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Abstract

This paper reports and models the discrepancy between the full bidding and endow and upgrade findings from a willingness-to-pay (WTP) elicitation Becker-Degroot-Marschak (BDM) experiment for an improved food, conducted in rural India. We found that the distribution of the WTP for exchanging 1kg local pearl millet (LPM) for 1 kg of biofortified high-iron pearl millet (HIPM) first-order stochastically dominated the distribution of the difference between the WTPs for 1kg HIPM and 1kg LPM. Thus the data (i) rejects preferences that are standard or have status quo reference points, in favor of an expectations-based reference dependence model of loss aversion for the new product; and (ii) is used to identify and estimate the loss aversion parameter and latent consumer valuations for HIPM in the consumer model. These point to a significant downward bias in conventional WTP estimates Of HIPM using the BDM procedure, suggesting caution when one is using standard incentive compatible mechanisms for value elicitation.

JEL Codes:C9, D03.

Keywords:Reference dependence, Biofortification, Adding up test, Incentive compatible.

1 Introduction

This paper reports, and provides an explanation and model for the discrepancy between the full bidding and endow and upgrade findings from a willingness-to-pay (WTP) elicitation Becker-Degroot-Marschak (BDM) experiment conducted in rural Maharashtra, India. The objective was to understand consumers' valuations of an *improved* food (*biofortified* high-iron pearl millet, or HIPM for short) in comparison with their valuations of locally available pearl millet (LPM), at a time when the HIPM was not yet available on the market. Our explanation of the discrepancy is based on consumer loss aversion for the novel HIPM, relative to expectations-based reference points, and optimal bidding by such loss averse consumers in a BDM mechanism.

Estimation of consumers' valuations for new products using incentive compatible mechanisms is a fairly common practice in economics. Colson and Rousu (2013) summarize findings from 100 studies eliciting WTP for genetically-modified (GM) foods in over 20 countries. Lusk and Shogren (2007) show that more than a hundred academic studies have utilized experimental auctions for the purpose of preference elicitation. However, the presence of consumer loss aversion for a novel product, relative to expectations-based reference points, as evidenced by this paper, suggests caution while interpreting reported values as true values.

Biofortification is a strategy of significantly enhancing micronutrient concentration in staple food crops using conventional breeding techniques, with the aim of helping to eliminate micronutrient deficiencies in vulnerable populations in developing countries. This study was conducted in 2012 in three major pearl millet growing districts of Maharashtra, the second-largest pearl millet producing state in India[1]. The sample consisted of farmers or household members who were producers and consumers of pearl millet; the HIPM used was provided by HarvestPlus, and was developed by HarvestPlus in partnership with the International Crop Research Institute for the Semi-Arid Tropics (ICRISAT) [2].

The BDM experiment was conducted over two rounds. In the first round, we elicited the WTP for 1 kg bags of biofortified high-iron pearl millet (HIPM) and local pearl millet (LPM) *without informing* participants about the identities of the two pearl millets or of the notion of a biofortified pearl millet. If a participant won the HIPM in the first round he or she exited the experiment; otherwise they proceeded to round 2. Before round 2, participants watched an 'infomercial', which communicated the benefits of adequate iron

[1]India has a large segment of population that is affected by iron-deficiency anemia (e.g. Gragnaloti et. al. (2005) estimates that 75 percent of children in 2005 were anemic).

[2]HarvestPlus (www.harvestplus.org) is the global leader in biofortification and a part of the CGIAR Research Program on Agriculture for Nutrition and Health (A4NH, http://www.a4nh.cgiar.org/).

in the diet, the nature of iron-deficiency anemia, and the existence of a new, high-iron form of pearl millet, branded and certified by an international agency.

For round 2, the identities of the two pearl millet varieties were distinguished by labeling the HIPM with the brand of the international agency mentioned in the infomercial. The participants who had won nothing in round 1 participated in a BDM WTP elicitation where they bid separately for LPM and HIPM, as they had done in round 1. This constituted Treatment 1. The participants who had won the LPM in round 1 participated in a BDM WTP elicitation where they bid to exchange the 1 kg of LPM they had won in round 1 for 1 kg of the HIPM. This was Treatment 2.

The BDM mechanism is incentive compatible, so it is optimal for participants with standard preferences to bid their true values/WTP. However, contrary to standard consumer theory we find that the distribution of the reported bids for exchanging 1 kg of LPM for 1 kg of HIPM in Treatment 2, first-order stochastically dominates the distribution of the difference between the reported WTPs for HIPM and LPM in Treatment 1.

Loss aversion theory with status quo reference points (eg. Kahneman, Knetsch and Thaler (1991), Tversky and Kahneman (1991)) is also contrary to our findings. That literature would expect the inequality to be the reverse, as subjects in Treatment 2, possessing the LPM, would be loss averse with respect to it, and thus be less willing to exchange it for HIPM.

To explain the data anomaly we observe, we use an adaptation of the expectations-based reference dependent loss aversion model of Koszegi and Rabin (2006) to the context of a BDM mechanism; (thus this paper follows an active recent literature modeling reference dependence in auction settings, including Lange and Ratan (2010), Ratan (2014), Banerji and Gupta (2014), Erhartt and Ott (2014) and Rosato (2014)). In particular, we provide a loss aversion parameter with respect to the loss experienced upon not being able to purchase the HIPM, as the HIPM is a novel and beneficial form of pearl millet.

In this model, the optimal bid for HIPM depends on the agent's value for it, the loss aversion parameter, and the support of the BDM price distribution. For consumer values for HIPM that are low compared to the BDM support, bids are shaded below value; while for values which are high compared to the BDM support, bids are marked up above the values. Intuitively, for the former case, a subject does not have much value for the HIPM and therefore bids lower than value to minimize his/her expectation of winning the HIPM to minimize losses relative to the expectation; for the latter case, bidding higher than value reduces the probability of expecting to purchase the highly-valued product but not being able to.

The model's prediction is consistent with the data. Suppose an agent informed about the benefits of HIPM has values v_H, v_L for the bags of HIPM and LPM respectively, and v_E for exchanging a bag of LPM for one of HIPM. Then $v_H - v_L = v_E$, but for a large range of such values, the difference in *bids* for HIPM and LPM is less than the *exchange bid*. Loss aversion for HIPM leads to shading of bids relative to the values v_H and v_E (over a large interval of values), but no shading for the locally available LPM; [3] thus squeezing the difference in the full bids $b_H - b_L$ for HIPM and LPM, relative to the exchange bid b_E.

We use the discrepancy between the full bidding and exchange bidding treatments to identify a loss aversion parameter in the data, and use it to identify the latent distribution of HIPM. This structural estimation suggests that the conventional estimate of average WTP for HIPM (that assumes BDM bids equal WTP) is biased downward by 12 percent.

Related Literature

The way the exchange bids (Treatment 2) and differences in full bids (Treatment 1) compare in our data is somewhat related to the findings of Elbakidze and Nayga (2015) and Corrigan and Rousu (2006) from their tests that adapt the "adding up test"; these papers also use the BDM mechanism. The "adding up test", (in addition to a scope sensitivity test), was used by Diamond and Hausman (1994), Diamond (1996), and Hausman (2012) to evaluate contingent valuation and conclude that "contingent valuation is hopeless". Elbakidze and Nayga (2015) tested if the WTP for two units of an item was equal to the sum of the WTP for the first unit and the WTP for the second unit. In one treatment, after eliciting the WTP for the first unit, they provided the first unit for free. And in another treatment the participants paid an amount equal to the BDM price drawn for the first unit. The WTP for the second unit was higher for the participants who got the first unit for free as compared to the subjects who had to pay for the first unit. The authors gave two possible explanations for this result: first, reciprocity effect, in that subjects wanted to reciprocate for receiving the first item for free by paying more for the second unit, or second, income effect, in that by paying for the first item subjects had suffered a reduction in their income set aside for activities like spending on experiments and therefore were willing to pay less for the second unit. Moreover, in both treatments, the sum of the two WTPs for the two units was greater than the WTP for two units of the good. Thus even taking into account lower income from paying for the first item, the WTP elicitation could not pass the adding up test. Corrigan and Rousu (2006) found that the WTP to pay for an additional unit of a good, after being endowed with the first

[3] In fact, we only require that the consumer be *more* loss averse for HIPM than for LPM.

unit for free, was 75 percent higher than the difference in WTP for two units minus the WTP for the first unit. They also attributed the result to a reciprocity effect.

Our design and objective are different: we do not vary the quantity of the good; we compare the WTP for an *additional attribute* [4], higher iron content, measured through the full bidding approach versus the endow-and-upgrade approach. Additionally, the participants pay the BDM price drawn for the LPM if they do win it. Thus, our endow and upgrade design is also different from the traditional method of actually endowing the subject with an object for free[5]. This removes the reciprocity motive for higher bidding for exchanging LPM for HIPM. The variation across participants in LPM bid minus the BDM price paid also enables us to test if the income effect is causing the exchange bids to be higher; we find this is not the case (Section 2.2).

Several studies have analyzed the performance of the BDM mechanism as a value elicitation mechanism: (Irwin et al (1998), Noussair, Robin, and Ruffieux (2004), Lusk et al (2004), Rutstrom (1997)); but since they use induced values they are not comparable to settings that have unobserved consumer values for commodities, such as ours. A few papers have looked at how bids relate to the BDM distribution, in different contexts (Bohm et al. (1997), Lusk et al (2007), Banerji and Gupta (2014), Urbancic (2011)). Found that bids in the BDM are sensitive to the choice of endpoints of the distribution of possible transaction prices, specifically that higher upper limit of BDM led to higher bids. Lusk et al (2007) analyzed how the distribution of the BDM affects the shape of the payoff function and the cost of deviating from truthful bidding. The relatively small but fast-growing literature on experimental evidence for expectations-based reference points includes Ericson and Fuster (2011), Abeler, Falk, Gotte and Huffman (2011), and Gill and Prowse (2012).

In what follows, Section 2 describes the experiment and the evidence, Section 3 presents the model and its data implications, Section 4 estimates the loss aversion parameter and the true values for HIPM. We then close with a discussion in Section 5.

[4] Loureiro et al (2013) tested if the WTP for a quasi-public good, elicited via the random n^{th} price auction, is sensitivity to the scope (that is adding attributes increases the WTP) of the good as the number of desirable attributes it posseses increases. They found that WTP is indeed scope sensitive in the case of simultaneous bidding.

[5] See Lusk et al (2004) for a survey of pros and cons of this method. Gracia et al (2011), Demont et al (2012), Demont et al (2013) are some of the recent studies using it.

2 Experiment and Evidence

2.1 The Field Experiment

We use data from a framed field experiment that was conducted to study consumer acceptance of a new variety of pearl millet among consumers in rural Maharashtra, a state in western India. At the core of the experiment is the use of the well known Becker-de Groot-Marschak (1964; henceforth BDM) mechanism to elicit a consumer's true value or willingness to pay for this new variety.

Twelve central locations were chosen across three major pearl millet growing districts; two villages were randomly selected from a radius of 10 kilometers around each location; from each village, 9 or 10 households were randomly selected; one participant was selected from each household. The selection, and invitation to participate, were made on the day before the experiment was conducted at the corresponding central location close to the village. Participants were told that they would have the opportunity to taste, evaluate and possibly purchase 1 kg of some variety of pearl millet. They were advised to carry adequate cash to be able to avail of the purchase opportunity.

At each central location, participants filled up a short socioeconomic survey. Apart from information on demographics (including that on production and consumption of pearl millet), the survey had questions on prior awareness of the need for iron in the diet and of iron-deficiency anemia, as well as several other information areas. Then they evaluated two varieties of pearl millet for sensory traits, following the food science literature (Tomlins et al (2007)): grain traits (color and size), and the taste, color and other characteristics of the *bhakri* (the form of bread in which pearl millet is consumed) made from the two varieties. They assigned a score between 1 and 5 on a Likert scale for each characteristic, as well as an overall score, for each of the two varieties. One variety was the local pearl millet available in shops; the other was the new variety whose consumer acceptance motivated the study. At this point, participants did not know that this was a new variety not available on the market, and the visible traits of the two varieties were close enough for the the new one not to appear unusual.

Following this, a participant's willingness to pay (WTP) for the two different varieties was elicited by applying the BDM mechanism. Participants were introduced and trained in this mechanism (see the instructions in the appendix). The training was standard and included explaining the incentive to optimally bid one's value or WTP; note though that this optimality may not hold outside of 'classical' preferences. Following the training, the participant put down his or her BDM bid for each variety. One of the two varieties was then randomly chosen as the 'binding' one, and a sale price for 1 kg of this variety was randomly drawn from a uniform distribution between INR 5 and INR 30. If the participant's bid for the variety was greater than or equal to this sale price, he or she 'won' and purchased the grain, paying the randomly determined sale price; else the participant did not win the grain.

We term the above part of the experiment as round 1. Subsequently, the participants who obtained the new variety left the venue. Those that won the local variety (henceforth LPM or local pearl millet), or did not win anything, were requested to stay on and watch an infomercial video. This infomercial explained the importance of sufficient iron in the diet, including its importance for vulnerable household members (e.g. women of child-bearing age). It explained that compared to the LPM, the new variety could provide the household significantly higher levels of iron, and was branded and certified by an international agency. The new variety was in fact a 'high-iron pearl millet' (HIPM) variety developed through conventional breeding techniques together known as biofortification.

Following the infomercial, there was another BDM round (round 2). In this round, the HIPM was labelled as a brand of the international agency. Participants that had not won anything bid once more for the two varieties in the same BDM setting as in round 1. This was Treatment 1. Those participants that, on the other hand, had won and purchased the LPM were asked in this BDM round to bid to *exchange* their LPM with a 1 kg bag of the biofortified HIPM; after they bid, a sale price was drawn randomly from the interval of INR 0 to INR 20 and if the bid was at least as high as the sale price, they exchanged their LPM for a 1 kg bag of HIPM, and paid the realized sale price. This was Treatment 2.

2.2 The Evidence

The standard benchmark to compare results with is this. Consider an individual whose willingness to pay, or value, for the 1 kg bag of LPM is v_L. Let $V(q, w), q = 0, H, L$ be her utility if she has wealth w and gets 1 unit of H or L or none of either at the experiment. So,

$$V(0, w) = V(L, w - v_L) \tag{1}$$

Following the infomercial, for an individual who did not win any pearl millet, his or her willingness to pay v_H for HIPM in round 2 satisfies

$$V(0, w) = V(H, w - v_H) \tag{2}$$

On the other hand, if the individual won and purchased LPM in round 1, at a price p_L, then following the infomercial his/her willingness to pay v_E to *exchange* the LPM bag of pearl millet for an HIPM bag satisfies

$$V(L, w - p_L) = V(H, w - p_L - v_E) \tag{3}$$

Since the expenditure on 1 k.g. of pearl millet, at about INR 15-18, is very small relative to wealth, even for the poorest households in the sample, it would be a negligible part of annual income. Therefore, the willingness to pay for it may not be significantly affected by small changes in wealth; then the v_E in equation 3 would be the same if wealth equalled $w - v_L$ rather than $w - p_L$. Substituting v_L for p_L in equation (3), it would follow from equations (1) and (2) that

$$v_H = v_L + v_E \tag{4}$$

With quasilinear utility ($V(q, w) = u(q) + w$), the result $v_H = v_L + v_E$ follows directly from equations (1) - (3). The intuition is straightforward in the absence of wealth effects: if an agent's willingness to pay for LPM is v_L, and her willingness to pay for HIPM, after watching the infomercial is v_H, then upon endowing her with a 1 k.g. bag of the LPM, she is willing to pay the difference, $v_H - v_L$ to exchange the LPM bag for an HIPM bag. So, $v_H - v_L = v_E$.

Due to the incentive compatibility of the BDM mechanism in the presence of standard preferences, the benchmark case is then that a participant's bid for LPM, b_L equals v_L; his bid for HIPM in round 2, following the infomercial, b_H equals v_H, and the post-infomercial exchange bid b_E equals v_E. Therefore, $b_H - b_L = b_E$.

We test the equality $b_H - b_L = b_E$ in our experiment by comparing the (round 2, post-infomercial) b_H, b_L bids from Treatment 1 with the b_E bids from Treatment 2. We compare (i) the mean and (ii) the distributions of $b_H - b_L$ from Treatment 1 with the those for b_E from Treatment 2. This amounts to a comparison across the treatments of the *premia* that people are willing to pay for the HIPM relative to the LPM. With standard preferences, negligible wealth effects, and successful randomized allocation to treatment, both these comparisons should give insignificant differences.

The data rejects equality of $b_H - b_L$ (Treatment 1 (round 2)) and b_E (Treatment 2 (round 2)). The Kolmogorov-Smirnov test statistic of 0.2607 (P-value 0.003) instead favors the alternate of b_E stochastically dominating $b_H - b_L$. The stochastic dominance over a large interval (possibly excluding very high premia) is evident from Figure 1. Table 1 indicates that the mean of b_E is significantly higher than that of $b_H - b_L$.

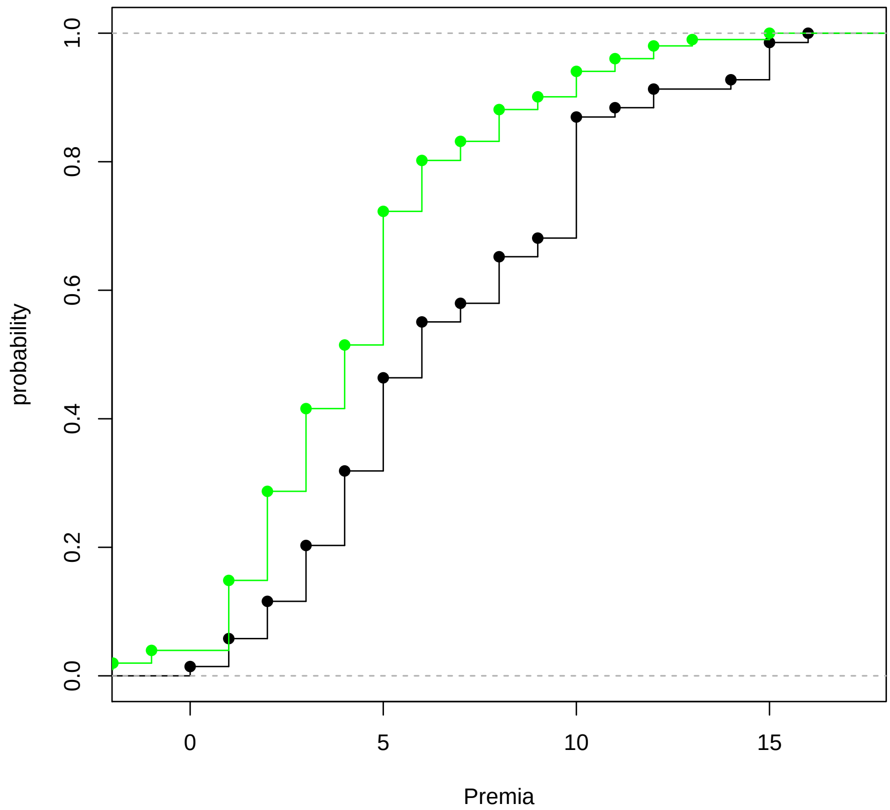
Table 1

Summary: HIPM-LPM Premia across Treatments

	Mean	Std. Dev.	Min	Max	Sample Size
Treatment 1	4.51	3.30	-5	15	101
Treatment 2	6.87	3.93	0	16	69

Note: (i) Treatment 1 premium: HIPM bid - LPM bid in round 2 ($b_H - b_L^2$). Treatment 2 premium: Exchange bid b_E. (ii) t-statistic for difference in means = 4.10. (iii) 1 observation of $b_E = 0$ (possible censoring); adjusting for this does not affect the rejection of equality of means.

Figure 1: Stochastic Dominance



The randomized allocation of participants to the two Treatments appears to have worked. The socioeconomic characteristics of landownership, years of schooling, and proportion of women are not significantly different across Treatments; however, Treatment 2 participants are 3 years older on average (significant at 10 percent; Table 2). But as illustrated in the regression in Table 4, for instance, variations in these characteristics do not explain any of the variation in stated WTP. Most importantly for the randomization, in round 1, prior to the infomercial, the *premium* $b_H - b_L$ is not significantly different across the Treatments.

Table 2

Demographic and Socioeconomic Characteristics

Means	Age	Schooling (years)	Proportion Female	Land (hectares)
Treatment1	39.3	9.0	0.33	2.1
Treatment2	42.8	8.2	0.43	2.2
Tests of equality	$t = -1.85^*$	$t = 1.15$	$\chi^2 = 1.61$	$t = -0.14$

Note: $*$: difference significant at 10 percent level.

This is apparent also from a difference-in-differences regression, involving a baseline comparison of the round 1 premia $b_H - b_L$ across the two Treatments (Table 3). The dependent variable in this regression is this premium, for Treatment 1 (both rounds) and Treatment 2, round 1; while for Treatment 2, round 2, it is the equivalent, exchange bid b_E. We have the regression:

$$\text{premium} = \beta_1 + \beta_2 * \text{Round } 2 + \beta_3 * \text{Treatment } 2 + \beta_4 * \text{interaction} \tag{5}$$

Table 3 shows that in round 1, in the absence of information about the HIPM, this premium is still significant, though low (0.79). The information on HIPM adds INR 3.71 to the premium in Treatment 1, and an *additional* INR 2.4 in Treatment 2.

Table 3

HIPM-LPM Bid Differences: Difference in differences regression

Variable	Estimate	std. error
Constant	0.79	0.02***
Round 2	3.71	0.00***
Treatment 2	-0.04	0.94
Round 2 * Treatment 2	2.40	0.00***

Note: Significance: *: 10 percent. **: 5 percent. ***: 1 percent. The dependent variable is HIPM-LPM bid difference $b_H - b_L$ for Round 1 and Treatment 1, Round 2; and HIPM exchange bid, b_E for Treatment 2, Round 2.

As another robustness check for the result that Treatment 2 b_E bids are significantly higher, on average, compared to Treatment 1 $b_H - b_L$ premia, we look for the presence of wealth effects. The subjects in Treatment 2 typically paid a price p_L for LPM that was less than their (Round 1) bid b_L for it. This bid equals v_L, their value or WTP for LPM in the classical interpretation; on this interpretation, $b_L - p_L$ is the compensating variation. The discussion around equation 4 above suggests that the attendant wealth effects may be very small; however, the literature has several studies that argue that in an *experimental* context, people may have a higher propensity to spend out of windfall income (the evidence is mixed: For example, Thaler and Johnson (1990), Harrison (2006) have provided evidence of such a 'house money' effect, whereas other studies like Clark (2002), Weber and Zuchel (2006) have provided evidence for the lack of such an effect). We examine whether such a 'house money' effect may explain part of the Treatment effect.

Table 4

OLS regression: HIPM exchange bids (Treatment 2 - Round 2)

Variable	Estimate	t-value
Constant	4.73	2.02**
Nashik	-3.40	-1.82*
Solapur	-0.70	-0.67
Taste Var1	0.47	1.15
Taste Var2	0.67	1.11
Round 1 HIPM bid	0.08	0.57
Female	0.73	0.72
Land	0.03	0.15
Age	0.00	0.10
Income Effect	0.14	1.34
Sample Size	69	

In particular, we examine whether variations in the $b_L - p_L$ wealth term for Treatment 2 participants can explain variations in their b_E exchange bids. The regression in Table 4 shows that controlling for other factors that may explain part of the variation in b_E, namely, consumers' tastes as revealed in sensory evaluation (the first two principal components of the matrix of grain and *bhakri* sensory characteristic variables), round 1 bids for HIPM, gender, land owned, age, and district dummies, compensating variations in wealth are not significant. An alternative to this would be including data from both Treatments as in the difference in differences regression, with a variable for compensating variation taking the value 0 for Treatment 1 and $b_L - p_L$ for round 2 - Treatment 2 observations. But this variable introduces collinearity and is not usable[6].

The stylized fact of Treatment 2 HIPM exchange bids (b_E) being higher than Treatment 1 premia ($b_H - b_L$) over a large interval is consistent with participants who, after watching the infomercial on the HIPM, are loss averse for this biofortified variety, relative to expected reference outcomes (Koszegi and Rabin (2006)). We now describe this model and its data implications.

3 The Anticipated Loss Aversion Model

3.1 The basic model

Koszegi and Rabin (2006) and the subsequent literature on (expectations-based) reference dependent preferences assumes that the utility from good t, $u_t(c_t|r_t)$, depends on the consumption level c_t and the reference level of consumption, or reference point, r_t. It is a sum of consumption utility, $v_t(c_t) \equiv u_t(c_t|c_t)$, and utility from gains and losses with respect to the reference level of consumption. Using the simplification in Lange and Ratan (2010), we normalize gains to zero. So,

$$u_t(c_t|r_t) = v_t(c_t) - \theta_t\{0, v_t(r_t) - v_t(c_t)\}$$

where $\theta_t > 0$ implies the agent is loss averse for good t: if her consumption c_t is less than the reference level r_t, she suffers a loss sensation. If the consumption and reference levels are random (with distributions F_c and F_r), then the agent gets an expected utility $\int\int u(c|r)dF_r(r)dF_c(c)$; which is a weighted average of utilities from all possible pairs of consumption and reference levels for consumption.

The reference point itself is determined by expectations of consumption. Consider a BDM setting with a single good, for which the agent bids; after which, a sale price is selected from a distribution F on an interval $[a, K]$. Since the sale price is random, the bid induces a distribution over consumption outcomes (that is outcomes consisting of obtaining the good and paying the sale price). In the models here, as in the literature, the reference level of consumption is random and its distribution coincides with that of the

[6]This variable is too highly correlated with the interaction dummy (0.96) in the DID regression, as it shares the large number of zeros. This is a more general problem in this dataset, because the interaction dummy (in Table 3) has a large number of zeros relative to ones (271 vs. 69). To illustrate this, we constructed a variable that shared the zeros of the interaction dummy, and had random numbers from the uniform [0,1] distribution elsewhere. This variable had spurious explanatory power in the difference in differences regression.

consumption distribution; moreover, the consumption outcome and reference outcomes are independent.

For instance, suppose the good is 1 bag of HIPM following the infomercial. We assume that due to the novelty of the good, and its unavailability on the market, the agent is loss averse towards it, (but not towards money). If her intrinsic value for the HIPM bag of grain is v (for cleaner notation, drop the subscript 'H' from v_H for the purposes of Proposition 1), her utility from a bid of b is given by

$$U(v, b, \theta) = \int_a^b (v - p) f(p) dp - \theta v F(b)(1 - F(b)) \tag{6}$$

This expression can be derived from the Koszegi-Rabin form $\int \int u(c|r) DF_r(r) dF_c(c)$ by accounting for all configurations of consumption and reference levels and then taking an expectation (see e.g. Banerji and Gupta (2014)). The first term gives the expected consumption utility. The second term corresponds to loss sensations: for all pairs of actual sale price p and reference sale price r s.t. $r < b < p$, the agent gets the good in the reference outcome but does not do so in the actual outcome, thus suffering a loss sensation of θv. The second term integrates over all such (r, p) pairs.

Proposition 1 gives us the optimal bid function for an agent with a loss aversion parameter in the interval $(0, (K - a)/(K + a))$.

Proposition 1 *Suppose* $0 < \theta < (K - a)/2K$. *The optimal bid function,* $b^*(v)$ *for all* $v \leq K$ *is given by:*

$$b^*(v, \theta) = \begin{cases} a & \text{if } v \leq (a/(1-\theta)) \\ \frac{v(K-a) - \theta v(K+a)}{(K-a) - 2\theta v} & \text{if } v \in (\frac{a}{1-\theta}, \frac{K}{1+\theta}) \\ K & \text{if } v \geq (K/(1+\theta)) \end{cases}$$

Proof.

Differentiating the utility function w.r.t. b, we get the interior first-order condition:

$$f(b) \left[(1 - \theta) v + 2\theta v F(b) - b \right] = 0$$

Since $f(b) = 1/(K - a)$, we can solve for b to get

$$b = \frac{v(K - a) - \theta v(K + a)}{(K - a) - 2\theta v}$$

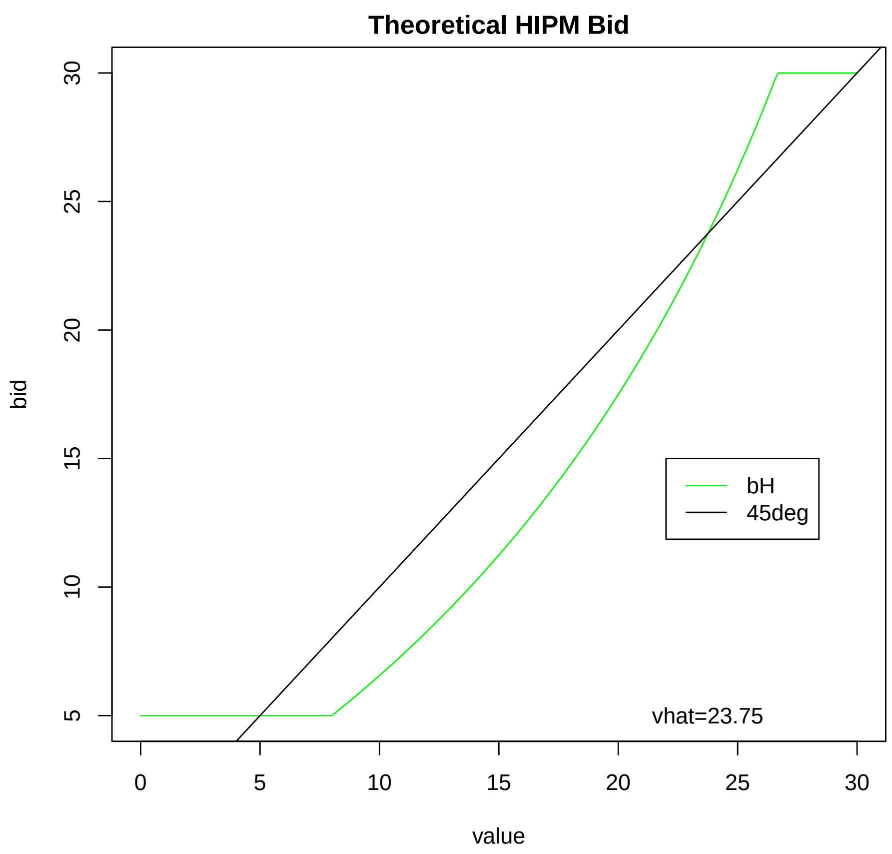
.

Differentiating the utility function twice w.r.t. b gives the second derivative $D_{22}u(v,b,\theta) = f(b)(2\theta v f(b) - 1)$, since $f'(b) = 0$ for the uniform density f. If $\theta \le (K-a)/2K$, this is negative for all values $v \in [0,K]$, so we have concave utility.

Finally, if bid $b = a$, utility $u(v,a,\theta) = 0$. And the derivative of u w.r.t. b, at $b = a$, $D_2(v,a,\theta) = f(a)[(1-\theta)v - a] > (<)0$ as $v > (<)a/(1-\theta)$. On the other hand, choosing bid $b = K$ wins the object with probability 1 ($F(K) = 1$), and $D_2(v,K,\theta) = f(K)[(1-\theta)v + 2\theta v - K] > 0$ if $v > K/(1+\theta)$. ■

In the intermediate interval $(a/(1-\theta), K/(1+\theta))$ of values, the optimal bid function is strictly increasing and convex, and cuts the 45-degree line at $v = (K+a)/2$; (Figure 2). From equation (6), the loss sensation from not winning the good when one expects to do so can be reduced by either reducing b (and therefore $F(b)$) (thus reducing reference expectations of winning), or by increasing b and reducing the chances of not winning. For lower values, it is optimal to reduce b, shading it below value v, and for higher values, to increase b and mark it up above v.

Figure 2



We use Proposition 1 as a model of optimal bidding in Treatment 2. The participant is already endowed with LPM, which she values at v_L. If her value for HIPM, post the infomercial, is v_H, then she assigns a value premium of $v_E = v_H - v_L$ for it. Thus if $v_E \in (\frac{a}{1-\theta}, \frac{K}{1+\theta})$, her optimal bid $b^*(v_E, \theta) = \frac{v_E(K-a) - \theta v_E(K+a)}{(K-a) - 2\theta v_E}$.

The BDM elicitation in Treatment 1 is different in that the participant bids for both LPM and HIPM, and then one of these is randomly selected, following which a random sale price is drawn. We assume he/she is loss averse for HIPM, but not for LPM that is available on the market[7]. For Treatment 1, a reference outcome consists of a pair (L, r) or (H, r) of a selected good, H (HIPM) or L (LPM), and a reference sale price r. A consumption outcome includes the actual selection of H or L and an actual sale price p. With probability 1/4 each, the reference variety - actual selected variety pairs are $(H, H), (L, L), (L, H), (H, L)$. In the last case, the participant, expecting HIPM to be selected, ends up with LPM being selected, and a corresponding loss sensation.

Suppose the participant bids (b_H, b_L) for the two varieties. Then her utility is given by $U(v_H, v_L, b_H, b_L, \theta) =$

$$\frac{1}{2}\int_a^{b_L}(v_L - p)dF(p) + \frac{1}{2}\left[\int_a^{b_H}(v_H - p)f(p)dp - \theta v_H F(b_H)(1 - F(b_H))\right] - \frac{1}{4}\theta v_H F(b_H) \tag{7}$$

With probability 1/2 each, utility is derived from consumption utility for LPM or consumption utility and gain-loss utility from HIPM, and with probability 1/4, there is a loss of $\theta v_H F(b_H)$ on account of expecting to have HIPM selected and win with probability $F(b_H)$. As we can see from this expression, it is still optimal to choose $b_L = v_L$ for LPM. Proposition 2 spells out the optimal bid $b_H^*(v_H, \theta)$ for HIPM.

Proposition 2 *Suppose* $0 < \theta < \frac{(K-a)}{2K}$. *The optimal bid function,* $b_H^*(v_H, \theta)$ *for* $v_H \in [0, K]$ *is given by:*

$$b_H^*(v_H, \theta) = \begin{cases} a \ if & v_H < \frac{a}{1-\frac{3}{2}\theta} \\ \frac{[K(1-\frac{3}{2}\theta) - a(1+\frac{1}{2}\theta)]v_H}{K - 2\theta v_H - a} \ if & \frac{a}{1-\frac{3}{2}\theta} \leq v_H \leq \frac{K}{1+\frac{\theta}{2}} \\ K \ if & v_H > \frac{K}{1+\frac{\theta}{2}} \end{cases}$$

Proof (Sketch). As in Proposition 1, the utility function in (7) is strictly concave(convex) in the bid according to whether θ satisfies $\theta < (>) \frac{(K-a)}{2v_H}$. Assuming that

[7]In order for our model to explain the data, we only need that participants are *more loss averse* for HIPM than for LPM; however, the data can only *identify* a single loss aversion parameter: so we associate this with HIPM.

the highest possible v_H in the population was K, we get the boundary value of $\frac{(K-a)}{2K}$, below which the utility function in (7) is strictly concave. ■

3.2 Data implications of the anticipated-loss aversion model

The interior $b^*_H(v_H, \theta)$ given in Proposition 2 is convex in v_H for all $\theta \in (0, \frac{(K-a)}{2K})$. Consider the value $\hat{v}(\theta)$ at which the bid is equal to the value, that is, $b^*_H(\hat{v}, \theta) = \hat{v}$. Simplifying, we get $\hat{v} = \frac{3K+a}{4} = 23.75$, which is not dependent on θ. Note that at $\hat{v}$, the optimal bid function will cross the 45 degree line, irrespective of θ; (see Figure 2, where the optimal bid function is drawn for $\theta = 0.25$). Similarly, $b^*(v, \theta)$ (Proposition 1) is also convex, and solving $b^*(v', \theta) = v'$ we get $v' = \frac{(K+a)}{2} = 10$ (independent of θ).

A hypothetical agent who is loss-averse for HIPM but not for LPM would have bids b_L, b_E and b_H that satisfy $b_L = v_L$, $b_E = b^*(v_E, \theta)$ and $b_H = b^*_H(v_H, \theta)$, where $v_L + v_E = v_H$. First, suppose $b_H < \hat{v} = 23.75$ and $b_E \geq 10$. Then b_H must correspond to a value $v_H < \hat{v}$ and be shaded below it; whereas $b_E > v_E \geq 10$.

So, we have $b_H < v_H = v_L + v_E \leq b_L + b_E$. By continuity of b^*, for $b_H < 23.75$, we have $b_H < b_L + b_E$, or $b_H - b_L < b_E$, for all $b_E \geq \bar{b}$, for some $\bar{b} < 10$. We can view this stochastic dominance of b_E over $b_H - b_L$ as follows: since $v_H = v_L + v_E$, and $b_L = v_L$ (no loss aversion for LPM), in terms of *bids*, $b_L + b_E$ marks down only *a part of* $v_L + v_E$, whereas b_H marks down the entirety if v_H (see Figure 3, drawn for a value $v_L = b_L = 10$ and $\theta = 0.25$).

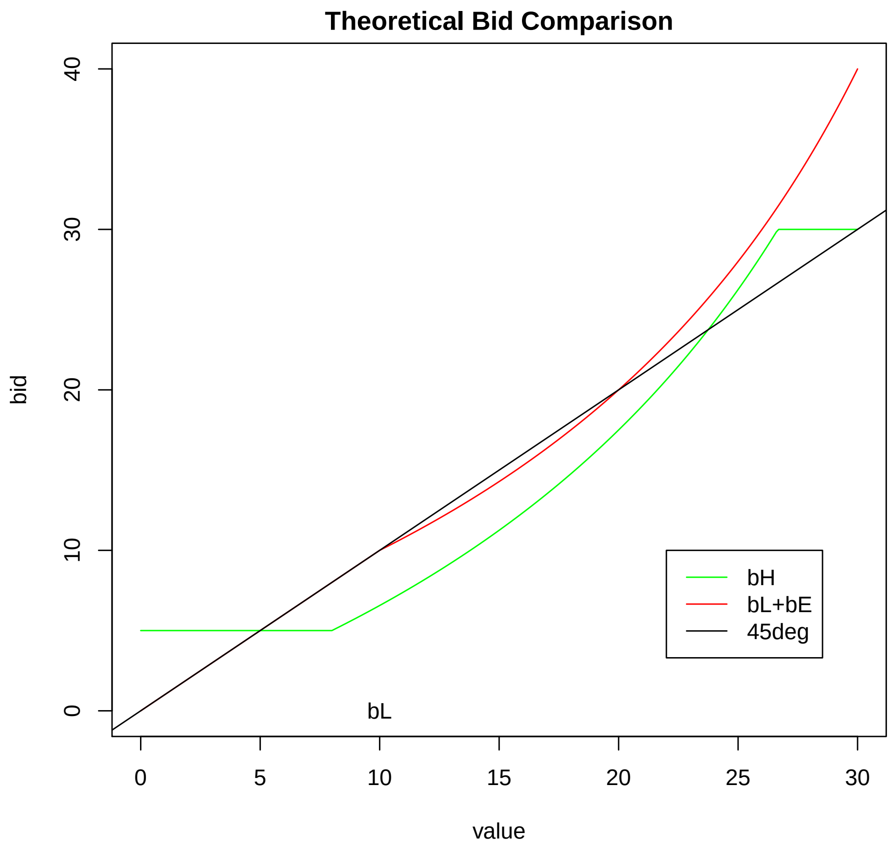
To summarize thus far, there exists $0 < \bar{b} < 10$ such that for any hypothetical agent with any $b_H < 23.75$ and $b_E \geq \bar{b}$ (and $v_H - v_L = v_E$), $b_H - b_L < b_E$. Additionally, for the specific design of our experiment, the model predicts that $b_H - b_L < b_E$ *for all* hypothetical agents with $v_E \in (0, 10)$ and $v_H < 23$ (with $v_H = v_L + v_E$ and $\theta \in (0, 0.4)$). This follows from a comparison of bid shading in the two Treatments. We have:

For all $v_H = v_L + v_E$, with $v_H < 23$ and $v_E \in (0, 10)$, and $\theta \in (0, 0.4)$,

$$v_E - b^*(v_E, \theta) < v_H - b^*_H(v_H, \theta) \tag{8}$$

Numerical optimization yields that the *maximum* value for the bid shading on the left-hand side of equation (8), over all $v_E \in (0, 10)$ and all $\theta \in (0, 0.4)$ equals about 0.025; and the *minimum* value for the bid shading on the right-hand side over all admissible θ and $v_H \leq 23$ equals 0.06. Replacing v_H by $v_L + v_E$ above, noting $b_L = v_L$, and rearranging, equation (8) yields $b^*_H(v_H, \theta) - b_L < b^*(v_E, \theta)$.

Figure 3



The model predicts greater bid shading in Treatment 1 (right-hand of equation (8)) for two reasons: (i) there is the additional possibility of loss sensations from winning LPM when one expects to win HIPM; for which reason people shade more if their v_H value is low; this is confirmed by a direct comparison of $b^*_H(v, \theta)$ and $b^*(v, \theta)$ for a given v. (ii) The BDM interval in Treatment 1 is larger ([5, 30] compared with [0, 20] for Treatment 2. Loss averse agents shade more if the BDM interval is larger (Banerji and Gupta (2014), Proposition 3).

Collecting the implications for comparing $b_H - b_L$ and b_E from equation (8) *and* the discussion preceding it, we have:

Implication 1 *The distribution of b_E, obtained from Treatment 2 first-order stochastically dominates the distribution of $b_H - b_L$, obtained from the subsample of Treatment 1 satisfying $b_H < 23$.*

A secondary implication (Implication 2) is that the stochastic dominance can reverse for bids involving b_H much larger than 23.75. For example $b^*_H(v_H, \theta) > v_H = v_L + v_E \geq b_L + b^*(v_E, \theta)$ if $v_H > 23.75$ and $v_E < 10$.

The first implication is borne out by the evidence, as discussed earlier (Section 2.2,

Table 1, Figure 1). Implication 2 is a possibility, but it is difficult in the present context of an improved food for a participant to have a high full value v_H for it, and yet a relatively low exchange value v_E. Figure 1 does suggest however that at some high bid less than the maximum, the cumulative distributions of b_E and $b_H - b_L$ come close together.

4 Estimation of loss aversion and HIPM distribution

The optimal bid functions, $b_H^*(v_H, \theta)$ and $b^*(v_E, \theta)$, are increasing in the value v_H over an interval; but we can't use them to invert bids to get values since we do not know the loss aversion parameter θ. In keeping with the tradition of identifying risk aversion from auction data, we assume that the agents share a common, true loss aversion parameter θ. Note first that if θ is known, then we can invert bids *in the interior* of the BDM distributions to get values as follows:

Proposition 3 *(i) If $b_E \in (a, K)$, using proposition 1, the inverse is given by:*

$$\phi_E(b_E, a, K, \theta) = \frac{b_E(K-a)}{2\theta b_E - \theta(K+a) + (K-a)} \text{ , } where\ \theta < min\{\frac{K-a}{K+a}, \frac{K-a}{2K}\}$$

(ii) If $b_H \in (a, K)$, using proposition 2, the inverse is given by:

$$\phi_H(b_H, a, K, \theta) = \frac{b_H(K-a)}{K(1-\frac{3}{2}\theta) - a(1+\frac{1}{2}\theta) + 2\theta b_H} \text{ , } where\ \theta < min\{\frac{K-a}{K+a}, \frac{K-a}{2K}\}$$

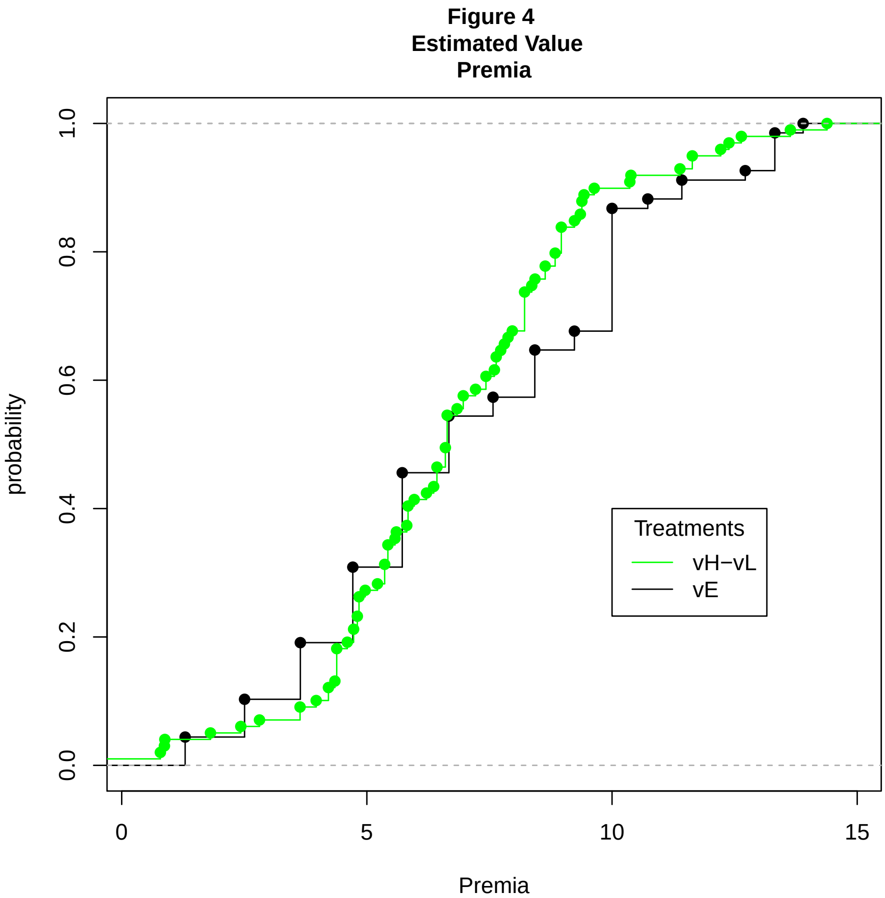
We first estimate θ from the data and then use Proposition 3 to invert bids to values. Our estimation is based on the fact that prior to the allocation to the two Treatments, the pre-nutrition-information premia (i.e. round 1 differences between bids for HIPM and LPM) are not significantly different in the two groups (Section 2.2 and Table 3). So it is reasonable to expect that brand and nutrition information enhances values v_H by similar amounts in the two Treatments. Thus if we invert bids to get values using the 'true' θ, there should not be any significant difference between the distribution $F_1(\theta)$ of $\phi_H(b_H, \theta) - b_L$ from Treatment 1 and the distribution $F_2(\theta)$ of $\phi_E(v_E, \theta)$ from Treatment 2.

Our estimate θ^* therefore solves

$$\theta^* \in \ \text{argmin}\left\{d_1\left(F_1(\theta), F_2(\theta)\right)|\theta \in \left[0, \frac{K-a}{K}\right]\right\} \tag{9}$$

where $a = 5, K = 30$, $F_1(\theta)$, $F_2(\theta)$ are the empirical distribution functions of $\phi_H(b_H, \theta) - b_L$ and $\phi_E(b_E, \theta)$, and d_1 measures the absolute difference between the two distributions on a grid of 4000 points in the interval $[-5, 20]$.[8]

We estimate $\theta^* = 0.25$ with a 95 percent confidence interval of $[0.18, 0.35]$ obtained by bootstrapping[9]. Figure 4 shows that the empirical distribution functions $F_1(\theta^*)$ and $F_2(\theta^*)$ almost overlap.



5 Discussion

We use the loss aversion parameter estimate $\theta^* = 0.25$, the bidding data for b_H in Treatment 1 (round 2) and the inverse formula $\phi_H(b_H, a, K, \theta^*)$ from Proposition 3 to

[8]The estimate of θ is robust to the choice of grid points.
[9]Estimates are rounded off.

estimate the participants' values v_H for HIPM following the infomercial. Figure 5 plots (i) the density of these latent values; it also plots (ii) the densities of the bids, and of (iii) the *first round* bids for HIPM, prior to the infomercial (labeled in Figure 5 as v_H, bH, b_{H1} respectively. Under our benchmark assumption that participants were not loss averse to HIPM in round 1, and their bids reflected true values, the difference between densities (i) and (iii) captures the true effect of brand and nutrition information on participants' valuations for HIPM.

Figure 5
Densities of Estimated HIPM Values vs. Bids

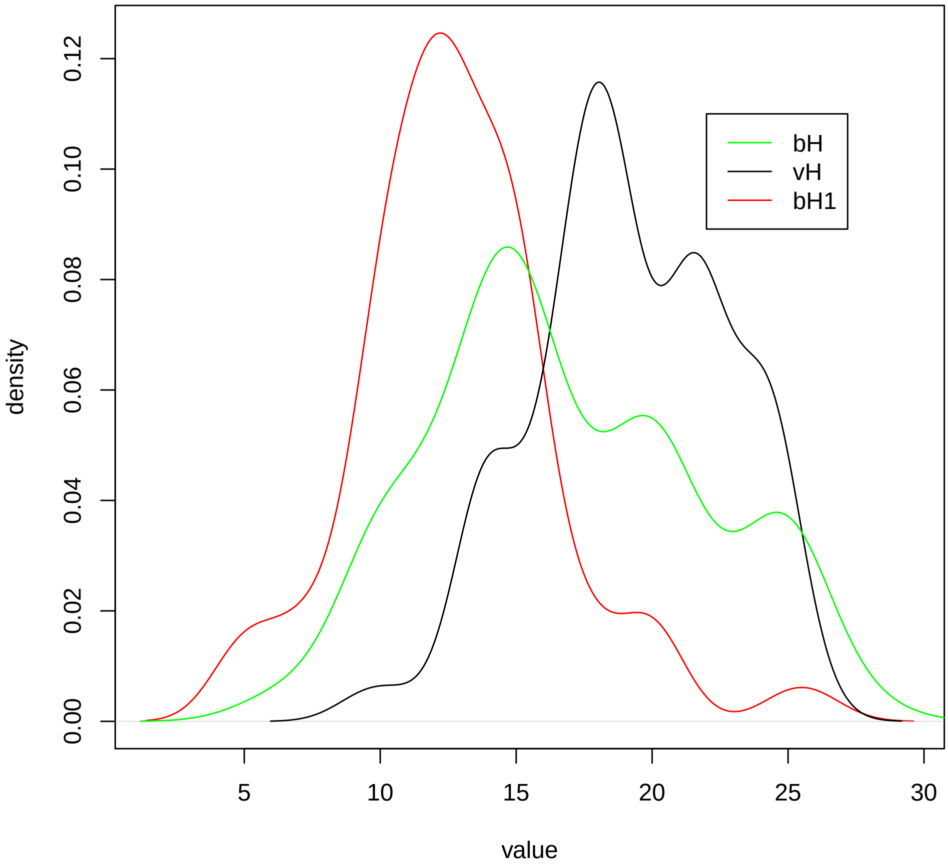


Table 5 summarizes the effect: the latent valuations for HIPM are on average INR 2.31 higher than the Treatment 1 bids for HIPM post nutritional information. As nutritional information raises average bids by INR 3.96 (column 2), factoring in loss aversion along with information raises bids by INR 6.27 (column 3) (all differences are significant at 1 percent). On a base of INR 12.99, (mean WTP for HIPM before information), the conventional measure of increase in WTP (the BDM bid in Treatment 2) has a downward bias of about 12 percent.

Table 5

Treatment 1: Estimated values versus bids for HIPM

Comparison	$v_H - b_H$	$b_H - b^1_H$	$v_H - b^1_H$
Difference in means	2.31***	3.96***	6.27***
t-value	3.76	6.32	12.12

Note: b_H, v_H are bids and estimated values for HIPM in round 2. The superscript 1 refers to round 1.

It is evident from the model that the mean of the latent values could in principle be higher or lower than the mean of the BDM bids, depending on the location of the BDM interval in comparison to the probability mass of these (unknown) values. For an individual's BDM bid however, we do know whether it underestimates or overestimates the latent value: this depends on whether the bid is less or greater than $\hat{v}$, the value at which bids switch from being marked down to marked up over value. The *extent* of under- or overestimation depends on two factors: (i) the magnitude of loss aversion; (ii) the length of the BDM interval; (see Banerji and Gupta (2014), and the discussion earlier in Section 3.2).

Additionally, Treatment 1 bids are shaded more relative to value (for values less than $\hat{v}$) because as discussed in Section 3.2, bidding for HIPM amidst the possibility of that the LPM will be selected instead, injects an extra loss aversion term in the utility function. On the other hand, in Treatment 2, the bidding is only for the HIPM, and the BDM interval is also smaller; this can explain why the distribution of BDM exchange bids b_E is not significantly different from the distribution of latent exchange values $\phi_E(b_E, \theta^*)$. Table 6, column 1, summarizes this result: the means of the latent values v_E and the bids b_E are not significantly different.

Table 6

Estimated exchange values, bids, and premium comparisons

Comparison	$v_E - b_E$	$v_E - (b^1_H - b^1_L)^{T2}$	$v_E - (b^1_H - b^1_L)^{T1}$	$v_E - (v_H - b^2_L)^{T1}$
Difference in means	0.2343	6.41***	6.36***	0.4217
t-value	0.38	11.27	13.19	0.89

Note: v_E, v_H are estimated exchange value and full value for HIPM. $T1, T2$ are Treatments 1 and 2. b^1_L, b^2_L, b^1_H are LPM bids in rounds 1 and 2 and HIPM bid in round 1. b_E is exchange bid in Treatment 2.

Prior to the brand and nutrition information, we have seen that the difference between the mean bids for HIPM and LPM is about the same across the two treatments; each of these is significantly lower than the mean post-information exchange bid or value, b_E or v_E (Table 5 columns 2 and 3). There is no significant difference between the latent, mean $v_H - v_L$ premium from Treatment 1 (round 2) and the latent v_E from Treatment 2.

The estimate for θ here is almost the same as that obtained by Banerji and Gupta (2014) in a different WTP elicitation design. That paper also studies implications of loss aversion of this magnitude for first- and second-price auction revenues.

Our paper shows that expectations-based reference dependence predicts the discrepancy that we observe between our full bidding and endow and upgrade treatments for the new product, HIPM. This discrepancy is an "adding-up test" failure in the context of an additional qualitative feature in a new product. We rule out an income effect, using a robustness check, and a reciprocity effect, due to the experimental design. The model predicts the discrepancy even if an individual is loss averse for both old and new products, provided she is more loss averse for the new product: however, the 2-treatment experimental design can identify a single loss aversion parameter. Standard, incentive-compatible elicitation procedures result in biased WTP estimates in the presence of loss aversion: the paper contributes a design that can identify loss aversion and correct this bias.

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