental Auctions. Cambridge J. Econ.

Lusk, J. L., and Tonsor, G. T. 2016. "How meat demand elasticities vary with price, income, and product category." Applied Economic Perspectives and Policy 38(4):673-711.

McFadden, D. 1986. "The Choice Theory Approach to Market Research." Marketing Science, 5(4):275–297.

McFadden, D. 1986. 1974. “The measurement of urban travel demand.” Journal of public economics 3(4):303-328.

McFadden, D., and Train, K. 2000. “Mixed MNL models for discrete response.” Journal of applied Econometrics 15(5):447-470.

Milgrom, P. R., and Weber, R. J. 1982. “A theory of auctions and competitive bidding.” Econometrica: Journal of the Econometric Society 1089-1122.

Murphy, J. J., Stevens, T. H., and Yadav, L. 2010. “A comparison of induced value and home-grown value experiments to test for hypothetical bias in contingent valuation.” Environmental and Resource Economics 47(1):111-123.

Noussair, C., Robin, S., and Ruffieux, B. 2004. “Revealing consumers' willingness-to-pay: A comparison of the BDM mechanism and the Vickrey auction.” Journal of economic psychology 25(6):725-741.

Ortega, D. L., and Ward, P. S. 2016. “Information processing strategies and framing effects in developing country choice experiments: results from rice farmers in India.” Agricultural Economics 47(5):493-504.

Ortega, D. L., Wang, H. H., Wu, L., and Olynk, N. J. 2011. “Modeling heterogeneity in consumer preferences for select food safety attributes in China.” Food Policy 36(2):318-324.

Otieno, D. J. 2011. “Choice experiments in developing countries: implementation, challenges and policy implications.” Journal of Agricultural Economics 62(1):245-247.

Priscilla. 2013. Our Cage Free Farms. Retrieved January 2, 2018, from http://cagefree.com.au/#!/a-new-kind-of-egg/

Rosato, A., and Tymula, A. A. 2019. “Loss aversion and competition in Vickrey auctions: Money ain't no good.” Games and Economic Behavior 115:188-208.

Rose, J. M., and Bliemer, M. C. 2009. “Constructing efficient stated choice experimental designs.” Transport Reviews 29(5):587-617.

Rutström, E. E. 1998. “Home-grown values and incentive compatible auction design.” International Journal of Game Theory 27(3):427-441.

Scarpa, R., Thiene, M., and Train, K. 2008. "Utility in willingness to pay space: a tool to address confounding random scale effects in destination choice to the Alps." American Journal of Agricultural Economics 90(4):994-1010.

Scarpa, R., and Willis, K. 2010. "Willingness-to-pay for renewable energy: Primary and discretionary choice of British households' for micro-generation technologies." Energy Economics 32(1):129-136.

Scarpa, R., Thiene, M., and Hensher, D. A. 2012. "Preferences for tap water attributes within couples: an exploration of alternative mixed logit parameterizations." Water Resources Research 48(1).

Shi, L., Xie, J., and Gao, Z. 2018. "The impact of deal-proneness on WTP estimates in incentive-aligned value elicitation methods." Agricultural Economics 49(3):353-362.

Shogren, J. F., Fox, J. A., Hayes, D. J., and Kliebenstein, J. B. 1994. "Bid sensitivity and the structure of the Vickrey auction." American Journal of Agricultural Economics 76(5):1089-1095.

Shogren, J. F., Margolis, M., Koo, C., and List, J. A. 2001. "A random nth-price auction." Journal of economic behavior & organization 46(4):409-421.

Street, D. J., Bunch, D. S., and Moore, B. J. 2001. "Optimal designs for 2 k paired comparison experiments." Communications in Statistics-Theory and Methods 30(10):2149-2171.

Street, D. J., and Burgess, L. 2004. "Optimal and near-optimal pairs for the estimation of effects in 2-level choice experiments." Journal of Statistical Planning and Inference 118(1-2):185-199.

Street, D. J., Burgess, L., and Louviere, J. J. 2005. "Quick and easy choice sets: constructing optimal and nearly optimal stated choice experiments." International journal of research in marketing 22(4):459-470.

Thurstone, L. L. 1927. "A law of comparative judgment." Psychological review 34(4):273.

Train, K. E. 2009. Discrete choice methods with simulation. Cambridge University Press.

Train, K. E. 1999. Halton Sequences for Mixed Logit. Retrieved from http://elsa.berkeley.edu/~train.

Train, K., and Weeks, M. 2005. "Discrete choice models in preference space and willingness-to-pay space." In Applications of simulation methods in environmental and resource economics. Springer, Dordrecht, pp. 1-16.

United States Code of Federal Regulations, 7 C.F.R. § 205.239. 2002.

Van Loo, E. J., Caputo, V., Nayga Jr, R. M., and Verbeke, W. 2014. "Consumers' valuation of sustainability labels on meat." Food Policy 49:137-150.

Van Loo, E. J., Caputo, V., Nayga Jr, R. M., Meullenet, J. F., and Ricke, S. C. 2011. "Consumers' willingness to pay for organic chicken breast: Evidence from choice experiment." Food Quality and Preference 22(7):603-613.

Van Wezemael, L., Caputo, V., Nayga Jr, R. M., Chryssochoidis, G., and Verbeke, W. 2014. "European consumer preferences for beef with nutrition and health claims: A multi-country investigation using discrete choice experiments." Food Policy 44:167-176.

Vickrey, W. 1961. "Counterspeculation, auctions, and competitive sealed tenders." The Journal of Finance 16(1):8-37.

Wertenbroch, K., and Skiera, B. 2002. "Measuring consumers' willingness to pay at the point of purchase." Journal of Marketing Research 39(2):228-241.

Wooldridge, J. M. 2016. Introductory econometrics: A modern approach. Nelson Education.