# On the Use of the BDM Mechanism in Non-Hypothetical Choice Experiments

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**ABSTRACT:**

To potentially reduce bias in hypothetical choice experiments, many studies have incentivized respondents to reveal more truthful choices by randomly choosing a binding choice set and then asking them to pay the price indicated for the chosen product alternative in this binding choice set. This approach, however, does not separate the price the respondent indicated he/she is willing to pay for the chosen product alternative from the price that he/she will end up paying. Would the use of the Becker-DeGroot-Marshack (BDM) mechanism make non-hypothetical choice experiments more demand revealing? Our results using a conventional homegrown choice experiment and an induced value choice experiment suggest that it does not. Choice behavior is associated with the degree of understanding about the experimental procedures and the amount of time devoted to examine the choice set.

**Keywords:** Real Choice Experiment, BDM mechanism, Homegrown Value Experiment, Induced Value Experiment, Incentive Compatibility.

Choice Experiments (CEs) are arguably becoming one of the most preferred stated preference methods used by economists interested in preference elicitation and valuation research. In CEs, respondents are normally presented with hypothetical purchasing scenarios (i.e., choice sets). In each choice set, respondents are asked to make trade-offs between a no-buy option and alternatives representing products that are characterized by different attributes and attribute levels. There are a number of advantages to using CEs and these contribute to their popularity. First, researchers can construct choice contexts that more closely represent real purchasing situations in comparison with other value elicitation methods such as Experimental Auctions (EAs), Contingent Valuation (CV), and Conjoint Analysis (CA) (Akaichi, Nayga and Gil 2013; Corrigan et al. 2009; Ginon et al. 2014; Gracia, Loureiro, and Nayga 2011; Lusk and Schroeder 2004). Second, with CEs it is possible to estimate consumers' preferences for different product attributes simultaneously. Finally, CEs are consistent with Lancaster's theory, which assumes that consumers make choices to maximize their utility considering that the total utility individuals derive from the consumption of a good can be segregated into partial utilities given by the different attributes of the good (Lancaster, 1966). It is also consistent with random utility theory, which assumes that individual choice behavior patterns can be derived from observing actual choices under specific assumptions on the distribution of the random (non-deterministic) component of utility (McFadden, 1974).

However, one limitation of hypothetical CEs is the potential formation of hypothetical bias in the estimation of consumers' preferences (Cameron, et al. 2002; Carlsson and Martinsson 2001; Hensher 2010; List and Taylor 2006; List and Gallet 2001; Murphy et al. 2005). Past studies observed that when individuals are not incentivized with an economic commitment, they tend to reveal values for a good which might be greater than the price they would actually pay (Carpenter and Harrison 2004; Grebitus, Lusk, and Nayga 2013; List and Gallet 2001; Lusk and Shogren 2007). Indeed, results from several studies have shown that consumers' valuations for different goods are significantly higher in hypothetical CEs than in non-hypothetical CEs (Chang, Lusk, and Norwood 2009; Johansson-Stenman and Sveds 2008; Loomis, et al. 2009; Lusk, Fields, and Prevatt 2008; Lusk and Schroeder 2004; Volinskiy, et al. 2009; Yue, Avenue, and Paul 2009).

Therefore, in order to mitigate possible hypothetical bias in consumers' willingness to pay (WTP) estimation when using CEs, more researchers have recently been turning to the implementation of Real (non-hypothetical) Choice Experiments (RCEs) (Alfnes et al. 2006; Alfnes, Yue, and Jensen 2010; Chang et al. 2009; de-Magistris and Gracia 2014; Gracia, Louriero, and Nayga 2011; Gracia 2013; Lee at al. 2015; Lusk and Schroeder 2004; Michaud, Llerena, and Joly 2012; Moser and Raffaelli 2012; Olesen et al. 2010). Generally, in RCEs, once a respondent has completed all the choice sets, one of those is randomly selected as binding and the respondent has to buy the chosen alternative in the binding choice set. The respondent then pays the price indicated for the chosen alternative. Several studies involving RCEs have indicated that the introduction of the economic incentive induces individuals to truthfully reveal their preferences (Alfnes et al. 2006; Chang, Lusk, and Norwood 2009; Lusk and Schroeder 2004).

However, an important issue in experimental economics theory is that a valuation method can be considered as incentive compatible when it "separates what people say from what they pay" (Lusk and Schroeder 2007, p. 19). Consequently, in an attempt to make respondents provide more truthful revelations of their choices, a number of studies (e.g, Richards, Hamilton, and Allender 2014; Palma et al. 2016) have employed the Becker-DeGroot-Marshack (BDM) mechanism to determine the price that a respondent would pay in RCEs (see Table 1). In their experimental design, once the binding choice set is selected, a random price from a uniform distribution is drawn. If the randomly drawn price is lower than the price of the chosen alternative in the binding choice set, then the respondent pays for the chosen product alternative at an amount equal to the randomly drawn price. If the randomly drawn price is equal or higher than the price of the binding chosen alternative, then the respondent does not get and does not pay for the product.

--Insert Table 1--

Recent research, however, has questioned the efficacy of the BDM mechanism in revealing individuals' preferences. For example, some recent literature showed that the BDM mechanism might be misunderstood by respondents, causing inaccuracy in revealing individuals' preferences. Cason and Plott (2014), in an induced value experiment, observed that students bid significantly closer to the induced value ($2) in bidding rounds that followed the completion of questions aimed at reinforcing attention to the rules and possible outcomes. On the other hand, Bartling, Engl, and Weber, (2015) investigated whether game form misconceptions could be a source of the gap between individuals' WTP and willingness to accept (WTA). They confirmed Cason and Plott's (2014) finding, observing that students who better understood the BDM mechanism tended to bid more strategically in comparison to students with a lower understanding. However, they observed that the level of understanding of the incentive properties of the BDM mechanism did not explain the emergence of differences between WTP and WTA.

So in designing RCEs, should researchers comply with the experimental economics theory and use the BDM mechanism or should researchers use the simpler conventional RCE mechanism? We attempt to get an answer to this question in the present article by specifically investigating whether the use of the BDM in RCEs more truthfully reveals individuals' preferences than the conventional RCE. While the use of the BDM mechanism could conceivably provide more truthful revelations in RCEs, to the best of our knowledge, no known study has explicitly examined whether and how choice behavior can be influenced by the application of the BDM mechanism. Specifically, no one has determined whether the use of BDM in RCEs can produce more accurate willingness to pay (WTP) estimates than the more conventional way of using the price stated in the chosen alternative in the binding choice set as the price to be paid by the respondent. This is an important issue since if the use of the BDM mechanism could indeed provide more truthful revelations in RCEs, then this could persuade future researchers to abandon the current conventional way of incentivizing CE studies, and instead use the BDM in RCE studies. This is the motivation for focusing on this important issue in this article.

In recent literature, different methodological issues have been tested in order to improve CE's ability to elicit more truthful WTP estimates (Alfnes et al. 2010; de-Magistris, Gracia, and Nayga 2013; Norwood and Lusk 2011). This is important since CEs are generally used not just for marketing purposes but also for policy and welfare analyses. However, no known study has examined whether RCEs can be improved by the application of the BDM mechanism. As mentioned above, we attempt to explore this important issue and gap in the literature. This study represents an important first step that will hopefully provide some needed insights into whether researchers should use the BDM mechanism in RCEs.

In this article, we investigate individuals' WTP formation with and without the implementation of the BDM mechanism in RCEs. We conducted a RCE in a supermarket using a between-subjects approach to assess consumers' valuations for a food product. In addition, in order to test the robustness of our RCE findings that we describe as a “Homegrown Value” (HV) experiment, we also conducted an “Induced Value” (IV) experiment using undergraduate students at a major university in the US. This is because in IV experiments, the true underlying value of the good in question is known. As such, individuals should not have any uncertainty in choosing the option that maximizes their utility (Smith, 1976). Thus, in contrast to the use of HV experiments, researchers who are using IV experiments should be able to determine whether respondents are providing truthful revelations or choices by observing potential deviations from the induced value of the good (Collins and Vossler 2009; Lusk and Shogren 2007; Murphy et al. 2005; Smith 2003; Smith, 1976). Following the experimental design of Luchini and Watson (2014), we used a fictitious commodity (i.e., tokens) in our IV experiment, which differed in terms of color and shape. For each choice alternative, it was possible for respondents to calculate the value of the token in question.

This article is structured as follows: first, we will describe the experimental procedures and the econometric analyses that were implemented in the HV and IV experiments. On the basis of the obtained results, we will then present conclusions and propose suggestions for future research.

## Experiments and Research Hypothesis

In this section, we illustrate the two experiments we implemented in this study: Homegrown Value (HV) and Induced Value (IV) experiments. The HV experiment is useful since it will provide us information on whether "homegrown" choice behavior is different with and without the use of the BDM mechanism. A vast majority of RCE studies for marketing and policy analyses use HV experiment. As previously discussed, the problem with the HV experiment is that we cannot definitively tell which of the valuations from the CE and CE-BDM treatments provide us with estimates that are more accurate. We can only test if there are significant differences in the estimates and perhaps assume that whichever procedure provides lower WTP values is the better approach since this could potentially indicate lower bias. Thus, in order to more definitively tackle this dilemma, we also conducted an IV experiment as discussed below.

### *Homegrown Value (HV) Experiment*

Data from our HV experiment were collected from a field RCE involving consumers in a supermarket located in Bologna, a city in the Emilia-Romagna region of Italy. Food shoppers were randomly intercepted and recruited at the entrance of the retail store. They were asked to take part in a survey on consumers' valuations for a food product. When approaching the participants, interviewers asked them a set of screening questions: whether they were the main household food shoppers, whether they were at least 18-years old, and whether they were available to taste a food product. Respondents were given a €5 purchase coupon as a reward for participation. Randomly intercepted consumers were given an informed consent form, where they were reassured that any given information would be anonymous, that participation in the experiment did not imply any risks, and that they could quit the experiment at any time.

We used applesauce as the product of interest in our HV experiment. In the RCE, different types of applesauce were proposed depending on price, method of production, and origin of production (Table 2).

--Insert Table 2--

Four price levels were specified to approximately reflect the actual market price for a package of two cups of applesauce, 100g each (€0.95, €1.45, €1.95, €2.45). The second attribute, method of production, was specified as either organic or non-organic. Lastly, the origin of production attribute used two levels: local (produced in Emilia-Romagna, the Italian region where the city of Bologna is located) and non-local (produced in Italy, but outside Emilia-Romagna).

The attributes and attribute levels were allocated to product alternatives using a sequential Bayesian design in order to minimize the $D_b$ error (Scarpa, Campbell, and Hutchinson 2007). Different design phases were performed. In the first phase, we created a choice set design following Street, Burgess and Louviere (2005). Accordingly, the selected attributes and their levels were used to come up with an orthogonal fractional factorial design for our first CE design, reducing the original 16 ($4x2^2$) combinations to just 8. Then the generators described by Street and Burgess (2007) were used to obtain a practical set of eight pairs, with a D-efficiency of 96.6%. The second phase used this design to conduct a pilot survey. In the third and last phase, data from the pilot study were utilized to estimate a Multinomial Logit (MNL) Model, whose coefficients were then used as Bayesian priors for the building of the final design. Each choice set was characterized by two product alternatives and a no-buy option. As such, respondents faced with eight different choice scenarios where they were asked to make trade-offs between two types of applesauce (i.e., the product alternatives) and a no-buy option[1].

Upon completion of the RCE, respondents were asked to complete a questionnaire that included questions related to attitudes towards origin and method of production and socio-demographic information.

In order to assess the effect of the implementation of the BDM mechanism in RCEs, we performed two treatments: (1) the CE treatment, where we used the conventional RCE mechanism; and (2) the CE + BDM treatment (CE-BDM), where we applied the use of the BDM mechanism in order to determine the final price of the chosen product (Palma et al., 2016; Richards, Hamilton, and Allender. 2014). We used a between-subjects design approach. Hence, respondents were randomly assigned to one of the two treatments. Before starting the RCE, participants in both treatments were given detailed instructions about the choice mechanism, followed by a practical example.

In the CE treatment, once the participants finished responding to the eight choice sets, a card was randomly chosen from a randomly arranged deck of eight cards. The cards, representing the choice sets, were numbered from one to eight. The randomly chosen card identified the binding choice set, which consisted of two product alternatives and a no-buy option. The respondent took home the product alternative

[1] Before answering the RCE questions, participants were asked to taste the four types of applesauce products (i.e., produced in Emilia-Romagna/organic, produced outside Emilia-Romagna/organic, produced in Emilia-Romagna/non-organic, produced outside Emilia-Romagna/non-organic). We chose to adopt a blind tasting approach so that the sensory characteristics of the different types of applesauce would not affect respondent's preferences for the production origin and production method attributes. After completing the blind tasting, participants also had the opportunity to visually examine the applesauce products.

he/she chose in the binding choice set and paid the corresponding price indicated in the chosen product alternative. If the respondent chose the no-buy option in the binding choice set, he/she took home no product and paid nothing.

In the CE-BDM treatment, the same procedures were used as in the CE treatment with the exception of the determination of the price that the respondent would pay when choosing one of the product alternatives in the binding choice set. Specifically, after randomly selecting the binding choice set using the card draw, the BDM mechanism was used to determine the price that the respondent would pay for the chosen product alternative. First, a random price was drawn from a uniform distribution of prices. If the randomly drawn price was lower than the price indicated for the chosen product alternative in the binding choice set, then the respondent took home the product at a cost equal to the randomly drawn price. If the randomly drawn price was equal to or higher than the price indicated for the chosen product alternative in the binding choice set, the respondent did not take home any product and paid nothing (Richards, Hamilton, and Allender 2014). As in the CE-treatment, the respondent would also not take home any product and would not pay anything if he/she chose the no-buy option in the binding choice set.

Using the data from the two treatments, we then tested the following hypotheses:

$$H_{01} : (WTP^{CE} - WTP^{CE\text{-}BDM}) \leqslant 0$$

$$H_{11} : (WTP^{CE} - WTP^{CE\text{-}BDM}) > 0$$

A failure to reject the null hypothesis would suggest that the commonly used RCE mechanism where individuals purchase the product at the indicated price for the chosen product alternative in the binding choice set can provide more truthful revelations. On the other hand, a rejection of the null hypothesis would indicate that the use of the BDM to determine the product price would increase the accuracy of RCE in revealing individuals' preferences.

*Induced Value (IV) Experiment*

Data were collected from a lab experiment conducted at a major university in the U.S., using undergraduate students as a subject pool. Students were invited to participate in an economic experiment, aimed at investigating individuals' decision-making in different choice settings. They were informed that they would receive a reward for participation of $8 for taking part in the experiment and that, depending on their choices, they would have the possibility to gain more money at the end of the survey. Before starting the experiment, students were asked to read and sign an informed consent form, where they were informed that they had the possibility to quit the experiment whenever they wanted and that their responses to the survey were anonymous and did not imply any risk for them.

Following Luchini and Watson (2014), the products used in this RCE were fictitious commodities, tokens, which differed in color, shape and price. We aimed at creating an experimental design similar to the one of the HV experiment in terms of the number of attributes and attributes' levels (Table 2). As such, we used two levels of color (red and blue), two levels of shape (square and triangle) and four levels of price ($0.5, $1.5, $2.5, $3.5).

The value of a token depended on the combination of the attributes, attribute levels and price[2]. The payoff that subjects could receive from a given token was equal to the sum of the attributes' values minus the cost of the token. Respondents were aware

[2] See Appendix

of the value of each level of the color and shape attributes. Respondents were given detailed instructions with a table describing the values of the levels of the attributes. Participants were allowed to consult this table for the duration of the entire experiment. The allocation of attributes and attribute levels to the product alternatives was designed using the Street and Burgess (2007) approach. Thus, using the generators described by Street and Burgess (2007), from an initial orthogonal fractional factorial design we obtained eight choice sets with a 96.6% D-efficiency[3]. Thus, each participant was presented with eight different choice sets, and was asked to make a choice in each choice set between two tokens and the “none of these” option

Before starting the RCE, the experimenter read the instructions aloud. In the instructions, it was explained in detail how respondents could gain the maximum earning based on their choices. Subjects were reminded that by participating in the experiment their initial reward was of $8, irrespective of their choices. Thus, if they chose one of the tokens, they had to sum the value of that token to the initial $8. If they chose the “none of these” option, their final earning would be equal to the participation reward of $8. In addition, they were given a practical example and a quiz to make sure they fully understood the procedures. Every question of the quiz was followed by an explanation of the correct answer. Following Collins and Vossler (2009), to incentivize subjects to carefully answer the quiz questions and pay close attention to the instructions, we also informed them that they would gain $2 more if they answered all the quiz questions correctly.

[3] In past IV choice experiments (e.g., Collins & Vossler 2009; Luchini and Watson 2014), the authors adopted a fractional factorial design. As such, in the IV experiment we used an experimental design where no priors were implemented for its construction.

We used the Qualtrics survey platform so that we could easily calculate each participant's final earning. In addition, participants were given paper sheets that they could use to help them in the calculation of the different alternatives' values. Finally, after the performance of the RCE, the students were asked to fill out a questionnaire related to socio-demographic information.

As in the HV experiment, we also used a between subjects approach with two treatments in the IV experiment, the CE treatment and the CE-BDM treatment. In the CE treatment we used the conventional RCE mechanism, while in the CE-BDM treatment, following Richards, Hamilton, and Allender (2014), we applied the use of the BDM mechanism to determine the final price of the chosen product/token alternative. We conducted three sessions for each treatment.

In the CE treatment, once all the subjects finished the IV experiment, one of the participants was asked to pick a card from a randomly arranged deck of eight cards, which represented the eight choice sets. Once the card was selected, the choice set that the card represented became binding. Hence, if the subject chose a token alternative, he/she would gain a final amount of money equal to the sum of the token value and of the $8 reward. If the subject chose the no-buy option in the binding choice set, he/she would obtain a final earning equal to the initial $8.

In the CE-BDM treatment, subjects were informed that their final earnings depended on the value of a randomly drawn price from a uniform distribution of prices. After the selection of the binding choice set, one of the subjects in the session was asked to randomly pick one marble from a bag. Each ball was marked with a price. If the price indicated on the randomly chosen marble was below the cost of the token a subject chose in the binding choice set, the subject would "purchase" the token at the randomly drawn price. As such, his/her final earning would be equal to the sum of the initial $8 reward for participation and the attributes' values of the token, minus the randomly drawn price. On the other hand, if the randomly drawn price was higher or equal to the price of the chosen token in the binding choice set, he/she would receive only the $8 reward for participation. It was emphasized to all subjects that if they chose a token, they could receive more or less than $8 depending on their choice in the binding choice set.

Theoretically, in induced value experiments, subjects should be willing to pay a maximum price equal to the known value of the good (the induced value) (Lusk and Shogren 2007; Smith, 1976). In our RCE, we estimated the marginal WTPs for the color and shape attributes. As such, the "marginal" induced value that a respondent should be willing to pay for an attribute of the token is equal to the difference between the two levels of the attribute (Collins and Vossler 2009). For example, the difference between the red ($3) and the blue ($1) color is equal to two; the difference between the triangle ($4) and square ($2) shape is equal to two as well. Thus, with our IV experiment, a preference elicitation mechanism can be considered incentive compatible when it reveals estimates equal to two.

We then test these hypotheses:

$$H_{02}: \ MWTP^{CE} \ \ \Delta\text{Color and } \Delta\text{Shape} = 2,$$

$$H_{12}: \ MWTP^{CE} \ \ \Delta\text{Color and } \Delta\text{Shape} \neq 2$$

$$H_{03}: \ MWTP^{CE\text{-}BDM} \ \ \Delta\text{Color and } \Delta\text{Shape} = 2,$$

$$H_{13}: \ MWTP^{CE\text{-}BDM} \ \ \Delta\text{Color and } \Delta\text{Shape} \neq 2$$

If $H_{02}$ is rejected and $H_{03}$ fails to be rejected, then we can confirm that RCEs are incentive compatible when the BDM mechanism is implemented. On the other hand, if $H_{02}$ fails to be rejected and $H_{03}$ is rejected, we would conclude that individuals truthfully reveal their valuations for a good when the BDM is not implemented.

**Econometric models**

In order to estimate respondents' WTPs, we implemented discrete choice models. The utility for individual *i* of choosing alternative *j* in the $t^{th}$ choice situation is:

$$U_{ijt} = \beta'_i x_{ijt} + \varepsilon_{ijt} \tag{1}$$

where $x_{ijt}$ is a vector of the observed variables relating to alternative *j* and individual *i* in choice set *t*; $\beta'_i$ is a vector of structural taste parameters characterizing choices; $\varepsilon_{ijt}$ is the unobserved error term, assumed to be independent of $\beta$ and *x*.

Researchers may use different choice models depending on the assumption about the distribution of the unobserved error term and the functional form of the utility. The Multinomial Logit Model (MNL), for instance, assumes that the error terms are independently and identically distributed (IID) with a Gumbel distribution, and implies independence within the alternatives and taste homogeneity across respondents. However, we assumed that heterogeneity existed across individuals' choices. As such, models such as the Random Parameter Logit (RPL) model should be considered since they can account for random taste variation and for panel structure (Train 2009). Specifically, in our study, the RPL takes into consideration that each respondent made eight repeated choices. In addition, the RPL relaxes the assumption of independence of the irrelevant alternatives (IIA), which is inherent in the MNL model (Train 2009).

For our analysis, we chose the RPL with Error Component model (RPL-EC) (Scarpa, Ferrini, and Willis 2005; Scarpa, Campbell and Hutchinson 2007). This model was chosen because the RPL-EC advances the RPL model in an important way. Our experimental design was characterized by two product alternatives and a no-buy option in each choice set. While the product alternatives varied choice sets, the no-buy option was constantly present. Hence, the unobserved utility of the two product alternatives might have a higher variance than the unobserved utility of the no-buy option, and so it is possible that the two product alternatives could have a higher correlation in comparison with the no-buy option (Caputo, Nayga and Scarpa 2013; Gracia, Barreiro-Hurlé, and Pérez y Pérez 2012, Gracia 2014; Scarpa, Ferrini and Willis 2005). To overcome the systematic effects associated with the product alternatives and the no-buy option, in the RPL-EC model the two product alternatives share an extra error component which has a zero mean and is normally distributed (Scarpa, Ferrini and Willis 2005; Scarpa, Thiene and Marangon 2007).

In addition, instead of using the more conventional preference space specification, we specified the RPL-EC in WTP space to capture the differences in the marginal WTP values for the different attributes across the treatments. This is because the use of a WTP space model facilitates the direct estimation of the marginal WTP distribution (Train and Weeks 2005; Thiene and Scarpa 2009). Past studies have shown that specification of the utility function in WTP space provides more reasonable distributions of WTP (Train and Weeks 2005) and produces more stable WTP estimates (Balcombe et al. 2009). The utility is re-parameterized such that the coefficients can be directly interpreted as marginal WTP effects (Train and Weeks 2005; Scarpa and Wills 2010) and the assumption of a fixed price coefficient is relaxed, defining the price preference to be random across individuals (Scarpa, Thiene and Train 2008; Thiene and

Scarpa 2009; Train and Weeks 2005). Hence, for our HV experiment the utility that individual *i* derives in choosing option *j* in choice situation *t* can be specified as follows:

$$U_{ijt} = \theta_{ijt}\,(ASC - PRICE_{ijt} + \omega_1 ORGANIC_{ijt} + \omega_2 LOCAL_{ijt} + \eta_{ijt}) + \varepsilon_{njt} \qquad (2)$$

where $\theta = \lambda/\alpha$, $\lambda$ is the Gumbel scale parameter and $\alpha$ is the coefficient of price. ASC is the alternative specific constant of the no-buy option. PRICE is a continuous variable populated with the four price levels in the design. ORGANIC and LOCAL are respectively dummy variables for method and origin of production. Hence, they take value 1 in case the product carries the claim, 0 otherwise. $\eta_{ijt}$ is the error component distributed normally with zero mean, which inflates the variance of utility for the options different from the no-buy option; $\varepsilon_{njt}$ is an unobserved random error term that is i.i.d. distributed extreme value type-I (Gumbel) over alternatives and independent of $\alpha$ and $\beta$.

If one wants to test the presence of a difference between two treatments, for instance treatments denoted by a dummy variable, one can specify an extended utility function by including a vector of WTPs related to a specific treatment. We, then, identified the treatment as a *dtreatment* binary variable, taking the value 0 for the CE treatment and the value 1 for the CE-BDM treatment and we specified the utility function as follows:

$$U_{ijt} = \theta_{ijt}\,(ASC - PRICE_{ijt} + \omega_1 ORGANIC_{ijt} + \omega_2 LOCAL_{ijt} + \delta_1(ORGANIC_{ijt}*dtreatment) + \delta_2(LOCAL_{ijt}*dtreatment) + \eta_{ijt}) + \varepsilon_{njt} \qquad (3)$$

where $\delta_1$ and $\delta_2$ respresent the treatment effect respectively on the organic and local production attributes. The significance of the estimated $\delta_1$ and $\delta_2$, and their signs establish the effect of the treatment on the marginal WTP estimate of interest. Hence, they determine if and how the marginal WTP for local and organic attributes differed across the the two treatments.

We adopted the same econometric approach we used in the HV experiment for the IV experiment. Following Collins and Vossler (2009), we assumed that the utility of individual *i* in choosing the token *j* (total induced value option) could be segregated in the marginal utilities of the red color and triangle shape attributes. Accordingly, we estimated a RPL-EC in WTP space, specifying the utility individual *i* derives in choosing induced value option *j* as follows:

$$U_{ijt} = \theta_{ijt} \,( ASC - PRICE_{ijt} + \omega_1 RED_{ijt} + \omega_2 TRIANGLE_{ijt} + \eta_{ijt} \,) + \varepsilon_{njt} \tag{4}$$

where RED and TRIANGLE are the dummy variables for the attributes of the tokens; RED takes the value of 1 if the token is red and 0 if not red (blue), while TRIANGLE takes the value of 1 if the token is triangle, 0 otherwise (square). The remaining terms are the same as the ones described in equation 1.

Finally, as in the HV experiment analysis, we estimated the treatment effect by conducting tests on the pooled sample:

$$U_{ijt} = \theta_{ijt} \,(ASC - PRICE_{ijt} + \omega_1 RED_{ijt} + \omega_2 TRIANGLE_{ijt} + \delta_1 (RED_{ijt} {*} dtreatment) + \delta_2 (TRIANGLE_{ijt} {*} dtreatment) + \eta_{ijt} \,) + \varepsilon_{njt} \tag{5}$$

where, in addition to equation 4, $\delta_1$ and $\delta_2$ are the treatment effects on the WTP of red color and triangle shape attributes. If $\delta_1$ and $\delta_2$ are statistically significant, we would then conclude that the use of the BDM mechanism significantly influences an individual's choice behavior in a RCE context.

## Results

### *HV Experiment Results*

In order to test our first hypothesis ($H_{01}$: ($WTP^{CE}$ - $WTP^{CE\text{-}BDM}$) $\leqslant$ 0;$H_{11}$: ($WTP^{C}$ - $WTP^{CE\text{-}BDM}$) > 0), we first estimated the marginal WTP for organic production and local origin in the CE treatment and CE-BDM treatment separately (table 3). Then, in order to test for treatment effect, we estimated the marginal WTP for local and organic applesauce using the pooled sample (table 4).

--Insert table 3--

-- Insert table 4--

Table 3 shows that marginal WTP both for the organic and locally produced attributes are higher in the CE-BDM treatment than in the CE treatment. In addition, the significant parameter estimate of the treatment interaction term (table 4) signifies that the differences in marginal WTP across the two samples are significant in both attributes. Hence, we cannot reject the null hypothesis $H_{01.}$ This indicates that when the BDM mechanism is used in RCEs, individuals tend to reveal higher WTP for a good in comparison with RCEs where the BDM mechanism is not used. An increase in WTP could be interpreted as an expression of bias in individuals' evaluations since the literature generally has shown that people in "less real" choice situations appear willing to pay more for a product than they would actually pay (de-Magistris et al. 2013; Lusk and Schroeder 2004; Murphy et al. 2005). Our results suggest that the use of the BDM in RCEs might induce individuals to, maybe, overestimate their real preferences.

*IV Experiment Results*

As in the HV experiment, we compared the estimates obtained from the RPL-EC model between the CE treatment and the CE-BDM treatment. In the IV experiment, we aimed at testing whether individuals' marginal WTP for the red and the triangle attributes are equal to the induced value (i.e., $2).

Although individually the marginal WTP for the red and the triangle tokens significantly diverge from $2[4], table 3 shows that the marginal WTP both for the red and blue tokens from the CE treatment are closer to $2 than marginal WTP from the CE-BDM treatment. This suggests that we fail to reject the hypothesis of equality with the induced value ($H_{02}$ : $MWTP^{CE}$ for $\Delta$Color and $\Delta$Shape = 2, $H_{12}$ : $MWTP^{CE}$ for $\Delta$Color and $\Delta$ Shape $\neq$ 2; $H_{03}$ : $MWTP^{CE\text{-}BDM}$ for $\Delta$Color and $\Delta$ Shape = 2, $H_{13}$ : $MWTP^{CE\text{-}BDM}$ for $\Delta$Color and $\Delta$ Shape $\neq$ 2) in both treatments. However, table 4 shows that the treatment effect is significant in both attributes, indicating that the use of the BDM in RCEs significantly affects individuals' choice behavior. Given that the marginal WTPs from the CE treatment are closer to $2 than those from CE-BDM treatment, then it might be reasonable to assume that the subjects taking part in the CE treatment tended to choose closer to the induced value than subjects in the the CE-BDM treatment. In order to confirm this conjecture, we estimated a simple probit model to determine the probability that respondents chose in each choice set the induced value, represented by the "maximum payoff" alternative (Collins and Vossler 2009). In the probit model, we used as dependent variable the choice of the induced value (which takes a value of 1 when individuals choose the maximum payoff, 0 otherwise), while

[4] Results are available from the authors upon request

the independent variable is the treatment dummy (i.e., CE-BDM takes value of 1; 0 for CE treatment).

Our assumption is confirmed by the results reported in table 5, signifying that the probability that individuals chose the induced value alternative significantly decreased in the CE-BDM treatment.

--Insert table 5--

This result then indicates that the use of the BDM mechanism in RCEs significantly decreases the probability that individuals will choose the option that maximizes their utility. This result suggests that the implementation of the BDM mechanism in RCEs does not provide more accurate revelations than those from the conventional RCE mechanism. This finding is consistent with results from the studies of Bartling et al. (2015) and Cason and Plott (2014) who observed that in induced value BDM auctions, individuals bid significantly differently from the induced value.

*In Search for a Potential Mechanism: Degree of Understanding of the Experimental Procedures and Time Devoted to complete the Choice Sets*

Our results made us wonder what the mechanism or reason is for the less than beneficial use of the BDM mechanism in our RCEs. Bartling et al. (2015) and Cason and Plott (2014) observed that respondents who did not understand the BDM mechanism made significantly less incentive compatible bids. Given this finding, we also assessed the effect of level of understanding of our subjects on their choice behavior in our IV experiment. Specifically, following Collins and Vossler (2009), we asked our subjects how well they understood the instructions given to them about the experiment, using a scale from 1, poorly understood, to 5, well understood.

Table 6 shows that in our IV experiment, subjects in the CE treatment understood the experiment better than those in the CE-BDM treatment.

--Insert Table 6--

In addition, we conducted a probit analysis to assess whether the probability of choosing the induced value is related to the self-assessed level of understanding[5] (table 7). Results suggest that this is the case in the CE treatment; subjects who better understood the experimental mechanism tended to choose the induced value with a significantly higher probability. On the other hand, the effect of the self-assessed level of understanding on CE-BDM subjects' choices is not statistically significant.

--Insert Table 7--

We also examined the amount of time that subjects devoted to responding to each choice set. Results indicate that on average, subjects in the CE-BDM treatment spent a significantly higher amount of time responding to the choice sets than subjects in the CE treatment[6] (33.17" for the CE-BDM treatment, 30.04" for the CE treatment). In table 7, we report results from a probit model, where we estimated whether the time individuals spent to answer each choice set had a significant effect on the probability that individuals chose the induced value option.

We did not find any significant effect in the case of the CE treatment. On the other hand, table 7 shows that in the CE-BDM treatment, the more time the subjects spent in choosing an alternative, the lower the probability that they chose the induced value option. While the reason for this finding is unclear, the results could indicate that,

[5] We included the "level of understanding" as a continuous variable to make results easier to understand for the reader. However, we had similar results when we included the "level of understanding" as an ordinal variable.
[6] Results from a t-test show significant difference in means across the treatments

when the BDM mechanism is used, the subjects might spend more time in trying to adopt a potential choice strategy instead of simply choosing the maximum payoff alternative. As such, we might deduce that when the BDM mechanism is implemented in RCEs, individuals tend to less truthfully reveal their preferences.

## Conclusions

Interest in discrete choice experiments has increased significantly in the fields of agricultural, environmental, and health economics as well as the marketing field since the 1990s. Undoubtedly, choice experiments are now one of the most popular stated preference methods used in marketing and applied economics to elicit individuals' preferences and WTP for private and public goods. For this reason, researchers have been increasingly testing and implementing methodological improvements to increase the accuracy of CEs in revealing individuals' preferences. One of these methodological improvements is the incentivization of respondents by implementing a RCE as described and discussed in the introduction. For example, the conventional way of implementing a RCE is to use the price indicated in the chosen product alternative in the binding choice set as the amount that the respondent must pay for the chosen product alternative. While this procedure indeed introduces an economic incentive into the choice experiment, there is the question of whether the additional use of a BDM mechanism in RCEs could provide more truthful revelations of subjects' preferences. Theoretically, it should since the use of the BDM mechanism separates the price that the respondent chooses for the chosen product alternative from the price that he/she ultimately pays. The BDM mechanism is also a natural mechanism to adopt in CEs since it can easily be implemented on an individual basis; i.e., it does not have to be implemented in a group setting.

Hence, our research objective in this study is simple but important. We simply wanted to assess whether the additional use of the BDM mechanism in RCEs could elicit more truthful revelations of respondents' preferences and WTP values. Given that there is now an increasing number of CE studies that are incentive-aligned (i.e., incentivized) as exhibited in table 1, this is a crucial topic to examine since results could provide new important insights on whether researchers should start using the BDM mechanism in RCEs.

Using both HV and IV experiments, our results generally suggest that the use of the BDM mechanism does not provide more accurate revelations of a person's WTP values. Specifically, results from our HV experiment indicated that the marginal WTP values for local and organic applesauce were significantly different (i.e., higher) in the CE-BDM treatment than in the CE-treatment. As such, since previous studies stated that lower WTP values tend to be more realistic, results from the HV experiment indicate that the use of the BDM mechanism might produce less accurate WTP estimations. However, this is only speculative given that in a HV experiment, even though we can test if there were significant differences in the estimates across the two treatments, we could not definitively tell which of the valuations from the CE and CE-BDM treatments provided estimates that are more accurate. For this reason, we also conducted the IV experiment to allow us to observe which experimental approach would produce estimates closer to the induced value, and therefore more accurately reveal individuals' utilities.

Results from the IV experiment confirmed our speculation about the results from the HV experiment. In the IV experiment, estimates from the CE-BDM treatment were less close to the induced value than the estimates from the CE treatment, suggesting that respondents from the CE treatment chose with a significantly higher probability the maximum payoff option. This finding seems to corroborate findings from recent studies that the use of the BDM mechanism might induce individuals to adopt dominance bidding strategies and therefore might not provide accurate WTP estimates. Indeed, estimates for the tokens in the CE-BDM are significantly higher than in the CE treatment. It is then possible that the use of the BDM mechanism could have caused more uncertainty in individuals when making their choices.

Importantly, Cason and Plott (2014) and Bartling, Engl, and Weber (2015) showed that the BDM mechanism might not be well understood by respondents. Because of this potential issue, we provided our subjects detailed instructions about the BDM mechanism with a practical example and an incentivized quiz. Remarkably, despite our efforts to make sure that our subjects completely understood the BDM mechanism, our results suggest that our subjects understood the conventional RCE approach significantly better than the CE-BDM approach. This finding seems to imply that the use of the BDM mechanism further complicates things for our subjects. Future research, however, should test the robustness of our findings by replicating our study or test other potential tools that could improve the accuracy of RCEs in eliciting preferences and WTP values. Hopefully, the present study will, at the very least, increase discussion and research about the use of BDM or other types of mechanisms that can potentially improve the truthful revelation properties of RCEs.

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# Tables

## Table 1: Previous RCE studies and their use of the BDM Mechanism

| Authors | Title | Year | Journal | Use of the BDM mechanism to determine the price of the chosen alternative |
|---|---|---|---|---|
| Carlsson, Fredrik<br>Martinsson, Peter | Do Hypothetical and Actual Marginal Willingness to Pay Differ in Choice Experiments? | 2001 | Journal of Environmental Economics and Management | No |
| Cameron, Trudy Ann<br>Poe, Gregory L.<br>Ethier, Robert G.<br>Schulze, William D | Alternative Non-market Value-Elicitation Methods: Are the Underlying Preferences the Same? | 2002 | Journal of Environmental Economics and Management | No |
| Lusk, Jayson L.<br>Schroeder, Ted | Are choice experiments incentive compatible? A test with quality differentiated beef steaks | 2004 | American Journal of Agricultural Economics | No |
| Alfnes, Frode<br>Guttormsen, Attle G.,<br>Steine, Gro<br>Kolstad Kari | Consumers' Willingness to Pay for the Color of Salmon: A Choice Experiment with Real Economic Incentives. | 2006 | American Journal of Agricultural Economics | No |
| List, John A.<br>Sinha, Paramita<br>Taylor, Michael H. | Using Choice Experiments to Value Non-Market Goods and Services: Evidence from Field Experiments | 2006 | Advances in Economic Analysis & Policy | No |
| Ding, Min | An Incentive-Aligned Mechanism for Conjoint Analysis | 2007 | Journal of Marketing Research | Yes |
| Chang, Jae Bong<br>Lusk, Jayson L.<br>Norwood, F. Bailey | How Closely Do Hypothetical Surveys and Laboratory Experiments Predict Field Behavior? | 2009 | American Journal of Agricultural Economics | No |

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|---|---|---|---|---|
| Loomis, John | A Comparison of Actual and Hypothetical Willingness to Pay of Parents and Non-Parents for Protecting Infant Health : The Case of Nitrates in Drinking Water | 2009 | Journal of Agricultural and Applied Economics | No |
| Volinskiy, Dmitriy<br>Adamowicz, Wiktor L<br>Veeman, Michele<br>Srivastava, Lorie | Does choice context affect the results from incentive-compatible experiments? the case of non-gm and country-of-origin premia in canola oil | 2009 | Canadian Journal of Agricultural Economics | No |
| Yue, Chengyan<br>Tong, Cindy | Organic or Local? Investigating Consumer Preference for Fresh Produce Using a Choice Experiment with Real Economic Incentives | 2009 | HortScience | No |
| Corrigan, Jay R.<br>Depositario, Dinah Pura T.<br>Nayga, Rodolfo M. Jr.<br>Wu, Ximing<br>Laude, Tiffany P. | Comparing open-ended choice experiments and experimental auctions: An application to golden rice | 2009 | American Journal of Agricultural Economics | No |
| Olesen, Ingrid<br>Alfnes, Frode<br>Rora, Mia Bensze<br>Kolstad, Kari | Eliciting consumers' willingness to pay for organic and welfare-labelled salmon in a non-hypothetical choice experiment | 2010 | Livestock Science | No |
| Alfnes, Frode<br>Yue, Chengyan<br>Jensen, Helen H. | Cognitive dissonance as a means of reducing hypothetical bias | 2010 | European Review of Agricultural Economics | No |
| Gracia, Azucena<br>Loureiro, Maria L.<br>Nayga, Rodolfo M. Jr. | Are Valuations from Nonhypothetical Choice Experiments Different from Those of Experimental Auctions? | 2011 | American Journal of Agricultural Economics | No |
| Kang, Min Jeong<br>Rangel, Antonio<br>Camus, Mickael<br>Camerer, Colin F. | Hypothetical and real choice differentially activate common valuation areas. | 2011 | The Journal of neuroscience : the official journal of the Society for Neuroscience | No |

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|---|---|---|---|---|
| Norwood, Bailey F.<br>Lusk, Jayson L. | Social desirability bias in real, hypothetical, and inferred valuation experiments | 2011 | American Journal of Agricultural Economics | No |
| Moser, Riccarda<br>Raffaelli, Roberta | Consumer preferences for sustainable production methods in apple purchasing behaviour: a non-hypothetical choice experiment | 2012 | International Journal of Consumer Studies | No |
| Michaud, Celin<br>Llerena, Daniel<br>Joly, Iragael | Willingness to pay for environmental attributes of non-food agricultural products: a real choice experiment | 2012 | European Review of Agricultural Economics | No |
| de-Magistris, Tiziana<br>Gracia, Azucena<br>Nayga, Rodolfo M. Jr. | On the Use of Honesty Priming Tasks to Mitigate Hypothetical Bias in Choice Experiments | 2013 | American Journal of Agricultural Economics | No |
| Gracia, Azucena | Consumers' preferences for a local food product: a real choice experiment | 2013 | Empirical Economics | No |
| Akaichi, Faical<br>Nayga, Rodolfo M. Jr.<br>Gil, Jose' M. | Are Results from Non-hypothetical Choice-based Conjoint Analyses and Non-hypothetical Recoded-ranking Conjoint Analyses Similar? | 2013 | American Journal of Agricultural Economics | No |
| Grebitus, Carola<br>Lusk, Jayson L<br>Nayga, Rodolfo M. Jr. | Explaining differences in real and hypothetical experimental auctions and choice experiments with personality | 2013 | Journal of Economic Psychology | No |
| de-Magistris, Tiziana<br>Gracia, Azucena | Do consumers care about organic and distance labels? An empirical analysis in Spain | 2014 | International Journal of Consumer Studies | No |
| Ginon, Emilie<br>Chabanet, Claire<br>Combris, Pierre<br>Issanchou, Sylvie | Are decisions in a real choice experiment consistent with reservation prices elicited with BDM 'auction'? The case of French baguettes | 2014 | Food Quality and Preference | No |

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|---|---|---|---|---|
| Richards, Timothy J.<br>Hamilton, Stephen. F.<br>Allender, William. J. | Social Networks and New Product Choice | 2014 | American Journal of Agricultural Economics | Yes |
| Lee, Sang Hyeon<br>Han, Doo Bong<br>Caputo, Vincenzina<br>Nayga, Rodolfo M. Jr. | Consumers' Valuation for a Reduced Salt Product: A Nonhypothetical Choice Experiment | 2015 | Canadian Journal of Agricultural Economics | No |
| Palma, Marco<br>Behe, Bridget K.<br>Hall R. Charles<br>Huddleston Patricia T.<br>Fernandez Tom | Tracking position premiums in discrete choice experiments | 2016 | Applied Economics Letters | Yes |

**Table 2: Attributes and Attributes Levels of the HV and IV experiments.**

| **HV Experiment** | | **IV Experiment** | |
|---|---|---|---|
| **Attributes** | **Levels** | **Attributes** | **Levels** |
| Price | € 2.45 | Price | $ 0.50 |
| | € 1.95 | | $1.50 |
| | € 1.45 | | $2.50 |
| | € 0.95 | | $3.50 |
| Method of Production | Organic | Color | Red |
| | Non-organic | | Blue |
| Origin of Production | Local | Shape | Triangle |
| | Non-local | | Square |

**Table 3: HV Experiment and IV Experiment: WTP Estimates**

| HV Experiment | | | IV Experiment | | |
|---|---|---|---|---|---|
| **Attribute** | **CE** | **CE-BDM** | **Attribute** | **CE** | **CE-BDM** |
| Organic | 0.775*** | 1.103*** | Red | 2.051*** | 2.359 ** |
| | (0.107) | (0.111) | | (0.221) | (1.006) |
| Local | 0.420*** | 0.720*** | Triangle | 2.229*** | 2.404*** |
| | (0.137) | (0.104) | | (0.204) | (0.595) |

Note: Numbers in parenthesis are Standard Errors

Note: two asterisks (**) and three asterisks (***) respectively denote significance at the 5% level and 1% level

**Table 4: HV Experiment and IV Experiment: Treatment Effect**

| **HV Experiment** | | | |
|---|---|---|---|
| | **Coefficient** | **Standard Error** | **p-value** |
| ***Organic x dtreatment*** | 0.486 | 0.208 | 0.019 |
| ***Local x dtreatment*** | 0.549 | 0.224 | 0.014 |
| **IV Experiment** | | | |
| | **Coefficient** | **Standard Error** | **p-value** |
| ***Red x dtreatment*** | 0.600 | 0.226 | 0.008 |
| ***Triangle x dreatment*** | 0.555 | 0.231 | 0.016 |

**Table 5: Probit Analysis of Treatment Effect on Induced Value Choice**

| | **Coefficient (std. err.)** | **Marginal Effect (std. err.)** |
|---|---|---|
| **Treatment Effect** | -1.063*** (0.113) | -0.277*** (0.029) |
| **Constant** | 1.373*** (0.087) | |
| | | |
| ***Log-likelihood*** | -330.122 | |
| ***X2 (df=1)*** | 94.81 (p-value=0.000) | |
| ***N*** | 736 | |

Note: Three asterisks (***) denote significance at the 1% level

**Table 6: Level of Understanding of the Experiment Across Treatments (%)**

| | CE Treatment | CE-BDM Treatment |
|---|---|---|
| 1=poorly understood | 1.89 | 12.82 |
| 2 | 1.89 | 20.51 |
| 3 | 20.75 | 33.33 |
| 4 | 24.53 | 28.21 |
| 5= well understood | 50.94 | 5.13 |
| *Mann-Whitney test: p-value=0.000* | | |

**Table 7: Probit Analysis of the Effect of Level of Understanding and Effect of Decision Time on Induced Value Choice Across Treatments**

| Effect of level of understanding | | | | |
|---|---|---|---|---|
| | CE Treatment | | CE-BDM Treatment | |
| | Coefficient (std. err.) | Marginal Effect (std. err.) | Coefficient (std. err.) | Marginal Effect (std. err.) |
| **Level of understanding (continuous variable)** | 0.312*** (0.091) | 0.044*** (0.012) | -0.014 (0.068) | -0 .005 (0.026) |
| **Constant** | 0.123 (0.360) | | 0.352** (0.211) | |
| ***N*** | 424 | | 312 | |
| ***Log-likelihood*** | -115.906 | | - 206.888 | |
| ***X2 (df=1)*** | 11.67 | | 0.04 | |
| **Effect of decision time** | | | | |
| | CE Treatment | | CE-BDM Treatment | |
| | Coefficient (std. err.) | Marginal Effect (std. err.) | Coefficient (std. err.) | Marginal Effect (std. err.) |
| **Time (continuous variable)** | - 0.005 (0.004) | -0.001 (0.001) | -0.005* (0.003) | -0.002* (0.001) |
| **Constant** | 1.527*** (0.145) | | 0.468*** (0.113) | |
| ***N*** | 424 | | 312 | |
| ***Log-likelihood*** | -122.378 | | -205.291 | |
| ***X2(df=1)*** | 1.84 | | 3.40 | |

Note: two asterisks (**) and three asterisks (***) respectively denote significance at the 5% level and 1% level

# Appendix

## Attributes Values

| **Characteristic** | **Value** |
|---|---|
| ***Color*** | |
| Blue | 1$ |
| Red | 3$ |
| ***Shape*** | |
| Square | 2$ |
| Triangle | 4$ |