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RESEARCH ARTICLE

Quick and easy? Respondent evaluations of the Becker–DeGroot–Marschak and multiple price list valuation mechanisms

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Abstract

This article is the first to investigate respondents' ease of understanding and answering valuation questions related to the Becker–DeGroot–Marschak (BDM) and multiple price list mechanisms. Using a between-subjects design, we elicit willingness to pay (WTP) for healthy snack bars using two mechanisms, ask questions about ease of understanding and answering the valuation questions, and record the response times to the valuation questions. We do not find significant differences in estimated WTP and response times between the two methods. However, the respondents in the multiple price list (MPL) sessions found it easier to understand this mechanism and decide on a response than those in the BDM sessions. As a result of our findings, we recommend that MPL is adopted over BDM when there is limited opportunity to explain or learn the method before the valuation or when one is concerned that a complicated design can affect the willingness to participate and thereby create selection bias. Both concerns will often apply when small and medium size agribusinesses conduct market testing of their products in stores or field markets. [EconLit Citations: C18, C19, D44, Q13].

1 | INTRODUCTION

In food marketing research, it is sometimes useful to collect realistic consumer willingness to pay (WTP) data for new food products (Lusk & Shogren, 2007). For new products or new attributes, information such as scanner data is often not available and sometimes difficult to handle or interpret (Lusk & Brooks, 2011; Lusk & McCluskey, 2018). Thus, food market researchers and analysts collect consumer data on food products and food product attributes using real consumer valuation experiments. However, in many situations, such as small scale market testing of new products in-store or field-market, there is a need for valuation methods that respondents understand easily and that can be conducted quickly with minimal explanation and training by less experienced moderators (Alphonce & Alfnes, 2017). Long and complicated experiments will also likely reduce willingness to participate and create validity problems related to sample selection bias (Hou et al., 2019). Inside stores or in field markets, typically food researchers and analysts can only engage with one respondent at a time and individual valuations must be completed within minutes. Hence, incentive-compatible valuation methods using groups of respondents, such as experimental auctions (EAs), are often not well suited to such experiments (Alfnes & Rickertsen, 2010; Lusk & Shogren, 2007; Vecchio & Borrello, 2019). In this article, we explore how easy respondents find two commonly used incentive-compatible valuation methods that can be used with individual respondents: Becker–DeGroot–Marschak (BDM; Becker, DeGroot, & Marschak, 1964) and MPL (Andersen, Harrison, Lau, & Rutström, 2006). We also investigate the average stated WTP and response time under these two methods, and we provide suggestions for method choice. This paper is one of the first to explore features of valuation experiments that are important for respondents understanding and participation, and thereby also the validity of the experiments beyond the incentive compatibility and individual WTP estimates.

In recent years, a considerable amount of research has been undertaken using incentive-compatible valuation methods to evaluate private goods that are sold using real money in different market settings, conducted in laboratories or in the field (Caracciolo et al., 2019; Grebitus, Lusk, & Nayga, 2013; Li, Messer, & Kaiser, 2020; Pomarici, Asioli, Vecchio, & Næs, 2018; Thorne, Fox, Sean, Mullins, & Wallace, 2017; Wolfe et al., 2018). The main advantage of these methods is that they are incentive compatible, meaning that they provide consumers with incentives to reveal their true WTP for a good and thereby avoid hypothetical bias[1] which is often a problem in hypothetical stated valuation methods (Alfnes & Rickertsen, 2010; Lusk & Shogren, 2007; Vecchio & Borrello, 2019). Under incentive-compatible valuation methods, respondents submit a bid, choose a product, or state at which prices they are willing to buy a product (Alfnes & Rickertsen, 2010). To be incentive compatible, products must be sold and it must be in the best interest of the respondents to reveal their true preferences (Alfnes & Rickertsen 2010; Lusk & Shogren 2007).

Among the different types of experimental valuation methods (for an overview, see Alfnes & Rickertsen, 2010, and more recently see Lee, Nayga, Deck, & Drichoutis, 2020; Lombardi, Vecchio, Borrello, Caracciolo, & Cembalo, 2019), the most popular in food consumer studies are Vickrey-style sealed-bid auctions (Vickrey, 1961) and the BDM method (Becker et al., 1964). However, there has been increasing interest in MPL experiments (Alphonce & Alfnes, 2017; Galati, Schifani, Crescimanno, & Migliore, 2019; Lombardi et al., 2019; Shew et al., 2017; Vecchio &

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[1]Hypothetical bias is the difference between values obtained through hypothetical methods and values obtained through non hypothetical methods.

Annunziata, 2018) and real choice experiments (Ballico & Gracia, 2020; Bazzani, Caputo, Nayga, & Canavari, 2017; Yin et al., 2019).

The incentive-compatible valuation methods used in the literature differ with respect to how easy it is to explain the methods, how easy it is to understand the dominant strategy and provide responses, and how time-consuming they are. Several studies have compared different incentive-compatible valuation methods, but they mainly focused on differences in WTP estimates of different methods (Alphonce & Alfnes 2017; Corrigan, Depositario, Nayga, Wu, & Laude, 2009; Gracia, Loureiro, & Nayga, 2011; Hamukwala, Oparinde, Binswanger-Mkhize, & Kirsten, 2019; Lusk & Schroeder 2006) rather than comparing other important practical aspects (e.g., ease of understanding the dominant strategy or revealing the price) which are of crucial importance when de-signing studies and in implementing these methods in experimental settings. Important reference articles are Lusk et al. (2004) that compare Vickery auction, English auction, BDM and random nth price auction, and Noussair et al. (2004b) that compare BDM with Vickery auction. More recently, Flynn et al. (2016) compare Vickery auction and BDM.

To the best of our knowledge, only a few articles have investigated the differences between BDM and MPL. One example is Alphonce and Alfnes (2017), who compare four incentive-compatible valuation methods that are suitable for individual respondents, including BDM and MPL. Investigate consumers' WTP for extrinsic attributes of tomatoes in an African field market, they found that the WTP estimates of the different methods were closely related. However, the moderators reported that many respondents found BDM somewhat difficult to understand, whereas MPL was easy to understand. Also others have argued or presented anecdotal evidence for the ease of understanding and using different valuation methods. Drichoutis and Lusk (2016) and Canavari et al. (2019) indicated that the MPL is easy to use and understand. Furthermore, Brebner and Sonnemans (2018) found that BDM and MPL methods produce approximately the same valuations (means and standard deviations), but say the MPL takes much more time. However, despite discussing timing and ease of using none of these papers presented data on time required to explain or conduct the methods, or respondents ease of understanding and responding in the various methods. This paper is the first to contribute with measurements on these topics often commented on by researchers, but not included in their designs and data collection.

In this article, we focus on the BDM and MPL mechanisms. These two experimental valuation mechanisms have several things in common: the price is a result of a randomization mechanism; sales depend only on the drawn price and the choice of an individual respondent; a single participant can complete the valuation alone or many can complete it simultaneously; implementation is quick and easy both in laboratory and field settings; and the widespread adoption of the methods in consumer food studies. There are also some notable differences. In BDM, there are no posted prices to consider, while in MPL there is a list of prices. In BDM, respondents must state a maximum WTP, while in MPL the respondents must say "yes" or "no" to a list of prices. Thus, there are two different decision-making processes, namely judgment where the respondents must come up with a value (BDM) and choice where the respondent must select the preferred option, yes or no (MPL) (Brebner & Sonnemans, 2018). From a behavioral perspective, stating a maximum WTP as is the case with BDM is an unfamiliar task for consumers used to posted prices. However, a list of prices as used in MPL may result in anchoring and require a response for each price on the list. From an analytic perspective, BDM with its continuous responses format gives detailed information about individual WTP, while MPL uses interval responses, resulting in an upper and lower limit for individual WTPs. These similarities and differences make it interesting to compare several properties of these two methods.

We will compare four properties of the BDM and MPL methods: (i) respondents' stated WTP for a private good, (ii) respondents' stated ease of understanding the BDM and MPL methods, (iii) respondents' stated ease of answering the valuation questions, and (iv) time it took the respondents to answer the valuation questions. The first of these properties is the only one that has been studied previously. We use data from a valuation experiment conducted in Norway in 2017 eliciting the values of healthy snack bars.

2 | INCENTIVE-COMPATIBLE VALUATION METHODS

2.1 | Becker–DeGroot–Marschak

BDM is one of the most widespread incentive-compatible valuation methods adopted in food consumer studies (Canavari et al., 2019). In BDM, each participant submits a sealed bid for a product (Becker et al., 1964; Lusk & Shogren, 2007). Then, a sale price is randomly drawn from a distribution of prices ranging from zero to a price that is higher than the anticipated maximum bid (Alfnes & Rickertsen 2010; Lusk & Shogren 2007). If the bid made by the participant is higher than the randomly drawn price, the participant receives one unit of the product and pays a price that is equal to the drawn price, and if the bid is lower than the randomly drawn price, the participant receives and pays nothing (Alfnes & Rickertsen, 2010). As the participant does not compete with others, BDM is not an auction *per se* (Alfnes & Rickertsen 2010; Lusk & Shogren 2007). However, the dominant strategy is equivalent to that for the incentive-compatible Vickrey auction (Noussair, Robin, & Ruffieux, 2004a). The main advantage of BDM over EAs is that it can be conducted for one participant at a time (Lusk & Shogren 2007). Thus, BDM is particularly suitable in cases where it is difficult to run a classical auction that requires the presence of many participants simultaneously (Alfnes & Rickertsen 2010; Lusk & Shogren 2007). Therefore, BDM is usually chosen in field studies such as experiments in stores or farmers' markets, where it is difficult to evaluate products with more than one participant at a time (Alfnes & Rickertsen, 2010). However, BDM also has some drawbacks. For BDM to work properly, respondents need to understand the game form (Cason & Plott, 2014) and be interested in the product (Lichters, Wackershauser, Han, & Vogt, 2019). Furthermore, responses may be affected by price expectations given by the span of possible prices (Vassilopoulos, Drichoutis, & Nayga, 2018). Researchers have also found that some respondents find it difficult to understand the BDM method without extensive explanation (Alphonce & Alfnes, 2017). Despite these issues, BDM is applied widely in consumer food studies (Marette, 2013; Ortega, Shupp, Nayga, & Lusk, 2018; Shi, Xie, & Gao, 2018; Waldman & Kerr, 2018; Wolfe et al., 2018).

2.2 | Multiple price list

MPL is an incentive-compatible valuation method in which participants are presented a column of ordered prices, and asked to respond with either "yes" or "no" for each price (i.e., if a respondent indicates "yes" then he or she is willing to pay the proposed price to receive the product, otherwise "no") (Andersen et al., 2006). The researcher then randomly selects one price, and the respondents' choice for that price is implemented (Andersen et al., 2006; Kahneman, Knetsch, & Thaler, 1990). As it is in a respondent's best interest to say "yes" if and only if the price is lower than his WTP for the product, the MPL method is incentive compatible (Alfnes & Rickertsen, 2010).

According to the literature, MPL has three main advantages. First, MPL can be conducted with only one participant at a time both in laboratory and field settings; thus, it is particularly well suited to be performed at the point of sale, such as in a store or filed market (Alfnes & Rickertsen, 2010). Second, it is easy to explain and implement. Note that this is claimed by several studies, but never previously tested (Alphonce & Alfnes, 2017; Andersen et al., 2006; Canavari et al., 2019; Drichoutis & Lusk, 2016). Third, and closely related to the second, it is relatively easy for respondents to see that truthful revelation is in their best interest. If respondents believe that their responses have no effect on which price is chosen, then the choice task collapses to a series of binary choices in which each participant receives what he/she wants if he/she answers truthfully (Andersen et al., 2006). However, MPL also has disadvantages. First, only interval and not continuous valuations are elicited; thus, in theory MPL provides less precise valuations (Andersen et al., 2006) than other incentive-compatible valuation methods such as BDM. Second, respondents can give answers reflecting inconsistent preferences, because they can switch back and forth as the prices increase (Andersen et al., 2006). Third, respondents may be drawn to the middle of the ordered list of prices irrespective of their true WTP (Andersen et al., 2006). Despite these issues, MPL is recently

applied in food consumer studies. For example, Lombardi et al. (2019) investigated Italian consumers' preferences for three different insects based food products. Alphonce and Alfnes (2017) explored the preferences for tomato attributes in a field market in Tanzania. MPL has also recently been used in a hypothetical survey format. For example, Shew et al. (2017) conducted a multicountry study of preferences for rice produced using different technologies. Galati et al. (2019) studied natural wine preferences in Italy. Furthermore, MPL is used to elicit risk preferences (Drichoutis & Lusk, 2016).

3 | MATERIALS AND METHODS

3.1 | The experiment

The experiment was conducted using a between-subjects design in the sensory laboratory of Nofima AS, located 30 km south of Oslo, Norway, in the fall of 2017. We conducted the experiment in a laboratory rather than in the field because we wanted to conduct both a controlled sensory test of the products involved and a controlled comparison of the two valuation mechanisms. By conducting an experiment in the laboratory rather than in the field, it is easier to have control over the whole experiment and collect all data that are needed using a controlled computerized environment (e.g., response time on the valuation questions).

Data collection was performed on individual computers using a survey on the EyeQuestion platform (Logic8 BV, The Netherlands). The experiment was split into two sections: sample evaluations (i.e., sensory evaluation, WTP, and sample description) and the questionnaire (i.e., consumers' habits, attitudes, and sociodemographics, as well as questions about the ease of understanding the methods and of responding to the valuation questions). Both sections was conducted in Norwegian. Regarding the sample evaluations, we conducted both a blind condition (i.e., only sensory testing) and a full-information condition (i.e., simultaneously sensory testing and packaging information), because both sensory and extrinsic information strongly affect consumer valuation of food products (Asioli et al., 2017; Grunert, 2005). The sensory evaluation was conducted before the economic valuation.

3.2 | Comparing four properties

To compare BDM and MPL, we compare four properties of the two methods.

(1) WTP estimates: Do the two methods give the same WTP estimates?
(2) Ease of understanding: Do the respondents find the two methods equally easy to understand?
(3) Ease of response: Do the respondents find the two valuation questions equally easy to answer?
(4) Time to respond: Do the respondents require the same amount of time to respond to the two methods?

To examine the WTP property, we used a random parameter interval regression model on the valuation data from the two methods. The econometric model is described below (see Section 4 for details). To examine the second property, we asked the participants the following question: "How easy did you find it to understand the pricing method?" using a seven-point scale ranging from 1—"Very difficult" to 7—"Very easy." To examine the third property, we asked the participants the following question: "How easy was it for you to decide on the values in the pricing method?" using a seven-point scale ranging from 1—"Very difficult" to 7—"Very easy." Finally, to examine the fourth property we recorded the time that each consumer required to give their response for each sample evaluated.

3.3 | Samples

The samples used in the experiment were 25 g healthy snack bars. We investigated five different types of products: the first four (P1–P4) were new experimental healthy snack bars containing different ingredients (i.e., P1 is "Oat and tomato," P2 is "Legumes and zucchini," P3 is "Almond and buckwheat," and P4 is "Legumes and chia seeds") not available on the food market and were supplied by the Italian company Macè srl,[2] while the fifth sample (i.e., P5 is "Almond and cranberry") was a conventional healthy snack bar consumed widely on the Norwegian food market and purchased from a local store.

Healthy snack bars were chosen for three main reasons. First, they represent a growing market (Grand View Research, 2019) and thus are a familiar and frequently purchased product in the Norwegian food market. Second, snack bars are often purchased as a single unit, and thus are particularly suitable for being evaluated using BDM or MPL methods. Third, snack bars are easy to prepare and manage during an experiment.

3.4 | Respondents

We ran the experiment using five sessions per day over two consecutive days on weekday afternoons, and the methods were randomly distributed over these periods. Participants did not know which treatment they were subject to. In total, 165 respondents were split into two separate treatments. On the first day, 81 participants ($N = 81$) valued the snack bar using the BDM method, and on the second day, 84 participants ($N = 84$) valued the snack bar using the MPL method. Random assignment of the respondents to treatments was performed by the computer system. We rewarded consumers with 330 NOK for their participation.

Participants were allocated randomly to the two treatments to achieve balance of observable characteristics across the treatments. The results show that the hypothesis of equality of means between sociodemographic characteristics across treatments is not rejected at the 5% significance level. Hence, we can confirm that the random assignment of respondents to the treatments provided a balanced sample in terms of socio-demographic characteristics across the two groups.

3.5 | Experimental valuation method

Each participant valued the five healthy snack bars using either BDM or MPL. The procedures used during the experiment for both valuation methods were identical, and we followed the same steps for both treatments. (i) Participants were welcomed, and individual codes were provided for later use in the laboratory (i.e., to access the computer questionnaire). (ii) Respondents were accompanied to a meeting room and instructed on how the respective experimental valuation methods (BDM or MPL) operate. The instructions included a practical example of the valuation method using real food products (i.e., juices) and real money (i.e., NOK). (iii) Participants entered the laboratory, took a seat in separate booths, entered their individual codes for the computer questionnaire, and started the experiment. (iv) Respondents were given five taste samples (sensory evaluation) without any additional extrinsic information and evaluated each sample individually, the blind condition. (v) Respondents stated their preferences for the samples using a scale ranging from 1 ("I dislike this very much") to 9 ("I like this very much"). (vi) Respondents gave their valuations: in the BDM group respondents indicated their maximum WTP for each sample, while in the MPL group respondents indicated if they were willing to pay each price proposed for each sample. (vii) Respondents described the samples using the check-all-that-apply (CATA) method (Varela & Ares, 2016).

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[2]Macè srl is a food manufacturer. For more details see http://www.macefruit.com/en/

(viii) Respondents were given the same five taste samples a second time, this time also with the extrinsic packaging information on the computer screen (full-information condition), and evaluated each sample individually. (ix–xi) Steps (v), (vi), and (vii) are repeated under the full information condition. (xii) Respondents answered a series of questions about their individual characteristics (i.e., food habits, food attitudes, and socio-demographics as well as ease of understanding the respective methods and responding to the valuation question). (xiii) After they had completed the valuation and questionnaire, respondents left their computer and came to a table where they were randomly assigned a binding condition (blind or full information). (xiv) A binding sample from the assigned condition (blind or full in-formation) was randomly drawn. (xv—a) For BDM, a binding price was randomly drawn from a distribution of prices ranging from zero to a price that was higher than the anticipated maximum bid. (xv—b) For MPL, a binding price from the proposed prices (i.e., 6, 9, 12, 15, 18, 21, 24, 27, and 30 NOK) was randomly drawn. (xvi) Respondents who purchased the sample (i.e., healthy snack bar) did so by paying the price determined by the random choices im-plemented in steps (xiii), (xiv), and (xv). (xvii) The experiment ended. The complete questionnaire is available upon request.

3.5.1 | Becker–DeGroot–Marschak

In the BDM group, the respondents were asked to bid for five snack bars, and they had to buy the randomly drawn snack bar at a randomly drawn price if their bid equaled or exceeded the drawn price. In the two conditions (blind and full information), each participant bid on the five snack bars individually. To avoid diminishing effects from multiple purchases, only one of the snack bars was randomly selected as binding. As the price was randomly drawn, the bids only determined if the participants were allowed to buy the snack bar or not. Thus, their dominant bidding strategy was to bid their WTP for each snack bar and thereby reveal their true preferences.

The response for each snack bar was to submit a bid. To measure the response time to the valuation question, we recorded the time from opening the webpage to submitting a response.

3.5.2 | Multiple price list

In the MPL group, the respondents were shown a payment card with nine price levels NOK 6, 9, 12, 15, 18, 21, 24, 27, and 30,[3] ordered from low to high. For each of the five snack bars, they were asked to indicate whether they were willing to buy the snack bars at each of the nine prices. One of the conditions (blind or full information), one of the snack bars, and one of the prices were randomly drawn as binding. The participants' choice for the drawn binding case (i.e., condition, sample, and price) was implemented. As the price was randomly drawn, the re-spondents' choices did not affect the price; rather it only determined if they were allowed to buy the product at the drawn price. Thus, their dominant strategy was to say "yes" to all prices up to their reservation price, and thereafter say "no," thereby revealing the interval containing their true WTP.

The response for each snack bar was given in the form of clicking on "yes" or "no" for the nine prices and then clicking a button to submit the response. To measure the time it took them to respond to the valuation question, we recorded the time taken from opening the webpage to submitting their response.

The datasets with WTP data, consumer data, and response time data are available in Supporitng Information Appendix A, while the corresponding code (i.e., scripts) are in Supporting Information Appendix A.

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[3]The prices for healthy snack bars were based on prices recorded at different Norwegian points of sale including grocery stores, specialty stores, organic stores, and supercenters.

4 | ECONOMETRIC MODELING

BDM data are typically analyzed using Tobit models (Lusk & Shogren, 2007), while MPL data are analyzed using interval regression models (Andersen et al., 2006). To compare the two methods, we used the interval regression model which can, as a special case, be specified for non interval data such as the BDM data. For the BDM data, we specified the upper and lower interval limits as equal to the stated values, while for the MPL data the upper and lower limits were given by the first price rejected and the last price accepted, respectively.

To estimate the econometric model, we used the *xtintreg* command in STATA 14.0 (StataCorp LP) and specified a panel interval regression model with individual random effects. The panel specification allowed us to capture that each respondent provided 10 valuations (i.e., five price valuations for the blind condition and five price valuations for the full-information condition). We estimated the following random effect panel interval regression model for the combined data from all the 165 respondents:

$$WTP_{it} = \sum_{t=1}^{20} \beta_t x_{it} + u_i + e_{it} \tag{1}$$

where WTP is the value given for the samples, $i \in \{1,n\}$ indicates the individuals, $t \in \{1,20\}$ indicates the five samples in blind and full conditions and valued in the two methods. The first five samples are BDM in blind condition, the second five samples are BDM full condition, then comes five samples in the MPL blind condition, and last five samples in the MPL full condition; x_{it} are dummy variables for the five samples, under blind and full-information conditions and using the two methods (as explained for i); β_t are the corresponding WTP values; u_i is the random effects term, and e_{it} is the error term.

5 | RESULTS

In this section, we present the results for the four properties investigated to compare the BDM and MPL methods.

5.1 | Property 1: WTP estimates

Table 1 shows the estimated WTPs and the corresponding standard errors (SEs) for the five samples under the blind and full-information conditions, and for the two methods (i.e., BDM and MPL). We note three interesting results. First, the estimated WTPs for the sample P5 (i.e., sweet healthy snack bar) is about two times higher than the estimated WTPs for the other samples (i.e., P1–P4 such as the salty healthy snack bars), while there are only minor differences among the latter salty samples. This holds for both methods under blind and full-information conditions. Second, the MPL estimates are slightly higher than the BDM estimates in nine of the 10 pairs, with P4 under full information being the only pair where the BDM yields the highest estimates. However, a Wald test of equality of average WTP between the two methods cannot be rejected (Wald = 1.66, p = .20). Third, the SEs for the parameters are equal. This is a result of the x-matrices consisting of only dummy variables representing the 20 sample–method–information combinations, and each of the 20 combinations being included equally many times in the regression model.

Given that the two methods do not differ significantly in terms of the estimated WTP values, properties such as ease of understanding, ease of response, and time to respond should be important for choice of methods in future research.

One interesting observation from the values given in the BDM is that two thirds of the bids were numbers ending with zero or five (i.e., NOK 0, 5, 10, 15, 20, 25, 30, and 35). This is more than three times more often than

TABLE 1 WTP estimates from interval regression model for BDM and MPL methods

Sample	BDM blind WTP (NOK) (SE)	BDM full WTP (NOK) (SE)	MPL blind WTP (NOK) (SE)	MPL full WTP (NOK) (SE)
P1	7.29 (0.68)	7.82 (0.68)	8.35 (0.68)	8.30 (0.68)
P2	6.80 (0.68)	7.05 (0.68)	8.83 (0.68)	7.90 (0.68)
P3	6.82 (0.68)	6.92 (0.68)	8.08 (0.68)	7.59 (0.68)
P4	7.01 (0.68)	7.56 (0.68)	7.78 (0.68)	7.51 (0.68)
P5	15.27 (0.68)	15.21 (0.67)	17.21 (0.68)	16.45 (0.67)
Sigma_u	4.96			
Sigma_e	3.54			
Rho	0.66 (0.03)			
# observations	10 × 165			
Wald chi2(20)	2017.05			
Prob > chi2	0.00			

Abbreviations: BDM, Becker–DeGroot–Marschak; MPL, multiple price list; WTP, willingness to pay.

expected if the respondents considered all possible responses. This indicates that the BDM respondents might be thinking categorically, and that the continuous response format is of less importance when choosing a valuation method.

5.2 | Property 2: Ease of understanding

We asked the participants how easy they found it to understand the pricing method, using a scale ranging from 1—"Very difficult" to 7—"Very easy." We used the nonparametric Kruskall–Wallis test to examine if they found the two methods equally easy to understand. The results show that equality of means across BDM and MPL is rejected at the 5% significance level, indicating that the respondents found MPL (mean = 5.95) easier to understand than BDM (mean = 5.59).

5.3 | Property 3: Ease of response

We asked the participants how easy it was to decide on the responses, using a scale ranging from 1—"Very difficult" to 7—"Very easy." We used the nonparametric Kruskall–Wallis test to examine if they found the two mechanisms equally easy in terms of responding. The results show that equality of means across BDM and MPL is rejected at the 1% significance level, indicating that the respondents found MPL (mean = 4.93) easier to respond to than BDM (mean = 4.22).

5.4 | Property 4: Time to respond

We measured the time that respondents took to answer the valuation question for BDM (i.e., state the maximum WTP) and MPL (i.e., state at each of the nine price levels if they are willing to pay the price or not). The time used is from opening the valuation page to completing the valuation task on the page. To check for significant differences across the methods and conditions, we used the nonparametric Kruskall–Wallis test. We present three main results. First, the overall (i.e., blind plus full-information) average time that respondents took to answer the valuation question is longer for MPL than BDM (00:16.2 vs. 00:12.2); however, the results show that the equality of means cannot be rejected at the 5% significance level (i.e., $p = .11$). Second, the average time respondents took to answer the valuation question is longer for the blind than for the full-information condition for both BDM (00:14.6 vs. 00:09.9) and MPL (00:17.7 vs. 00:14.8); however, the results show that the equality of means cannot be rejected at the 5% significance level (i.e., respectively $p = .24$ and $p = .40$). Third, comparing the average time respondents took to answer the valuation question under the blind and full-information conditions for BDM and MPL shows that the equality of means cannot be rejected at the 5% significance level for the blind condition ($p = .49$), while for the full-information condition, the equality of means is rejected at the 5% significance level ($p = .02$).

More specifically, Figure 1 compares the response times for BDM and MPL as well as for the blind and full-information conditions. We note several interesting outcomes. First, the average time that respondents needed to answer the valuation question for the first tested sample was much longer than for the next samples (i.e., two, three, four, and five), especially for the blind conditions. Second, the time required to evaluate the fifth (and last) sample was longer than for samples two, three, and four. Third, comparing the blind and full-information conditions, we find that the trends are similar (i.e., the time taken to evaluate the sample was longest for the first sample, much shorter for samples two, three, and four, and slightly shorter for the final sample), but the time needed to evaluate the first sample was much shorter for the full-information condition than the blind condition. Fourth, and interestingly, the time needed to answer the valuation question for the third and fourth samples was similar under both blind and full-information conditions. Finally, the maximum time any of the respondents required to evaluate one product was less than 30 s, indicating that one can add additional products under both these methods without significantly increasing the length of the experiment.
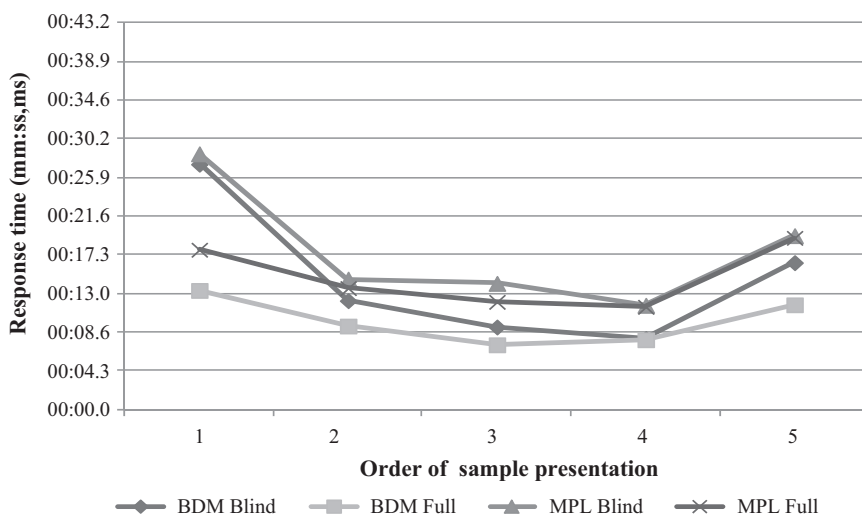

FIGURE 1 Time needed to select prices under BDM and MPL methods for blind and full-information conditions for each sample. BDM, Becker–DeGroot–Marschak; MPL, multiple price list

Finally, we investigated if there is correlation between the response time and ease of understanding and response. We found that for BDM there is a moderate negative (−0.30) and significant (p value: 5%) correlation between the time required to answer the question and ease to response.

6 | DISCUSSION AND CONCLUSIONS

This article compared four properties related to the use of BDM and MPL, whereof three have not been evaluated before. Data from a laboratory experiment investigating consumers' WTP for healthy snack bars in Norway were collected. First, we compared the average WTP distributions across the two methods. We found that on average, the two methods do not differ significantly in terms of estimated WTP as found by Alphonce and Alfnes (2017). It is here important to note that previous studies have compared WTP estimates from BDM and other EAs with mixed results (Flynn et al., 2016; Lusk et al., 2004; Noussair et al., 2004b).

Second, we investigated respondents' stated ease of understanding of the two mechanisms. The results show that respondents on average stated that it was easier to understand MPL than BDM. One possible explanation is that the choice based response task under MPL is closer to the actions taken by respondents at supermarkets (i.e., decide to buy or not based on posted prices) than the judgment task in the BDM (i.e., provide maximum WTP). This finding support Brebner and Sonnemans (2018), who argue that BDM is quite abstract and participants may misunderstand the mechanism, and Alphonce and Alfnes (2017), who's moderators reported that respondents found MPL easier to understand than the BDM.

Third, we investigated respondents' stated ease of answering the valuation question under the two methods. Respondents found it easier to respond under MPL than BDM. This finding is supported by the fact that under BDM, the more difficult the respondents state they found it to answer the valuation question, the more time they used to respond to the question. This results is consistent with statements by Brebner and Sonnemans (2018), who stated that an advantage of MPL over BDM is its simplicity, and statements by Drichoutis and Lusk (2016) and Canavari et al. (2019) who say the MPL is easy to use and to understand. Asking respondent to choose yes or no to list of posted prices rather than asking them to think about their maximum WTP requires less effort from them.

Fourth, we investigated the time it took respondents to answer the valuation questions. The results show that on average, respondents took a similar amount of time to answer the valuation questions for BDM and MPL. In addition, consistent with both methods and conditions, we found that the time that respondents needed to give their responses for the first sample was larger than the subsequent samples. This may be because the respondents required more time to understand the method or time to decide the valuation level the first time. Indeed, when respondents have made a valuation once, it is easier to decide on a value for subsequent samples. However, when the sample being evaluated is very different in terms of sensory and packaging attributes, such as P5 (i.e., P5 is the sweet snack bar) in contrast to the previous samples (i.e., P1–P4 are salty bars), the time required for the valuation increases, probably because respondents need more time to re-adapt and readjust their valuation for the more contrasting product. At the same time, we also need to note that BDM and MPL have two different modes of response to the two questions. While for each sample the BDM respondents give one value (i.e., for example, NOK 13), the MPL respondents give nine responses (i.e., marks) in terms of either "yes" or "no." If respondents know their WTP, selecting two numbers should be faster than making nine decisions, while if respondents are uncertain about their WTP it may be easier to select either "yes" or "no" on the prices under MPL. However, overall the time differences are so small that they should not play an important role in choosing between BDM and MPL. Our finding is in contrast to Anderson et al. (2007) and Brebner and Sonnemans (2018) who stated that MPL request much more time to perform.

Hou et al. (2019) point to several important benefits of using the BDM and MPL methods, including that they can be used on one respondent at a time, can start when the respondents arrive, and make it easy to randomize between groups. They also argue that methods that are easy to understand and quick to conduct can increase

respondents' willingness to participate in the experiment, and thereby reduce selection bias. Following this line of thought, the new issues explored in this paper, are important factors with respect to the internal and external validity of the experiment. Future studies should look further into how choice of methods affect how the respondents see and experience the experiments, and how this affect respondents' willingness participate and selection bias. These are issues so far neglected in the food experiment literature.

For small and medium size agribusinesses conducting market testing of their product in stores or field markets, both methods are easy to conduct and give similar WTP results. The fact that MPL is easier to understand, makes it less likely that there will be misunderstandings or other problems when used by less experienced field investigators under less than optimal conditions. Both likely when small and medium size agribusinesses conduct their market testing in stores or field markets.

This study has three main limitations. First, given the sample of our study the findings cannot be generalized to the entire Norwegian population. However, our research does not aim to be representative for the entire Norwegian population, but to compare the BDM and MPL methods. Second, the BDM and MPL are methods which are particularly suitable for experiments in field settings rather than in lab settings. However, we cannot with certainty say that the results would be the same in an in-store or filed-market setting. Third, since we used goods of low value our results can suffer from measurement errors which may be partly due to the lower cost of misbehaving for low value goods (Canavari et al., 2019).

To conclude, our results indicates that MPL may be preferable to the more popular BDM in situations where there is little room to explain or practice the method before the valuation. This makes the MPL especially suitable to use by small and medium size agribusinesses conducting market testing in stores or field markets. Future research is needed to test the robustness of our findings in other contexts, countries, and using other food products.

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SUPPORTING INFORMATION

Additional Supporting Information may be found online in the supporting information tab for this article.

APPENDIX A

*SOCIO-DEMOGRAPHICS CALCULATIONS

　　*IMPORT
　　import excel using "Asioli_etal_appendix_a1," sheet("consumer data") firstrow

　　*SAVE AS STATA DATA SET
　　save consumerdata.dta, replace

　　*USE NEW STATA DATA SET
　　use consumerdata.dta, clear

　　*SOCIO-DEMOGRAPHICS

　　*Gender
　　tabulate gender if mechanism==1//gender percentage for treatment 1
　　tabulate gender if mechanism==2//gender percentage for treatment 2
　　tabulate gender mechanism, chi2//tabulate - association between gender and treatments

　　*Age

　　*Transform continuous in categorical variables
　　//creation of categorical variable for age
　　generate catage=1//creation of categorial variable all 1
　　replace catage=2 if age>30 & age <44//replace with 2 if condition (30-43) is satisfied
　　replace catage=3 if age>43 & age <57//replace with 3 if condition (44-56) is satisfied
　　replace catage=4 if age>56//replace with 4 if condition (57+) is satisfied
　　tabulate catage if mechanism==1//age percentage for treatment 1
　　tabulate catage if mechanism==2//age percentage for treatment 2
　　tabulate catage if mechanism//age percentage for pooled
　　kwallis catage, by(mechanism)//association between age and treatments

　　*Household size
　　//creation of categorical variable for household size
　　generate cathousehold=1//creation of categorial variable all 1
　　replace cathousehold=2 if household>3 & household <7//replace with 2 if condition (3-6) is satisfied
　　replace cathousehold=3 if household>7//replace with 3 if condition (7+) is satisfied
　　tabulate cathousehold if mechanism==1//cathousehold percentage for treatment 1
　　tabulate cathousehold if mechanism==2//cathousehold percentage for treatment 2
　　tabulate cathousehold if mechanism//cathousehold percentage for pooled
　　kwallis cathousehold, by(mechanism)//association between cathousehold and treatments

　　*Area of leaving
　　tabulate area_liv if mechanism==1//area of leaving percentage for treatment 1
　　tabulate area_liv if mechanism==2//area of leaving percentage for treatment 2
　　tabulate area_liv if mechanism//area of leaving percentage for pooled
　　tabulate area_liv mechanism, chi2//tabulate - association between area of leaving and treatments

```
*Education
tabulate education if mechanism==1//education percentage for treatment 1
tabulate education if mechanism==2//education percentage for treatment 2
tabulate education if mechanism//education percentage for pooled
kwallis education, by(mechanism)//association between education and treatments

*Employment
tabulate employment if mechanism==1//employment percentage for treatment 1
tabulate employment if mechanism==2//employment percentage for treatment 2
tabulate employment//employment percentage pooled
tabulate employment mechanism, chi2//tabulate - association between employment and treatments

*Income
tabulate income if mechanism==1//income percentage for treatment 1
tabulate income if mechanism==2//income percentage for treatment 2
tabulate income//income percentage for treatments 1,2
kwallis income, by(mechanism)//association between income and treatments
clear

*1° PROPERTY: WTP CALCULATION

*IMPORT
import excel using "Asioli_etal_appendix_b1," sheet("wtp data") firstrow

*SAVE AS STATA DATA SET
save wtpdata.dta, replace

*USE NEW STATA DATA SET
use wtpdata.dta, clear

*GENERATE NUMERIC VARIABLE OF A STRING VARIABLE FOR USE IN THE ANALYSIS
gen product1=0
replace product1=1 if product_name=="Salty1"
replace product1=2 if product_name=="Salty2"
replace product1=3 if product_name=="Salty3"
replace product1=4 if product_name=="Salty4"
replace product1=5 if product_name=="Sweet"

*FIX DATA PROBLEM
tab order
replace order=3 if order==8
tab order

*GENERATE DUMMIES PRODUCT*INFORMATION*METHOD
gen pro1bBDM=0
replace pro1bBDM=1 if product1==1 & informed==0 & BDM==1
gen pro2bBDM=0
```

```
replace pro2bBDM=1 if product1==2 & informed==0 & BDM==1
gen pro3bBDM=0
replace pro3bBDM=1 if product1==3 & informed==0 & BDM==1
gen pro4bBDM=0
replace pro4bBDM=1 if product1==4 & informed==0 & BDM==1
gen pro5bBDM=0
replace pro5bBDM=1 if product1==5 & informed==0 & BDM==1
gen pro1bMPL=0
replace pro1bMPL=1 if product1==1 & informed==0 & MPL==1
gen pro2bMPL=0
replace pro2bMPL=1 if product1==2 & informed==0 & MPL==1
gen pro3bMPL=0
replace pro3bMPL=1 if product1==3 & informed==0 & MPL==1
gen pro4bMPL=0
replace pro4bMPL=1 if product1==4 & informed==0 & MPL==1
gen pro5bMPL=0
replace pro5bMPL=1 if product1==5 & informed==0 & MPL==1
gen pro1iBDM=0
replace pro1iBDM=1 if product1==1 & informed==1 & BDM==1
gen pro2iBDM=0
replace pro2iBDM=1 if product1==2 & informed==1 & BDM==1
gen pro3iBDM=0
replace pro3iBDM=1 if product1==3 & informed==1 & BDM==1
gen pro4iBDM=0
replace pro4iBDM=1 if product1==4 & informed==1 & BDM==1
gen pro5iBDM=0
replace pro5iBDM=1 if product1==5 & informed==1 & BDM==1
gen pro1iMPL=0
replace pro1iMPL=1 if product1==1 & informed==1 & MPL==1
gen pro2iMPL=0
replace pro2iMPL=1 if product1==2 & informed==1 & MPL==1
gen pro3iMPL=0
replace pro3iMPL=1 if product1==3 & informed==1 & MPL==1
gen pro4iMPL=0
replace pro4iMPL=1 if product1==4 & informed==1 & MPL==1
gen pro5iMPL=0
replace pro5iMPL=1 if product1==5 & informed==1 & MPL==1

*SET PANEL IDENTIFIER
xtset ID

*INTERVAL REGRESION MODEL VERSION 1
xtintreg WTPL WTPU pro1bBDM pro1bMPL pro1iBDM pro1iMPL///
pro2bBDM pro2bMPL pro2iBDM pro2iMPL///
pro3bBDM pro3bMPL pro3iBDM pro3iMPL///
pro4bBDM pro4bMPL pro4iBDM pro4iMPL///
pro5bBDM pro5bMPL pro5iBDM pro5iMPL, intm(gh) intp(100) noconstant
```

```
*FIRST WALD TEST. BDM = MPL
test pro1bBDM+pro1iBDM+pro2bBDM+pro2iBDM+pro3bBDM+pro3iBDM+pro4bBDM+pro4iBDM+pro5bBDM
+pro5iBDM=pro1bMPL+pro1iMPL+pro2bMPL+pro2iMPL+pro3bMPL+pro3iMPL+pro4bMPL+pro4iMPL+pro5bMPL
+pro5iMPL


*SECOND WALD TEST. INFORMATION EFFECT BDM = INFORMATION EFFECT MPL
test pro1bBDM-pro1iBDM+pro2bBDM-pro2iBDM+pro3bBDM-pro3iBDM+pro4bBDM-pro4iBDM+pro5bBD
M-pro5iBDM=pro1bMPL-pro1iMPL+pro2bMPL-pro2iMPL+pro3bMPL-pro3iMPL+pro4bMPL-pro4iMPL
+pro5bMPL-pro5iMPL


clear


*2° and 3° PROPERTY: EASINESS TO UNDERSTAND AND GIVE PRICE


*IMPORT
import excel using "Asioli_etal_appendix_b1," sheet("consumer data") firstrow


*SAVE AS STATA DATA SET
save consumerdata.dta, replace


*USE NEW STATA DATA SET
use consumerdata.dta, clear


*COMPARE MECHANISMS
*Easy understand mechanism
sum understand if mechanism==1
sum understand if mechanism==2
sum understand
kwallis understand, by(mechanism)


*Easy give price
sum decide if mechanism==1
sum decide if mechanism==2
sum decide
kwallis decide, by(mechanism)


*4° PROPERTY: RESPONSE TIME


*IMPORT
import excel using "Asioli_etal_appendix_b1," sheet("response time data") firstrow


*SAVE AS STATA DATA SET
save responsetimedata.dta, replace


*USE NEW STATA DATA SET
use responsetimedata.dta, clear
```

*CALCULATE DESCRIPTIVE STATISTICS

sum time if mechanism==1 & condition==1//descriptive statistics for BDM in blind condition

sum time if mechanism==1 & condition==0//descriptive statistics for BDM in full condition

sum time if mechanism==0 & condition==1//descriptive statistics for MPL in blind condition

sum time if mechanism==0 & condition==1//descriptive statistics for MPL in full condition

sum time if seq==1 & mechanism==1 & condition==1//descriptive statistics for BDM in blind condition order 1

sum time if seq==2 & mechanism==1 & condition==1//descriptive statistics for BDM in blind condition order 2

sum time if seq==3 & mechanism==1 & condition==1//descriptive statistics for BDM in blind condition order 3

sum time if seq==4 & mechanism==1 & condition==1//descriptive statistics for BDM in blind condition order 4

sum time if seq==5 & mechanism==1 & condition==1//descriptive statistics for BDM in blind condition order 5

sum time if seq==1 & mechanism==1 & condition==0//descriptive statistics for BDM in blind full order 1

sum time if seq==2 & mechanism==1 & condition==0//descriptive statistics for BDM in blind full order 2

sum time if seq==3 & mechanism==1 & condition==0//descriptive statistics for BDM in blind full order 3

sum time if seq==4 & mechanism==1 & condition==0//descriptive statistics for BDM in blind full order 4

sum time if seq==5 & mechanism==1 & condition==0//descriptive statistics for BDM in blind full order 5

sum time if seq==1 & mechanism==0 & condition==1//descriptive statistics for MPL in blind condition order 1

sum time if seq==2 & mechanism==0 & condition==1//descriptive statistics for MPL in blind condition order 2

sum time if seq==3 & mechanism==0 & condition==1//descriptive statistics for MPL in blind condition order 3

sum time if seq==4 & mechanism==0 & condition==1//descriptive statistics for MPL in blind condition order 4

sum time if seq==5 & mechanism==0 & condition==1//descriptive statistics for MPL in blind condition order 5

sum time if seq==1 & mechanism==0 & condition==0//descriptive statistics for MPL in blind full order 1

sum time if seq==2 & mechanism==0 & condition==0//descriptive statistics for MPL in blind full order 2

sum time if seq==3 & mechanism==0 & condition==0//descriptive statistics for MPL in blind full order 3

sum time if seq==4 & mechanism==0 & condition==0//descriptive statistics for MPL in blind full order 4

sum time if seq==5 & mechanism==0 & condition==0//descriptive statistics for MPL in blind full order 5

*CALCULATE SIGNIFICANT DIFFERENCES ABOUT TIME RESPONSE FOR PRICE VALUATION ACCROSS BDM and MPL and TEST CONDITION

kwallis time if seq==1 & condition==1, by(mechanism)//significant differences between product order 1 in blind condition between BDM and MPL

kwallis time if seq==2 & condition==1, by(mechanism)//significant differences between product order 2 in blind condition between BDM and MPL

kwallis time if seq==3 & condition==1, by(mechanism)//significant differences between product order 3 in blind condition between BDM and MPL

kwallis time if seq==4 & condition==1, by(mechanism)//significant differences between product order 4 in blind condition between BDM and MPL

kwallis time if seq==5 & condition==1, by(mechanism)//significant differences between product order 5 in blind condition between BDM and MPL

kwallis time if seq==1 & condition==0, by(mechanism)//significant differences between product order 1 in full condition between BDM and MPL

kwallis time if seq==2 & condition==0, by(mechanism)//significant differences between product order 2 in full condition between BDM and MPL

kwallis time if seq==3 & condition==0, by(mechanism)//significant differences between product order 3 in full condition between BDM and MPL

kwallis time if seq==4 & condition==0, by(mechanism)//significant differences between product order 4 in full condition between BDM and MPL

kwallis time if seq==5 & condition==0, by(mechanism)//significant differences between product order 4 in full condition between BDM and MPL

kwallis time if condition==1, by(mechanism)//significant differences between BDM and MPL in blind condition

kwallis time if condition==0, by(mechanism)//significant differences between BDM and MPL in full condition