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Flexible valuations for consumer goods as measured by the Becker-DeGroot-Marschak mechanism

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Abstract

Economists have long been interested in mechanisms that lead to truthful revelation of the relative values individuals place on different goods. In this paper we take one of the most popular of such mechanisms, and show that valuations obtained using the Becker-DeGroot-Marschak (BDM) procedure depend on the distribution of prices presented to subjects when the mechanism is implemented. We show that this effect of price distribution occurs quite frequently, significantly impacts reported valuations, and that it is unlikely to be caused by misconceptions about BDM. This effect is the largest when pricing distributions show a large peak just above or just below an individual's average valuation of the good being considered. We also show that a simple non-incentive compatible subject rating of the desirability of goods can be used to predict the likelihood that pricing distributions will influence BDM valuations. Valuations for goods subjects report that they most want to purchase are most likely to be influenced by distributional structure. Our results challenge some of the dominant theoretical models of how BDM-like valuation procedures relate to standard notions of utility.

Keywords: utility, reference, valuation

1 Introduction

Knowing a person's true valuation for a good is important for research on human decision making, marketing, and for policy decisions on the provision of public goods. Of course, simply asking someone to state their valuation, without giving them any incentive to tell the

truth, has been found to sometimes lead to inflated value estimates (Harrison & Rutström, 2008; List & Gallet, 2001; Wertenbroch & Skiera, 2002). To increase the accuracy of value measurements, incentive-compatible value elicitation methods that guarantee that misstating valuation is costly for participants are thus often used. In the Becker-DeGroot-Marschak mechanism (BDM), which is the most widely used such method, subjects are asked to state the maximum amount they would be willing to pay for a given good. The actual price for the good is then determined randomly from a distribution of possible prices (known in advance to the subject). If the stated willingness to pay is higher than the randomly determined price, the subject buys the good from the experimenter, paying the randomly determined price. If the maximum stated willingness to pay is lower than the randomly determined price, the subject does not buy the good (Becker, DeGroot, & Marschak, 1964). This procedure is widely assumed to provide the right incentives for subjects to truthfully reveal their valuation; by reporting truthfully they both maximize their odds of getting the good at an acceptable price and avoid any risk of overpaying.

However, as Karni and Safra (1987) and Horowitz (2006) have shown, elicitation of the true *certainty equivalents* of both lotteries and goods using BDM can be problematic. In the BDM mechanism, when placing a bid the subject faces uncertainty regarding whether or not she will actually get to buy the good and at what price she will be purchasing the good. If the utility function of the chooser depends on any of these attributes (as in for example certain types of reference-dependent utility, anticipatory utility or disappointment aversion models) then it may be optimal for her to bid an amount different from her *true value* (her maximum willingness-to-pay when there is no uncertainty about whether or not she will purchase and no uncertainty about how much she will actually pay to purchase) for the good. Indeed, as Horowitz (2006) pointed out theoretically, both the likelihood of winning and the expected price should in fact depend on the distribution of prices used by the experimenter under some conditions. Hence manipulations to pricing distribution could well be expected to change individual bids if individuals are not simple expected utility maximizers.

In line with these theoretical concerns, existing experimental evidence suggests that the BDM does not elicit subjects' truthful valuations under some conditions (Kaas & Ruprecht, 2006; Noussair, Robin, & Ruffieux, 2004; Rutström, 1998; Shogren et al., 2001) and it has been suggested that bidders may, in line with Horowitz (2006)'s theoretical contribution, be influenced by the price distribution (Bohm, Lindén, & Sonnegård, 1997; Mazar, Koszegi, & Ariely, 2013; Urbancic, 2011) such that the negatively skewed price distributions induce higher valuations. It is not clear, however, whether distributional dependence in the BDM mechanism is a genuine and significant reflection of some preference structure inherent in human nature or whether it just stems from misconceptions of the – admittedly quite complicated – rules of the BDM procedure (Cason & Plott, 2012).

In this empirical paper, we set out to investigate in detail the nature of the distributional dependence in the BDM mechanism in an effort to explicitly examine Horowitz (2006)'s theoretical claim. Our main goal was to create an environment where misconceptions about the BDM mechanism were minimized while pricing distributions were systematically manipulated. We not only provided clear and complete instructions to our subjects, but also allowed only subjects who passed all comprehension questions to participate in this study. We then asked them to repeatedly (rather than just once) value each of three goods for on average more than 50 rounds per good. Importantly, after every round we told them which price was realized in that round, and whether they would purchase the good if this round was later counted for payment, thus reinforcing their understanding of the mechanism. We hypothesized that if subjects had any doubts about the procedure in the beginning, after tens of rounds with feedback they should have had a clear understanding about how the BDM works during the bulk of our empirical measurements. Under these conditions, we found that subjects bid higher (lower) when the pricing distribution included a *most likely price* that was higher (lower) than the subject's average bid for that good. This effect remains significant, and does not weaken, throughout many rounds of bidding.

One central feature of our study that may be of empirical significance was our use of a continuum of pricing distributions rather than just two extreme price distributions (Bohm et al., 1997; Mazar et al., 2013). In the beginning of every round, one price from the fixed support of the price distribution (from $0 to $50) was randomly selected to be the *most likely price*; all other prices were equally likely. With this information available, subjects then stated their valuation. This novel design allowed us to make interesting observations that shed light on the discrepancies in the findings observed in previous studies. Specifically, we found that the biasing of stated willingness-to-pay was strongest when the most likely price was relatively close to the subject's average bid for the respective good, explaining why some studies may find stronger and other weaker effects. Further, we found that the effect of the price distribution was strongest when subjects were bidding on goods that they stated (in a non-incentive compatible survey) that they *most wished to buy.* All in all, these results suggest that distributional dependence of the BDM mechanism is empirically robust and persists even after thorough training and experience. Extant theoretical models of the BDM do not offer a framework that is able to capture this dependence.

2   Material and Methods

Twenty-seven paid volunteers (12 females) participated in this experiment. At the beginning of the experiment, participants were informed that they would be repeatedly asked to state their maximum willingness-to-pay (bid) for three different goods: a backpack, an iPod shuffle, and a pair of noise-cancelling headphones. To ensure that subjects had enough information

about the goods to understand what they were bidding on, they were given substantial time to inspect the products. They were informed that the suggested retail price of all three products was higher than the maximum possible price in the experiment ($50) but were not told the exact market prices. (At the time of the experiment the actual market prices of the goods were: iPod Shuffle $49 + tax, Sony noise cancelling headphones $49 + tax, Case Logic Laptop Backpack with iPad pocket: $59 + tax.) Participants learned that, out of all rounds they completed, one randomly selected round would be selected at the conclusion of the experiment and implemented. Following the standard BDM procedure, they would purchase the good at the randomly selected actual price if their bid on that trial were higher than or equal to the randomly selected actual price. If they had bid lower than the actual price, they would not purchase the good. Each participant was endowed with $50 that she could use towards her purchase. Participants could keep any money not spent during the experiment. Participants who made no purchase would keep the full endowment of $50 and receive no goods.

Each round followed the same structure: First, participants learned which good they were bidding on in that rounds and which price was most likely to be selected as the actual price (that price would be selected with probability equal to 0.51) ($41 in Figure1 A). We refer to the most likely price as the *revealed price*. All other prices between $1 and $50 (in steps of $1) had an equal probability of .01 to be selected as the actual price (represented as "?" in Figure1 A). Second, after observing the information on the good and the *revealed price*, participants could enter a bid (constrained to be between $0 and $50) for the current good and round ($37 in Figure 1 B). Third, the actual price for this round was then determined randomly by drawing from the specified distribution and revealed to the subject. Subjects were also told whether they would buy the good or not if this round was later selected for payment, so as to reinforce their understanding of the BDM procedure (Figure 1 C).

Each participant worked through the experiment at their own pace and in private, completing on average 140 rounds ($SD = 33.98$). The number of rounds experienced was determined by one of a small set of *termination rules*, varying by subject, that did not affect the results presented here (see the appendix for the description and result, Table 5 in Appendix B). Note that, irrespective of the termination rule used on that subject, for all of our subjects, standard theory predicts that the subject should be insensitive to the price distribution; constantly bidding the same amount for a given good.

Before the beginning of the experiment, these procedures were explained to the participants in detail using written instructions and extensive examples (see Appendix A). The instructions stressed that the actual price of a good was determined randomly, and could not be influenced by the subject's bid. Only participants who, after they had been briefed on the structure of the experiment, answered all of the task comprehension questions correctly, were allowed to participate in the experiment. Answering comprehension questions incor-
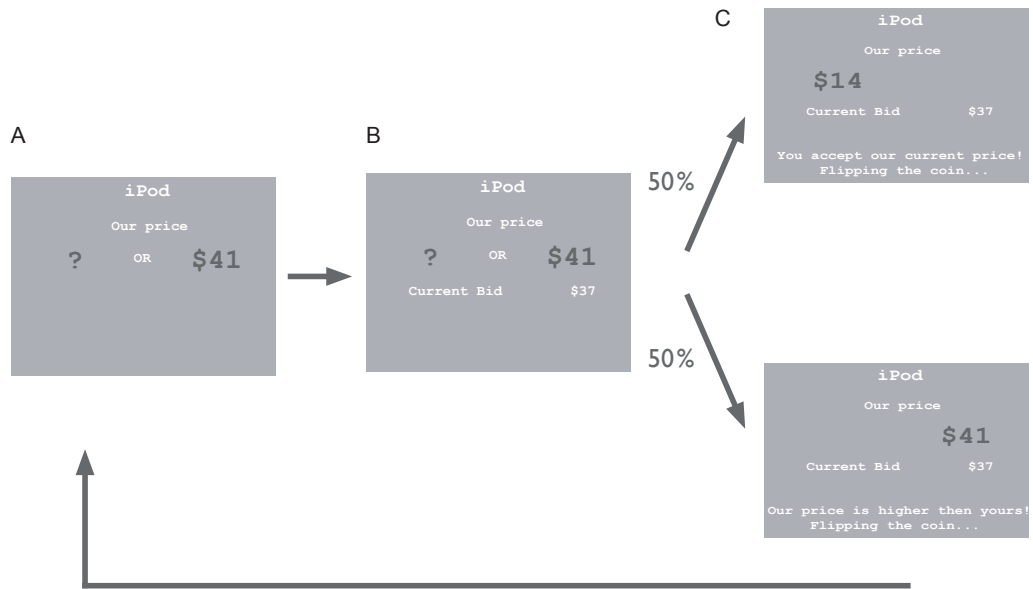
Figure 1: Structure of the experiment

rectly resulted in a compensation of $5 and exclusion from the experiment. In the debriefing questionnaire all participants indicated that the instructions were either clear or very clear. In order to familiarize participants with the experiment, they were also given five practice rounds, which were not relevant for their payoff.

Data were collected at the Center for Experimental Social Science (CESS) at New York University. All procedures were approved by the NYU Institutional Review Board and all participants gave informed consent. Sessions lasted approximately 90 minutes. The task was programmed using ePrime 2.0 software (Psychology Software Tools, Pittsburgh, PA).

3   Results

Subjects bid on average $19.57, indicating that they were interested in buying the goods on offer. Mean bids for each good and standard deviations are shown in Table 1. Subjects tended to bid multiples of 5 much more often than all other prices, which resulted in a multimodal distribution of bids (see Figure 2). Overall, 62% of the bids were placed on these focal points.

Importantly, contrary to the prediction under expected utility theory (Becker et al., 1964), subjects did not state a constant maximum WTP for each good. The bid of an average subject for a given good varied substantially, with an average standard deviation of 3.35. Subjects differed with respect to the variability in the bids, one subject bidding constantly the same amount for a good and some subjects changing their WTP substantially from round

4

Table 1: Descriptive statistics for bids

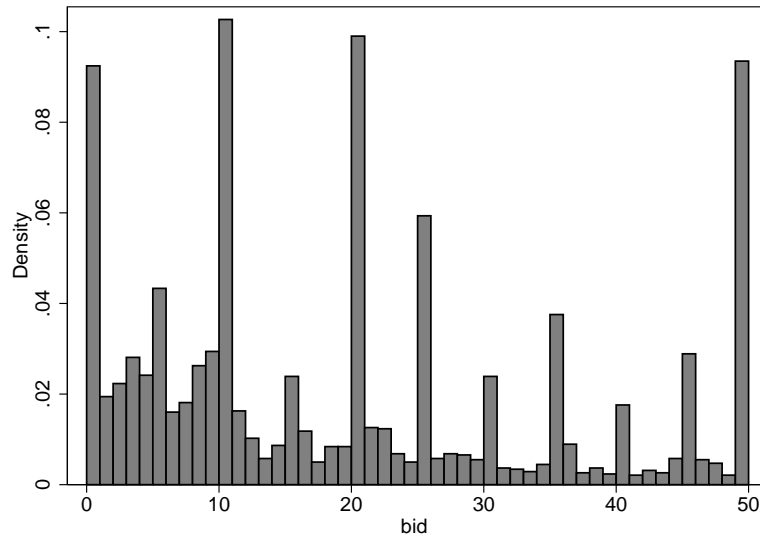| Good	Mean bid	SD bid
Backpack	$17.16	15.62
Headphones	$20.60	14.90
iPod	$21.10	16.52
Total	$19.57	15.78

Figure 2: Histogram over the bids

to round. There was a decrease in variability over time, but bids still varied considerably in the second half of the experiment (Table 2).

3.1 The effect of the *revealed price*

We found that bids were significantly higher when the revealed price was high (equal to or higher than $25), than when it was low (below $25) ($20.3 versus $18.8, $p < 0.01$, two-sided t-test) suggesting that the distribution of prices used in the BDM may affect the WTP in a systematic way. To verify if this is indeed true, we first plot the bid in each round as a function of the revealed price in that round. To account for between-subject variability we plot both bid and revealed price relative to the subject's mean bid for the respective good. A scatterplot of these normalized bids against normalized revealed price shows that the data

Table 2: Summary statistics for standard deviations of the bids an individual subject placed for one specific good

	mean	median	min	max
First half	3.46	2.30	0	16.38
Second half	2.42	1.71	0	13.96
All	3.35	2.30	0	15.88

points are separable into two very distinct patterns (see Figure 3). For some, there is a strong influence of the revealed price on the bid (with a slope near 1), whereas for others there is no influence of the revealed price at all.
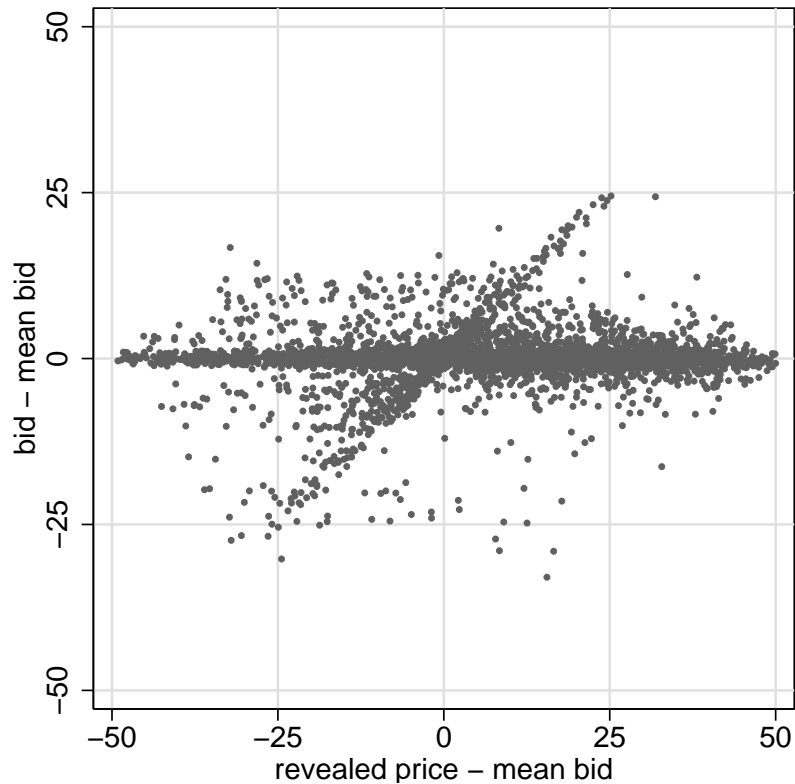
Figure 3: Scatterplot of bid against revealed price, both centered on the mean bid that the subject placed for the respective good over the course of the experiment.

Figure 3 also suggests that the revealed price affects bids, not across the whole range of possible values, but mostly when it is relatively close to the mean bid a subject places on a good. To verify whether this is indeed the case and to quantify the effect, we regressed the bid in each round on the revealed price on the full data set, as well as on reduced data sets which include only rounds where the revealed price was relatively close to a subject's mean

bid for a good (see Table 3). The coefficient for the revealed price is larger when considering only rounds where the revealed price was relatively close to the subject's average bid. When the revealed price is in the range of $+/- 1$ \$3.35 (equivalent to 1 mean SD) of the mean bid, the bid increases by \$0.41 on average for each \$1 increase in the revealed price. The bid and the revealed price on the preceding round did not affect the bid on the current round. There was no systematic change in the bids or in the effect of revealed price on the bids over the course of the experiment.

Table 3: The effect of the revealed price on the bid

dep. var.: bid	all data	within +/-2SD	within +/-1.5SD	within +/-1SD
	Coef./se	Coef./se	Coef./se	Coef./se
revealed price	0.09*	0.23***	0.31***	0.41***
	(0.05)	(0.07)	(0.07)	(0.08)
previous bid	0.14	0.11	0.09	0.11
	(0.10)	(0.08)	(0.08)	(0.09)
previous revealed price	−0.00	−0.01	−0.01	−0.00
	(0.01)	(0.01)	(0.01)	(0.01)
round	0.02	−0.01	−0.01	−0.01
	(0.01)	(0.01)	(0.01)	(0.01)
revealed price*round	−0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
constant	13.85***	13.59***	12.04***	9.25***
	(2.81)	(1.83)	(1.88)	(3.07)
R^2	0.086	0.172	0.175	0.216
No. of obs.	3781	861	654	444

Note. Subject/good fixed effects included. Standard errors clustered by subject.
*$p < 0.10$,** $p < 0.05$,*** $p < 0.01$

3.2 Variability in the effect of the *revealed price*

Figure 3 shows that sometimes there is a strong effect of the revealed price, but sometimes no effect at all. In order to understand whether this effect occurs only for some people or some goods, we regressed the bid on the revealed price separately for each good and each subject (this means running three regressions for most subjects, and two or one regression for those who finished the experiment before they got a chance to bid on all three goods). In these individual regressions, 52 % (44 %) of the subjects showed a significant effect of

the revealed price for at least one good at the 10% (5%) level. Interestingly, many subjects show a significant effect for one or two of the goods, but not for another good, suggesting that individual and good-specific factors play a role in determining how strongly a person responded to the revealed price.

Table 4: The effect of the revealed price depends on how strongly the subjects wants to buy the good

dep. var.: bid	all data	within +/-2SD	within +/-1.5SD	within +/-1SD
	Coef./se	Coef./se	Coef./se	Coef./se
revealed price	0.01	0.37***	0.48**	0.68
	(0.03)	(0.09)	(0.17)	(0.41)
previous bid	0.14	0.11	0.10	0.12
	(0.10)	(0.09)	(0.09)	(0.10)
previous revealed price	−0.00	−0.01	−0.01	−0.00
	(0.01)	(0.01)	(0.01)	(0.01)
round	0.01	0.01	0.01	0.02
	(0.01)	(0.01)	(0.01)	(0.01)
wanting*	0.02**	−0.02	−0.04	−0.06
revealed price	(0.01)	(0.03)	(0.05)	(0.12)
constant	15.02***	12.43***	11.44***	8.41*
	(2.68)	(2.67)	(2.53)	(4.12)
R^2	0.095	0.154	0.148	0.168
No. of obs.	3491	787	592	400

Note. Subject/good fixed effects included. Standard errors clustered by subject.
$^*p < 0.10,^{**}p < 0.05,^{***}p < 0.01$

Finally, we attempted to determine whether we could identify a predictor which would correlate with the stronger or weaker distributional dependence of a subject's valuations of each good. To do that, we had each subject rate her "desire to buy" each of the three goods on a 5-point *Likert scale* (Likert, 1932), which ranged from "not at all" to "really wanted to buy". As can be seen in the regression results presented in Table 4, subjects who report a high Likert number (a strong "wish to buy") for a particular good are more likely to be influenced in their bidding behavior by the price distribution, even if the high probability price is relatively far away from their average bid (the interaction term of the revealed price and the self-reported "wish to buy" the good is significant in the full data set). When restricting the range of the revealed price to the vicinity of the mean bid, the interaction

is insignificant and the revealed price itself is a strong predictor of the bid, suggesting that when people do not express a strong "wish to buy" the good, they will still react to the revealed price, but only if it is close to their mean bid.

4 Discussion

We find that most subjects' bids in the BDM mechanism not only depend on the price distribution used but also, surprisingly, that distributional dependence persists and does not weaken over a long period of time (more than 140 rounds). This is true even when subjects repeatedly bid on the same three goods and receive feedback regarding outcomes on every round. This and the fact that we had careful instructions and comprehension questions, leads us to conclude that the effects that we observe here are not likely to be due to misconceptions about the BDM mechanism, but rather reveal something about the valuation process and the underlying preferences of our subjects. The main novel insights from this study are that: 1) the effect of the "revealed price" on individual bids is strongest when the revealed price is close to the individual mean willingness-to-pay for a good; 2) individuals often exhibit distributional dependence in their bids for some but not all the goods; 3) subjects show the effect over a wider range of revealed prices for goods for which they report a strong desire to buy.

Surveying the existing literature on the distributional dependence of valuations obtained using the BDM procedure, we found two conceptually different types of explanations for this dependency. Neither of these ideas and models seems, however, to fully account for the effects that we observed. Explanations of the first type focus on the idea that differences in bids under different price distributions stem from imprecise knowledge about the subject's own valuation of the item. The second type assumes that subjects know their valuation of the good, but that their utility directly depends on the changes to the distribution of prices in the BDM.

Assuming that subjects are unsure of their valuation for the product on offer, there are several ways that the price distribution could influence the subjects' bids. Price distribution could serve as a credible signal of market value and quality. Thus higher price distributions may lead to higher bids because subjects believe they are bidding on a more valuable product. Prices which are close to a person's initial guess for her valuation may also provide an incentive to think more about one's exact value for a good, and thus could lead a subject to come to a more precise estimate of that value (Wathieu & Bertini, 2007). It is known that bringing random numbers, such as digits of the individual social security number, to subjects' attention can exert influence on WTP for consumer goods under some conditions (Ariely, Loewenstein, & Prelec, 2003; Fudenberg, Levine, & Maniadis, 2012). In a similar way, Lusk, Alexander, and Rousu (2007) and Kaas and Ruprecht (2006) have discussed imprecise

preferences as a potential cause of distributional dependence. Here, we do observe a slight decline in the variability of individual bids over time, consistent with the idea that in the beginning of the experiment subjects may be unsure how much to bid, and thus they change their mind more often early on. However, the effect of the revealed price on the bid remains equally strong throughout our experiment, suggesting that even if subjects are refining their knowledge of their own preferences, this is not reducing the effect of the price distribution on their bids. For this reason the above explanations, each suggesting that the influence of the price distribution should be reduced by experience, seem to be insufficient to explain our results.

Assuming that subjects do know their fixed valuation for the good and respond optimally to the BDM, their bid could still be affected by the price distribution. This may be the case if bidders care about the buying probability, or the probability of certain prices as shown theoretically by (Horowitz, 2006). The probability distribution can, for example, define a reference point against which outcomes are compared. Outcomes that fall below expectation create disutility, possibly driven by feelings of regret, disappointment or loss, and those that exceed expectations give positive utility. In our study, one could imagine subjects experiencing feelings of disappointment and regret when they expected to buy a product but end up not buying. Since most people do not value gains and losses equally, most are loss averse and dislike losses more than similarly sized gains (Kahneman & Tversky, 1979), this may create incentives to manage one's expectations in order to minimize the feeling of loss.

Interestingly however, some of the most prominent models of reference-dependent preferences that incorporate this idea do not make predictions in line with our empirical findings. For example, if a subject had preferences such as those modeled in (Heidhues & Köszegi, 2010; Köszegi & Rabin, 2006), she could maximize her reference-dependent utility by adjusting the expectation regarding probability of purchase to its optimal, equilibrium level. In our BDM experiment, these expectations are influenced by two factors: the revealed price that is out of subject's control (for a given bid, the subject is more likely to buy the good if the revealed price is below or equal to her bid than if it is above her bid) as well as the subject's own bid (for a given revealed price, the higher the bid, the more likely the subject is to buy). Notice that this implies that in order to maintain the optimal level of expectations about buying (and maximize utility), the subject would need to adjust her bid in the following way: for higher (lower) revealed prices, that imply lower (higher) probability of buying, subject should bid less (more). This prediction is completely at odds with our empirical findings.

To account for our finding that subjects are willing to bid more on the products when the revealed price is higher, an individual would have to have a utility function $U(x, p, p_r)$ such that $\frac{dU(x,p,p_r)}{dp_r} > 0$, where x is the value of the good, p is the price paid and p_r is the revealed price that for a given bid affects the probability of winning and the expected price. In our

experiment, as the revealed price exceeds the subject's bid, buying probability decreases sharply. One way to think about our results is the following: When the revealed price is above but close to a subject's valuation, by placing a bid equal to the revealed price, the subject can significantly increase her chances of buying at a small cost. When the revealed price is far from the subject's valuation, the cost of matching the revealed price is much higher and thus the subject prefers to stick to her "true valuation". In such a setting, it would be natural for subjects to be willing to match higher revealed prices for goods that they wish to buy more, just as we observed (Table 4).

Two recent empirical studies have aimed at investigating the nature of distributional dependence on WTP (Mazar et al., 2013; Urbancic, 2011). In line with our finding, both observed strong distributional dependencies. Interestingly, Mazar et al. (2013) found that distributional dependence was decreased when subjects reported their maximum WTPs simultaneously for two different distributions, or when prompted to reflect on the stated WTP. Although statistically insignificant, the average WTP in that study was still considerably higher when high prices were more likely. Our results, as well as those of Urbancic (2011), show that even if distributional dependence is decreased in a within-subject design, it is not eliminated and is the strongest when the manipulation occurs close to the subject's valuation for the good. In the study by Mazar et al. (2013) only either the maximum or minimum of the price distribution served as the most likely price and the distribution support was selected such that the subject's valuation should be somewhere in the middle of the distribution. It is likely then, that the results reported by Mazar et al. (2013) underestimate the true extent of distributional dependence.

5   Conclusions

We demonstrated that in repeated rounds of the BDM mechanism, subjects do not bid constantly the same amount for the same good, but are surprisingly flexible in their bids. Subjects tend to submit higher valuations when the price distribution assigns a high probability to a high price, and bid lower when a low price is highly probable. Interestingly, distributional dependence is more frequent when the likely price is close to the average bid a subject places on a given good. Subjects who report a strong "wish to buy" a particular good are more likely to show distributional dependence for a wide range of price distributions for that good. Such bidding behavior cannot be reconciled with the standard assumption that consumers have a fixed valuation for a good and maximize expected utility. Distributional dependence in our experiment is unlikely to result from misunderstanding the BDM, because subjects repeatedly bid on the same products and received detailed instructions and feedback on the BDM mechanism. Taken together, these results show that distributional dependence in the BDM mechanism is a robust, but complex phenomenon. Further understanding the

driving factors of this phenomenon would contribute towards a better understanding of value construction. Moreover, it would enable us to modify the BDM in such a way that elicited valuations are more valid.

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A   Instructions

Welcome! You are participating in an experiment on economic decision making and will be asked to make a number of choices. The study will last about 90 minutes, which consist of filling out questionnaires and participating in the experiment. Your choices are very important in this task and will determine your final payment. Read the instructions carefully. Your final earnings will be determined by the decisions you make in the experiment.

This is the procedure of the whole experiment:

1. You will read the instructions for the experiment
2. Comprehension questions. If you answer comprehension questions correctly, you will be allowed to participate in the study and you will receive $50 from the experiment that is yours to keep. If you do not answer the questions correctly, you will receive $5 show up fee and will not be allowed to participate in the study. You will be allowed to use these written instructions while answering comprehension questions.
3. You can practice the task
4. The task (60 min)
5. The computer will show your earnings to you.
6. A short questionnaire (10 min)

Please proceed to reading the instructions on the next pages. Whenever you have a question, please ask the experimenter for clarification.

1

Instructions

Task:

In this experiment, you will have an opportunity to buy one of three products from our store using the $50 that you received from the experimenter. The products that are available in this experiment are real: an iPod shuffle, a backpack and a pair of noise-cancelling headphones. You can have a look at these goods before the experiment. **Your task in this experiment is to decide and tell us the maximum amount that you would be willing to pay for one of these goods right now, at this moment.** We will call this amount **your current bid**. You may be asked this question multiple times for each good, depending on chance as explained below.

Round structure:

The experiment thus may consist of many rounds, all of which would have a similar structure. In each round:

1. First, you would see which good is on offer in this round, and you would be shown two prices in our store.

One of the prices will be **revealed** and the other will be **hidden. The prices in our store range from $1 to $50.** Both prices are **randomly selected** each time and are always **below the suggested retail price** of the good.


2. After you are shown the store's prices, there will be a short delay. Then you will submit **your bid** (the maximum amount that you are willing to pay) for the good during this round. You will need to enter a number between 0 and 50.

IMPORTANT: Your bid does not influence hidden the price!

2

3. After you enter your bid, the computer will **randomly** choose and let you know which price, the revealed price or the hidden price, will be our store's price in this round. We call it **current store price**.
IMPORTANT: Your bid does not influence whether the revealed or hidden price is chosen by the computer. There is equal chance that it will be the revealed price or the hidden price.

Then, the computer compares your bid to the current store price and you can see whether your bid is higher or lower than the store price:
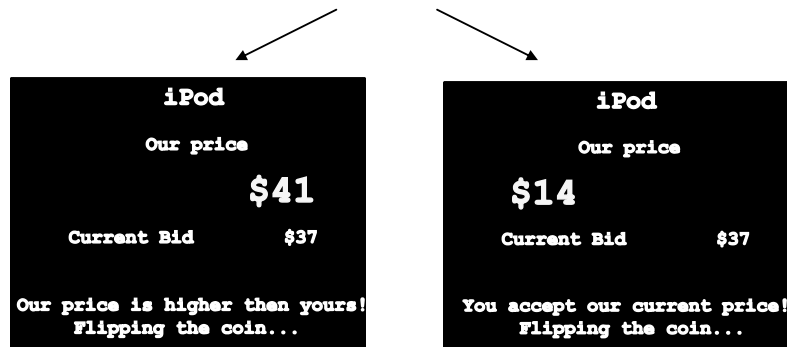
4. The computer now randomly determines whether this round is implemented for payoff or the experiment continues. If it continues, then you will see the following screen and move on to the next round without any disruption:

If this trial is implemented for payoff, whether you buy the good or not and at what price is now determined.

3

iPod	iPod
Our price	Our price
$41	$14
Current Bid $37	Current Bid $37
This trial counts for payment! You won't buy the iPod and you will keep $50. Please wait for everybody to finish.	Lucky! You buy the iPod for $14. Please wait for everybody to finish.

If your bid in the payment round is <u>lower</u> than the chosen current store price, then our price is too high for you. You do not buy and keep $50.

If your bid in the payment round is <u>higher or equal</u> to the chosen current store price, then you accept our price. You buy the good that was offered on this trial at the price equal to the current store price and keep the change.

If you continue to play for more than 21 rounds, you will be allowed to take a break every 21 rounds. After the break, you can press a button to continue whenever you're ready.

When does a trial get played for real and experiment ends?
Any round can be played for real. Therefore, it is really important that you pay attention on each round and treat it as the one that will determine your earnings. On average over 90% of the study participants will stop at some randomly determined round. On average each trial has over a 1.8% chance of being played for real. For the remaining 10% of the participants the experiment will end after the 8th block. They will keep $50 and will not buy anything.

Your earnings:
At the beginning of the experiment, you received $50 dollars. You can use this money to bid on the goods. If you don't end up buying, you keep your initial $50. If you buy a good, then you receive the good and get to keep the difference between $50 and the price you paid, just like in an everyday transaction.

4

A few examples:

*Example 1: The **revealed price** for the **backpack** is **$15**. Manuel decides that **his current bid is $10**. The computer randomly selects **the hidden price, equal to $40, to be the current store price**. The computer randomly generates a number to determine whether the current trial is the one played for real. The current trial is not the one played for real.*
The experiment continues and Manuel's earnings are not determined yet.

*Example 2: The **revealed price** for the **iPod** shuffle is **$20**. Manuel decides that **his current bid is $25**. The computer randomly selects **the revealed price ($20) to be the current store price**. The computer randomly generates a number to determine whether the current trial is the one played for real. The current trial is the one played for real.*
*Manuel **buys the iPod Shuffle for $20** because the current price ($20) is smaller than his maximum willingness to pay ($25) and keeps the remaining $30.*

*Example 3: The **revealed price** for the **headphones** is **$35**. Manuel decides that **his current bid is $38**. The computer randomly selects **the hidden price, equal to $8, to be the current store price**. The computer randomly generates a number to determine whether the current trial is the one played for real. The current trial is the one played for real.*
*Manuel **buys the headphones for $8** because his bid is greater than the current price.*

*Example 4: The **revealed price** for the **iPod** shuffle is **$40**. Manuel decides that **his current bid is $45**. The computer randomly selects **the revealed price ($40) to be the current store price**. The computer randomly generates a number to determine whether the current trial is the one played for real. The current trial is not the one played for real. Throughout the whole experiment, the computer did not pick a trial to count for payment. Manuel does not buy anything and keeps the money.*

*Example 5: The **revealed price** for the **headphones** is **$10**. Manuel decides that **his current bid is $15**. The computer randomly selects **the hidden price, equal to $25, to be the current store price**. The computer randomly generates a number to determine whether the current trial is the one played for real. The current trial is the one played for real.*
*Manuel **does not buy the headphones** because his bid is smaller than the current price.*

PLEASE PROCEED TO ANSWERING THE COMPREHENSION QUESTIONS

LET THE EXPERIMENTER KNOW WHEN YOU'VE COMPLETED ANSWERING THE QUESTIONS

5

19

Comprehension questions (first part): (Choose all that apply)

1. *Suppose that, after seeing the **revealed price** for an iPod, you decide that your current **bid is $48** and the **current store price** turns out to be **$3**. The computer randomly decides that this is the last round. What happens? Choose all that apply.*

   a) *The experiment continues*
   b) *The experiment ends*
   c) *I buy the iPod for $48*
   d) *I buy the iPod for $3*
   e) *I don't buy the iPod*
   f) *My earnings in cash are $50*
   g) *My earnings in cash are $47*
   h) *My earnings are not determined yet*

2. *Suppose that, after seeing the **revealed price** for a backpack, you decided that your current **bid is $8** and the **current store price** turns out to be **$35**. The computer randomly decides that this is the last round. What happens? Choose all that apply.*

   a) *I do not buy the backpack*
   b) *I buy the backpack for $8*
   c) *I buy the backpack for $35*
   d) *The experiment continues*
   e) *The experiment ends*
   f) *My earnings are not determined yet*
   g) *My earnings in cash are $15*
   h) *My earnings in cash are $50*

3. *Suppose that after seeing the **revealed price** for the iPod, you decided that your current **bid is $27** and the **current store price** turns out to be **$24**. The computer randomly decides that this is not the last round. What happens? Choose all that apply.*

   a) *I buy the iPod for $24*
   b) *I buy the iPod for $27*
   c) *The experiment continues*
   d) *The experiment ends*
   e) *My earnings in cash are $26*
   f) *My earnings in cash are $50*
   g) *My earnings are not determined yet*

6

Comprehension questions (second part): (Choose all that apply)

4. *Suppose that, after seeing the **revealed price** for the iPod, you decide that your current **bid is $48** and the **current store price** turns out to be **$49**. The computer randomly decides that this is the last round. What happens? Choose all that apply.*

    a) *The experiment continues*
    b) *The experiment ends*
    c) *I buy the iPod for $49*
    d) *I buy the iPod for $48*
    e) *I don't buy the iPod*
    f) *My earnings in cash are $50*
    g) *My earnings in cash are $1*
    h) *My earnings are not determined yet*

5. *Suppose that, after seeing the **revealed price** for the headphones, you decided that your current **bid is $28** and the **current store price** turns out to be **$3**. The computer randomly decides that this is the last round. What happens? Choose all that apply.*

    a) *I do not buy the headphones*
    b) *I buy the headphones for $28*
    c) *I buy the headphones for $3*
    d) *The experiment continues*
    e) *The experiment ends*
    f) *My earnings are not determined yet*
    g) *My earnings in cash are $47*
    h) *My earnings in cash are $50*

6. *Suppose that after seeing the **revealed price** for the iPod, you decided that your current **bid is $17** and the **current store price** turns out to be **$14**. The computer randomly decides that this is not the last round. What happens? Choose all that apply.*

    a) *I buy the iPod for $14*
    b) *I buy the iPod for $17*
    c) *The experiment continues*
    d) *The experiment ends*
    e) *My earnings in cash are $36*
    f) *My earnings in cash are $50*
    g) *My earnings are not determined yet*

7

B Versions

The experiment was conducted in minimally different versions (treatments). The effect of the revealed price did not differ across the treatments. As shown in Table 5 the interaction term composed of the treatment indicator variable and revealed price was not significant for any of the treatments suggesting that the revealed price did not affect participants more or less depending on the version. We therefore pooled these data for our analysis presented in the main text. Eight participants completed a fixed number of 156 rounds and the three goods were presented in random order. At the end of the experiment, one of the rounds was chosen at random and the participant's decision was implemented (treatment1). For 9 of the participants, goods were presented in random order as well, but a constant hazard function was applied that could end the experiment at any round, after which the last played round would be implemented for payment. For 5 of these participants we used a constant hazard rate of 1% (treatment2). The remaining 4 participants were informed that over 90% of the study participants would stop at some randomly determined round and that on average each round had more than a 1.8% chance of being played for real. If the experiment was not ended after 156 rounds (10% of the participants in expectation), it ended at this point and no round was implemented, so they kept their endowment (treatment3). For another 5 participants the same hazard function was applied, but in order to make the revealed price more salient to the subjects the good was kept constant (did not vary randomly) for a block of 28 rounds. Each good was presented at most for two blocks of 28 rounds (treatment4). We used a dynamically adjusting hazard function of the following form:

$$p(end) = 0.01 + (\frac{round\#}{125})^{10}$$

The remaining 5 participants were endowed with $100 at the beginning of the experiment and were given a chance to purchase all of the goods (treatment5). The good was kept constant for one block with a maximum of 56 rounds and the following hazard function was applied for each block:

$$p(end) = 0.01 + (\frac{round\#}{40})^{10}$$

Table 5: Versions effects

	Coef./se
revealed price	0.04 ***
	(0.01)
treatment2*revealedprice	0.14
	(0.15)
treatment3*revealedprice	−0.00
	(0.04)
treatment4*revealedprice	0.01
	(0.05)
treatment5*revealedprice	−0.01
	(0.03)
constant	−1.08 ***
	(0.39)
Adj. R^2	0.911
No. of obs	3808

Standard errors are clustered by subject.
$^*p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$