Reminder Nudge, Attribute Nonattendance, and Willingness to Pay in a Discrete Choice Experiment

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Abstract

Attribute non-attendance (ANA) is one of the choice simplification strategies respondents employ in choosing among alternatives in stated preference elicitation methods. Studies have shown the importance of accounting for ANA in estimating demand functions for non-marketable quality differentiated goods and services. This study addresses the question whether reminding respondents on the need to attend to all attributes in discrete choice experiments (DCE) affects ANA and improves quality of model fitting. We compare ANA patterns and willingness to pay (WTP) values '*before'* and *'after'* a *reminder* for attention to all attributes. We report on a study using DCE data elicited from 960 respondents generating 11520 observations. Bayesian D efficiency criterion was used to design the experiments and attribute non-attendance was inferred using constrained latent class econometric models. We employed mixed logit model in WTP space to estimate WTP values for the different livestock market services in Ethiopia. We find that a nudge in the form of reminding full attention improves data fitting quality, reduces ANA and distributes WTP more evenly across the different services considered. Our results imply that researchers studying behaviors of rural communities in developing countries might be able to estimate the implicit prices of attributes more precisely if they employ *reminders* while conducting DCE.

Key words: attribute non-attendance, willingness to pay, latent class models, mixed logit model, market facilities, Ethiopia.

JEL Codes: D110, D120, Q120

Introduction

Discrete choice experiments [DCEs] are multi-attribute based instruments for eliciting stated preferences and for estimating willingness to pay for attributes of quality-differentiated goods and services (Ben-Akiva, McFadden, and Train 2019, Hensher, Rose, and Greene 2015, Holmes, Adamowicz, and Carlsson 2017). DCEs are supposed to be close-to-reality representation of what the respondents face in the real markets of goods and services. When carefully designed and implemented, DCEs have proved to be very useful and relevant tools to analyze preferences and, hence, willingness to pay for the different attributes that characterize the commodity (Train 2009). Early applications of DCEs to estimate preferences for livestock choice in developing countries include works on cattle breeds (Scarpa, Ruto, et al. 2003, Ruto, Garrod, and Scarpa 2008) and native pig breeds (Scarpa, Drucker, et al. 2003).

Theoretically, Lancaster's characteristics theory of value (Lancaster 1966) and McFadden's random utility theory (McFadden 1974) form the basis of DCEs. There are other underlying assumptions made in estimating the perceived relative utility that supposedly drives the choice decisions. The application of DCEs assumes compensatory decision-making and well-formed preferences. Compensatory choice implies that respondents consider all or most of the available information and make trade-offs between product attributes (Denstadli Jon, Lines, and de Dios Ortúzar 2012, Gigerenzer, Hertwig, and Pachur 2011, Louviere and Lancsar 2009). Well-formed preferences imply that individuals have consistent preferences and they can retrieve an appropriate response to any preference-elicitation question (Denstadli Jon, Lines, and de Dios Ortúzar 2012, McFadden 1999).

These assumptions imply that the consumer is expected to be a rational decision maker, portraying behavior as a planned and consistent activity, which aims to maximize some subjective measure of value (McFadden 1999). Rationality is, however, bounded because of the limitations the decision makers have in thinking capacity, available information, and time (Simon 1990). Economists and psychologists have reported detailed accounts of consumer behavior that do not necessarily synchronize with the neoclassical theories of ‘rational’ consumer and ‘consistency’ in choices. Non-compensatory and adaptive decision-making have been observed among consumers in all lifestyles (Chater et al. 2003, del Campo et al. 2016, Gigerenzer and Goldstein 1996, Olshavsky and Acito 1980, Payne et al. 1992, Weber and Johnson 2008).

Making choices when there is so much, or so little information and limited time could be a daunting task. When faced with complex choice decisions, individuals employ cognitive shortcuts or heuristics to simplify the choice decisions under uncertainty (Hensher 2014, Hensher, Rose, and Greene 2015, Mousavi and Gigerenzer 2017). Heuristics in DCEs, include attribute nonattendance, anchoring, imposing thresholds on attribute levels to represent acceptable levels, and attribute aggregation where they are in common units (Hensher 2014, Louviere and Lancsar 2009, Nguyen et al. 2015, Scarpa, Thiene, and Hensher 2010).

The need to understand the mechanics with which respondents are making decisions in DCEs is growing in importance along with the popularity of the experiments as preference elicitation tools (Ben-Akiva, McFadden, and Train 2019, Byrd, Widmar, and Ricker-Gilbert 2017, Hole, Kolstad, and Gyrd-Hansen 2013, Scarpa et al. 2009). Ben-Akiva, McFadden, and Train (2019) suggested that DCEs need to embed tests for response distortions that are commonly observed in cognitive experiments, such as anchoring to cues in the elicitation format, reference point or status quo bias, extension neglect, hypersensitivity to context, and shadowing from earlier questions and elicitations.

Scarpa et al. (2009) warned that pooling observations where some respondents attend to all attributes while others attend to only a subset would lead to erroneous and biased estimates. Similarly, Hole, Kolstad, and Gyrd-Hansen (2013) indicated that taking into account heuristics - in the form of attribute nonattendance - improves model fit with little or no effect on marginal rates of substitution. The predominant recommendation is, however, that including the decision process in the analytical models is necessary and informative given the context (Campbell, Hensher, and Scarpa 2011, Campbell, Hutchinson, and Scarpa 2008, Hensher 2006, Hensher and Rose 2009, Hensher David 2010, Hole 2011, Hole, Kolstad, and Gyrd-Hansen 2013, Leong and Hensher 2012, Scarpa et al. 2009, Scarpa, Thiene, and Hensher 2010).

Quite a lot has been done in identifying the types of heuristics in choice experiments, their causes, and their impact on preferences and willingness to pay for attributes or attribute levels of the hypothetical profiles (see Leong and Hensher (2012) and Hensher, Rose, and Greene (2015) for a detailed discussion). The scientific literature, however, does not have anything on ways of dealing with heuristics to have more consistent and realistic elicitation of preferences and estimation of implicit prices of the attributes. Ben-Akiva, McFadden, and Train (2019) recently affirmed that there is currently no good theoretical or empirical foundation for applying these tradeoffs to assess well-being in real markets for complex products where filtering influences consumer behavior. There is, however, a general consensus that there is very little of the decision processing literature incorporated into discrete choice modeling which is increasingly becoming the mainstream empirical context for preference measurement and willingness to pay [WTP] derivatives (Hensher, Rose, and Greene 2015). There is a focus on the outcomes in analyzing economic decisions (Weber and Lindemann 2011). We agree with Denstadli Jon, Lines, and de Dios Ortúzar (2012) that no studies have so far made detailed investigations of decision making in conjoint experiments and how elements of different decision strategies are combined in order to make choices.

In this study, we looked into the effects of a simple '*reminder'* on key factors in DCEs; i.e., estimates of preference and their implied willingness to pay for livestock market services. Behavioral economists argue that a *nudge* in the form of a reminder can have a significant impact on how decision makers behave (Sunstein 2019, Thaler and Sunstein 2008). A nudge is any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives (Sunstein 2019). To count as a mere nudge, the intervention must be easy and cheap to avoid. Our nudge is a simple reminder of attending to all services and it was framed for all respondents as "***Some of the respondents I talked to before you were not paying attention to all of the***

services while comparing the markets. We expect respondents to consider all the services in comparing the two markets on each of the choice cards." Our nudge references peer activity and is expected to increase cognition and get people think a little bit more about their decision-making process. The reminder nudge is expected to influence the choice behavior of our respondents without compulsion to act on it.

To analyze this causality we estimated latent class models and mixed logit models with continuous and discrete distributions of using maximum likelihood and Bayesian estimators. The findings of the paper contribute in three important ways. First, there is a policy contribution. To the best of our knowledge, this is the first livestock market study focused on estimates of implicit prices for different livestock market services in Ethiopia or Sub-Saharan Africa. This information is key to develop self-sustainable market infrastructure. Secondly, we address an important theoretical and empirical question on whether a reminder nudge can influence the heuristics decision makers adopt in DCEs. Our expectation is that the nudge increases fully compensatory choice behavior, and given the fact that local communities never had a say in policy design and objectives and their lack of experience with market facilities, nudging should provide a more comprehensive mapping of the preferences which will certainly help designing market development plans. Thirdly, nudging of this sort has not been studied in the context of stated preferences in developing countries, and our understanding of their use is still limited. Our application and its results add to our understanding of this preference elicitation technique.

Methodology

Context and Sampling

The role markets play in the livelihoods of rural communities in a developing country context can hardly be overemphasized. Ethiopia is a country with an agrarian economy where agriculture accounts for about 50% of the gross domestic product, employs 85% of the national labor force, and generates 90% of the foreign earnings. Ethiopia claims to have the largest livestock population in Africa and yet the sector contributes only about 27% of the agricultural value added (Bachewe et al. 2015, Welteji 2018). Despite the relatively large livestock population, the country's economy struggles with the low and declining performance of the sector. One of the critical challenges the livestock sector faces is a lack of efficiency of its marketing system. Livestock markets are usually marginal and/or abandoned plots of land with little or no facility. If there is any facility, it is usually a fence around the market mainly for fee collection and sheds for collectors. Otherwise, lack of infrastructure, limited physical accessibility, and bargaining power skewed towards the traders characterize rural livestock markets in the country (Kassie et al. 2019, Solomon et al. 2003).

Cognizant of the indispensable role of the markets in the growth and transformation agenda of the country, the government of Ethiopia has integrated market improvement in its recently developed livestock master plan and livestock sector analysis (Shapiro et al. 2015, Shapiro et al. 2017). These plans are developed with considerable level of uncertainty due to lack of grass roots level information on the interest in and willingness to pay for market development interventions. We are, therefore, estimating the demand for the key market facilities that rural communities would like to have in the markets they depend on.

Lack of market services significantly undermines the market-based revenue margins livestock keepers generate from their production and elevate their cost of agricultural inputs. This limits the financial sustainability of the supply chain and impedes forward planning in herd composition, making the overall herd management unsustainable or suboptimal from the resilience viewpoint in the long run. Transaction costs of agricultural markets in general are quite high and the decision on what livestock market to direct your livestock to is one of the most salient ones livestock keepers make. In rural livestock markets, such costs are particularly high due to, among others, lack of transport facilities that force marketers to trek their animals, exposing herds to lack of feed and watering services on their way to and around markets, poor access to veterinary services, and lack of other handling facilities.

Establishing and sustaining these facilities in or around the livestock markets needs to be an integral part of the plans developed. In our context of study, markets are physically owned by the government – as it is the sole owner of land in Ethiopia – and yet it is the marketers' demand for the market facilities that determines to what extent these facilities would help the rural communities make more out of their livestock. It is, therefore, imperative for self-sustainable infrastructure investment, to emphasize the need for understanding the willingness to pay for access to marketing services and their potential impact on the marketing performance of smallholder livestock keepers.

Accordingly, this study assesses the preferences and WTP for market services identified by farmers and traders in three sites in different parts of the country. The sites are *Abergelle* in Northern Ethiopia, *Menz* in central north Ethiopia, and *Horro Gudru* in central west of Ethiopia (Figure 1). In these sites, we covered seven administrative districts where livestock are crucial component of the rural livelihoods. Markets are places where farmers visit almost every week not only to buy and sell but also to have social interactions and garner information. Therefore, our population was the rural community in the selected sites. In Menz area, we randomly sampled 120 households from each of the three districts, namely, *Menz Gera*, *Menz Keya*, and *Menz Mamma*. In Horro Gudru, we randomly selected 240 farm households from *Horro* and 120 from *Jimma Geneti* district. In Abergelle site, we selected 120 farm households from each of the two districts, *Sekota* and *Abergelle.* Our study has hence a total sample of 960.

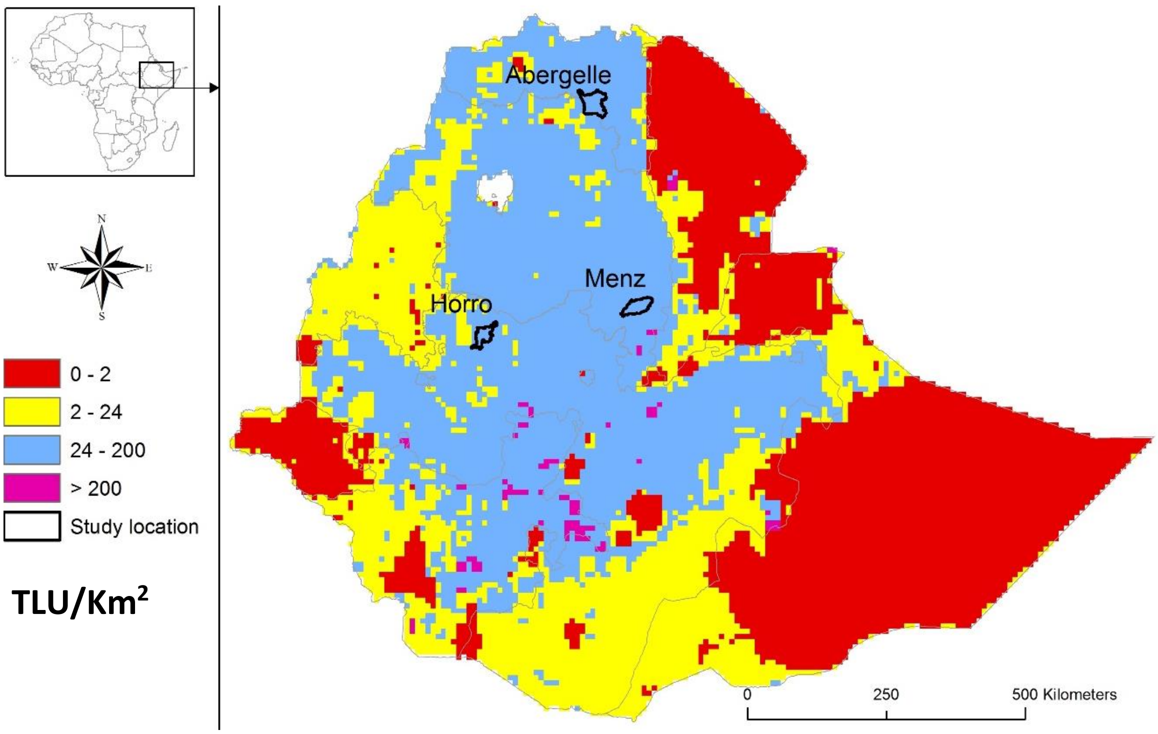

Figure 1: Locations of the study

Choice experiment

We used a discrete choice experiment to elicit the preferences of survey respondents. A series of structured meetings with farmers, livestock traders, and local development agents enabled the identification of market shed with and without fences, veterinary clinic, resting or holding sheds, watering trough, toilet, and feed stalls or shops as the most important services livestock markets needed to have in the study sites (Table 1).

The design of the choice experiment was articulated in two stages. First, we developed an efficient design with flat or no priors. Then, we collected data on 20 respondents in the study area, analyzed the data, generated priors and developed a Bayesian efficient design. The design had 48 profiles of markets facilities, described by different combinations of services and service levels. We blocked the profiles into two and added an opt out option in each of the choice sets. Each respondent was presented with 12 choice situations and asked to choose his/her preferred alternative. With three alternatives in each choice situation, we were able to generate 34560 rows of data. The reminder nudge was introduced right after the sixth choice situation. The choice situations were presented in a random order both before and after the reminder.

Table 1. Services (Attributes) and Delivery Levels in the Discrete Choice Experiment

Service	**Levels**
Market shed	No shed
	Unfenced market shed (SUNF)
	Fenced market shed (SFEN)
Veterinary clinic close to the market	No
	Yes (VET)
Resting/holding shed close to the market	No
	Yes (HLD)
Watering trough in the market	No
	Yes (WAT)
Toilet in the market	No toilet
	Toilet with a cleaner (TCLN)
	Toilet with no cleaner (TNCL)
Feed stall/shop in the market	No
	Yes (FDSH)
Service charge/sold sheep	5 Eth Birr
	7.5 Eth. Birr
	10 Eth. Birr
	12.5 Eth. Birr

Analytical framework

Choosing an alternative in a choice situation is an intricate behavioural decision where both the process and the outcome are important. Responses collected in DCEs are most commonly analysed based on assumptions from a theory of value based on characteristics of composite goods (Lancaster 1966) and that of random utility (McFadden 1974). Therefore, the decision on which livestock market to visit is expected to be the result of marketers' interest in the different facilities in the experimentally profiled markets and the chosen market is expected to be the one that maximizes the perceived relative utility of the respondent. Given a sample of N respondents, the utility an individual 'n' derives from choosing an alternative 'j' in a choice set can be formulated as:

$$U_{nji} = \beta_n' x_{njt} + \varepsilon_{njt} \tag{1}$$

where β_n is conformable vector of unknown individual-specific utility coefficients; x_{njt} is a vector of explanatory variables including attributes of alternatives and interactions of attributes and *reminder nudge* (for the *after nudge* scenario), and ε_{njt} is unexplained utility assumed to be independently and identically distributed (*i.i.d.*) across individuals, alternatives and choice sets with extreme value type I distribution. Conditional on knowing β_n, the probability of respondent n choosing alternative i in choice set t is given by the logit:

$$L_{nit}(\beta_n) = \frac{\exp(\beta_n' x_{nit})}{\sum_{j=1}^{J} \exp(\beta_n' x_{njt})} \tag{2}$$

The cumulative distribution function (cdf) of β_n is denoted by $F(\beta | b, W_\beta)$ and it depends on the parameters of the distribution (b, W_β), where b is the mean and W_β is the covariance matrix of β_n (McFadden and Train 2000, Revelt and Train 1998). The distribution can be continuous or discrete, different elements in β may follow different distributions, and the elements of β be correlated with each other (Hess and Train 2017).

With continuous F, the choice probability for the individual's sequence of choices, given the researcher's information, is:

$$P_{nit} = \int L_{nit}(\beta_n) f(\beta | b, W_\beta) d\beta \tag{3}$$

where f is the density associated with F.

If F is discrete, then the mixed logit formula is

$$P_{nit} = \sum_{r \epsilon S} L_{nit}(\beta_r)\pi_r(\beta_r | b, W_\beta) \quad (4)$$

where π is the probability mass function associated with F, and S is its support set with elements indexed by r. We have assumed that all estimated parameters of services are normally distributed.

The generalized multinomial model (GMNL) and Latent class models we estimated can be considered as different specifications of the mixed logit model (Hess and Train 2017). The GMNL is the specification we started with to explore the pattern of the effect of the *nudge* on mean WTP values of market services. The model is developed with the intention of accounting for scale heterogeneity in conditional logit models (Fiebig et al. 2010, Greene and Hensher 2010, Keane 2006).

The role of scale in utility can be examined more formally by writing the utility function **[Eqn. 1]** as:

$$U_{nji} = \alpha_n' x_{nji} + \frac{1}{\sigma_n}\varepsilon_{nji} \quad (5)$$

Where σ_n is inversely proportional to the standard deviation of the error term, and α_n is a random vector. Since utility has no units, the equation above can be written as:

$$U_{nji} = (\alpha_n \sigma_n)' x_{nji} + \varepsilon_{nji} \quad (6)$$

GMNL specification starts with decomposition of each element of α_n into a mean and an individual-specific deviation: for the l^{th}element, $\alpha_{nl} = \alpha_l + \tilde{\alpha}_{nl}$. Then the utility coefficient for the element, β_{nl}, is expressed as:

$$\beta_{nl} = \sigma_n \alpha_l + \big(\gamma + \sigma_n(1-\gamma)\big)\tilde{\alpha}_{nl} \quad (7)$$

where γ (bounded between 0 and 1) determines the differential influence of scale σ_n upon the individual-specific deviations $\tilde{\alpha}_{nl}$. The scale $\sigma_n$is assumed to be log-normally distributed with its mean normalized to 1 for identification purposes.

The estimation of γ is difficult, and many applications set it to 0 (Czajkowski, Hanley, and LaRiviere 2014, Kassie et al. 2017). The utility coefficients then take the simpler form:

$$\beta_{nl} = \sigma_n \alpha_l + \sigma_n \tilde{\alpha}_{nl} = \sigma_n \alpha_{nl} \tag{8}$$

Implying that the impact of σ_n is the same on the means and deviations (Hess and Train 2017).

Attribute nonattendance patterns before and after the nudge were analyzed using coefficient-constrained latent class models (LCM), as discussed in Scarpa et al. (2009). We are using latent class modeling to infer attribute nonattendance from the choices by the individual decision makers as our study design did not collect self-reported statements on attention given to the attributes. The literature is rich with empirical scientific evidence on the appropriateness of LCM in analyzing information processing strategies, attribute nonattendance in particular, in the application of DCEs (Campbell, Hensher, and Scarpa 2011, Lagarde 2013, Scarpa et al. 2009). In this study, the classes imply the clusters based on the patterns of attribute nonattendance before and after the nudge and relate to attendance in choice behavior (attendance heterogeneity) rather than on separating respondents in clusters with different intensities of attribute preferences (taste heterogeneity). The number and type of attributes/services unattended to would decide whether a respondent belongs to a group or not.

LCMs are mixed logits in the form of equation 4. Each element r of set S represents a "class." The utility coefficients β_r are different in each class, and $\pi(\beta_r)$ is the share of the population in class r. β_r and $\pi(\beta_r)$ for all $r \epsilon S$ are the parameters we will be estimating (Hess and Train, 2010). The covariance matrix for utility coefficients is $Cov(\beta) = \sum_{r \epsilon S} \pi(\beta_r)[(\beta_r - \bar{\beta})(\beta_r - \bar{\beta})']/R$ where R is the number of classes, and $\bar{\beta}$ is the mean of β_r over classes.

We estimated the mixed logit model through Hierarchical Bayes (HB) procedures as well (Scarpa et al. 2009, Train 2001). The HB mixed logit model was used to generate posterior estimates that were used to show the distributions of the marginal WTP values for the different services. The Bayesian estimator is more parsimonious than the maximum simulated likelihood estimator in that it allows for a continuous distribution of heterogeneity in the mean estimated parameter and non-attendance of the attributes (Scarpa et al. 2009). Following the discussions in Gilbride, Allenby, and Brazell (2006), Train (2001), Train (2009), and Scarpa et al. (2009), equation 3 above can be specified with explicit augmentation by the cumulative density of the taste parameters $\beta_n \sim N(b, W)$ where $N(.,.)$ is the multivariate normal distribution as

$$L(y_n|b, W) = \int L(y_n|\beta)\phi(\beta|b, W)d\beta \tag{9}$$

where the priors for the mean and variance are given as $k(b, W) = k(b)k(W)$, $k(b)$ is $N(b_0, \nu_0)$ with extremely large variance (ν_0), the posterior distribution on W, $K(W)$, is inverted Wishart (IW) with $K + N$ degrees of freedom and scale matrix $(KI + N\nu_1)/(K + N)$, and where $\nu_1 = \left(\frac{1}{N}\right)\sum_n(\beta_n - b)(\beta_n - b)'$ is the sample variance of the β_n's around the mean b.

The conditional posteriors or the layers of the Gibbs sampling are specified (Train 2009) as:

$$k(\beta_n|b, W, y_n) \propto \prod_t \frac{e^{\beta_n' x_{ny_{nt}t}}}{\sum_j e^{\beta_n' x_{njt}}} \ \phi(\beta_n|b, W)\forall_n, \tag{10}$$

$$k(b|W, \beta_n\forall_n) \text{ is } N(\bar{\beta}, \frac{W}{N}), \text{ where } \bar{\beta} = \sum_n \beta_n/N \ , \tag{11}$$

$$K(W|b, \beta_n\forall_n) \text{ is } IW(K + N, KI + \frac{N\bar{\nu}}{K+N}), \tag{12}$$

where $\bar{\nu} = \sum_n(\beta_n - b)(\beta_n - b)'/N$.

The first layer (eqn. 10) for each n depends only on data for that person, rather than for the entire sample. The second (eqn. 11) and third (eqn.13) layers do not depend on the data directly, only on the draws of β_n, which themselves depend on the data (Train 2009).

Our interest is examining the distribution of the individual parameters over the sample. Given a sample of P respondents, the individual coefficients can be estimated by:

$$\hat{\beta}_n = \frac{1}{P}\left(\sum_{p=1}^{P} \beta_n^{(p)}\right)$$

Detailed descriptions of the Bayesian procedure are presented, *inter alia*, in Scarpa et al. (2009), Train (2009), Elshiewy, Zenetti, and Boztug (2016), Akinc and Vandebroek (2018), and Bansal et al. (2020).

Results and Discussion

The sample respondents

Our sample composed of both men (73.65%) and women (26.35%). About 85% of the respondents were heads of their respective households. In fact, only 50.4% of the women respondents were heads of their households whereas more than 97% of the male respondents headed theirs. The average respondent in our sample was 42.4 years old, had education of 4.3 years, had a family of 6 people, visited the livestock market about 7 times in a year walking for about 1.2 hours, and owned 1.12 hectares of land (Table 2). The mainstay of livelihood was reported to be farming by 96% of our respondents remotely followed by petty trading (2.29%) and running own small business other than farming (1.04%). Majority (96.35%) of the sample households owned livestock at the time of the survey. In tropical livestock units, the average small ruminant holding per household is only 0.92. This ownership ranges from none to 16.5 units.

Table 2. Summary of the Characteristics of the Sample Respondents

	N	Mean	St. Dv.	Min.	Max.	Kurtosis	Skewness
Age of respondent in years	960	42.4	12.65	10	87	2.82	.48
Education of the respondent in years	952	4.28	4.1	0	30	4.21	.89
Household size	960	5.88	2.22	1	17	3.39	.36
Walking distance to the nearest livestock market (hrs.)	960	1.22	.9	0	4	2.94	.76
Frequency of visit to livestock market in a year	956	6.49	10.83	0	120	27.69	4.2
Small ruminant owned - in TLU	960	.92	1.41	0	16.5	33.32	4.5
Farmland owned by the HH in hectare	952	1.12	.98	0	8.75	12.70	2.32

Reminder-nudge and attribute nonattendance

Table 3 summarizes the key results of the Latent Class Model (LCM) estimations that quantified the probability of individual respondents falling into classes of different attribute nonattendance (ANA) levels. The table compares results before and after the reminder-nudge. Class 1 represents the conventional compensatory substitution of attributes specification (full attendance, fully compensatory class), and class 2 represents the decision rule with the assumption that all services were ignored (total random choice). Class 3 to Class 9 are specifications with one attribute nonattendance each, while the other taste parameters are constrained to be equal across classes. Finally, class 10 to 30 are LCM specifications with two services ignored at the same time. The parameter estimates are constrained to be equal across classes to control for other sources of preference heterogeneity among individuals other than the probabilistic decision rule or heuristics they employ (Scarpa et al. 2009).

Before the reminder-nudge

The first model with nine classes (Model 1_B) showed that class 3 (ignoring market fee only) has the highest membership probability of 0.58 followed by class 8 (ignoring veterinary clinics only, with 0.126), class 9 (ignoring market sheds only, with 0.109), and class 5 (ignoring toilets only, with 0.109). All other classes have membership probability of less than 0.025.

The second before-nudge model (Model 2_B) shows much worse BIC values than Model 1, but better AIC values. Model 2 retains all classes in Model 1 with the addition of all two-service non-attendance combinations, with a total of 30 classes. The class with all attributes attended to has a much higher-class membership probability of 0.094. This could imply that a more flexible specification of the model could better reveal the heuristics respondents employ than a rather parsimonious specification. Most of the one and two attribute nonattendance classes ended up with very small class membership probabilities. There were seven classes with class membership probabilities greater than 0.05. All these classes are related to the fee attribute. Class three (ignoring market fee only) has a membership probability of 0.19. Of the interactions, the class with market fee and sheds ignored (Class 25) has the highest membership probability of 0.16. In the third LCM model (Model 3_B), we dropped the classes with probabilities of membership less than 0.01, while retaining full attendance and complete non-attendance classes. Model 3 has a total of 14 latent classes and the results are comparable with those in Model 2, with a better fit to the data according to both AIC and BIC. Once again, the classes with high membership probabilities are all related to ignoring the market fee (Table 3).

After the reminder-nudge

Model 1_A to Model 3_A are the models estimated on the data generated after the reminder nudge. All common model selection criteria show that the models fit on the after-nudge data are better than the ones fitted on the before-nudge data (Table 3), which shows that the responses are more consistent in keeping with the underlying assumptions of the model. The nudge also enhanced the membership probability of the full-attendance class. Together these indicate that the nudge has increased the compensatory behavior of the respondents. The exploratory estimations (Model 1_A and Model 2_A) show that the introduction of the nudge has also evened out the probabilities of ANA class membership. More interestingly, the probability of membership in the fee-only-ignored class has gone down from 18% (Model 3_B) to 0.8% (Model 3_A). This implies that the heuristics respondents were employing before the nudge was quite deliberate and the reminder nudge has influenced the way they were making choices. Particularly, respondents considered the market fee along with the services characterizing the alternative markets in choosing one.

The payment mechanism in DCEs (in our case market fee) is usually the one subjected to nonattendance (Carlsson, Kataria, and Lampi 2010, Sever, Verbič, and Sever 2019). It is clear that the fee is the source of disutility for the respondents and probably the most hypothetical component of many of the DCEs. It is not, therefore, unexpected that our respondents paid less attention to the fee attribute compared to the services. The membership probabilities of classes for one-attribute and two-attribute non-attendance have now been concentrated into four classes whereas all other classes have probabilities less than or equal to 0.05. These four classes showed high membership probabilities even on the model estimated on responses collected before the nudge. The probabilities that have changed most due to the nudge are the membership probabilities of class 10 (fee & feed ANA), reduced membership probabilities of Classes 3 (fee ANA), 5 (fee & toilet ANA), and 7 (fee & holding shed ANA).

The results of the LCM show that respondents do not comply with the axiom of fully compensatory continuous preferences, but a simple reminder or nudge seems to make the respondents decide more in line with the rationality assumptions of consumer behavior theory. It is clear that respondents have either put more effort in the choice process or were forced to change the relative importance they attach to the different services after the nudge.

Table 3: Latent Class Model Estimates of Probabilities of ANA Classes before and After the Nudge

Class		Before Nudge			After Nudge		
		Model 1_B	Model 2_B	Final 3_B	Model 1_A	Model 2_A	Final 3_A
		Cl. prob.	Cl. prob.	Cl. prob.	Cl. prob.	Cl. prob.	Cl. prob.
1	Full attendance (No ANA)	0.40%	9.39%	12.39%	0.30%	5.34%	17.24%
2	No attendance (Full ANA)	1.30%	0.22%	0.32%	0.60%	3.51%	0.34%
3	Fee only ANA	58.20%	18.69%	17.77%	28.80%	1.19%	0.78%
4	Feed only ANA	1.80%	0.09%		15.10%	0.03%	
5	Toilet only ANA	10.90%	0.83%		9.20%	0.73%	
6	Water trough only ANA	1.70%	0.10%		3.20%	0.07%	
7	Holding shed only ANA	2.30%	0.02%		5.10%	0.13%	
8	Vet clinic only ANA	12.60%	0.20%		14.70%	0.13%	
9	Mkt shed only ANA	10.90%	0.14%		23.00%	0.16%	
10	Feed & fee ANA		7.49%	7.59%		5.16%	14.80%
11	Fee & toilet ANA		6.12%	6.77%		3.80%	2.82%
12	Feed & toilet ANA		0.08%			6.62%	
13	Fee & water trough ANA		5.06%	4.96%		5.75%	7.06%
14	Feed & water trough ANA		0.82%			0.71%	
15	Toilet & water trough ANA		0.13%			1.06%	
16	Fee & holding shed ANA		7.89%	8.79%		12.69%	5.06%
17	Feed & holding shed (ANA)		1.08%	1.14%		0.04%	0.35%
18	Toilet & holding shed ANA		0.35%			0.03%	
19	Water & holding shed ANA		0.50%			4.03%	
20	Fee & vet ANA		12.70%	12.93%		10.83%	16.45%
21	Feed & vet ANA		3.70%	3.81%		0.01%	2.65%
22	Toilet & vet ANA		0.24%			1.61%	
23	Water trough & vet ANA		0.09%			3.10%	
24	Holding shed & vet ANA		0.18%			0.32%	
25	Fee & shed ANA		16.21%	15.41%		25.25%	22.05%
26	Feed & shed ANA		0.06%			0.10%	
27	Toilet & shed ANA		1.90%	2.50%		0.94%	4.29%
28	Water trough & shed ANA		3.19%	3.24%		1.27%	1.34%
29	Holding shed & shed ANA		0.00%			2.69%	

30	Vet & shed ANA		2.53%	2.39%		2.67%	4.77%
	LL	-4005.33	-3974.94	-3974.69	-3947.15	-3904.24	-3919.94
	BIC(LL)	8189.20	8272.62	8162.26	8072.83	8131.22	8052.75
	AIC(LL)	8062.66	8043.87	8011.39	7946.29	7902.48	7901.88
	Df	934	913	929	934	913	929
	p-value	3.7e-1104	2.5e-1102	9.8e-1095	7.6e-1082	3.6e-1075	9.6e-1074
	Class.Err.	0.33	0.62	0.60	0.48	0.55	0.51
	R^2	0.34	0.42	0.41	0.38	0.49	0.45

Reminder–nudge effects on marginal willingness to pay estimates

Mean and marginal WTP values

We started our analysis with exploratory regressions using the conditional logit model in utility space. The coefficients of the conditional logit models served as starting values for the more flexible estimations in willingness to pay space (Scarpa, Thiene, and Train 2008, Train and Weeks 2005). We will report results of estimations of the GMNL model (Fiebig et al. 2010, Keane and Wasi 2012) and the MXL model (McFadden and Train 2000, Revelt and Train 1998) estimated in WTP space. The main intention here is to the see the effect of the *nudge* on the mean and marginal WTP values of the market services.

We estimated four GMNL models where two of them compared before (GMNL_B) and after (GMNL_A) nudge observations. We have also reported a pooled GMNL model along with these four models. No difference is found in the signs of the coefficient estimates of the marginal WTP between the before-nudge and after-nudge models. The magnitudes of the coefficients are, however, considerably different. Mean WTP values of the after-nudge model are less than the mean WTP estimates of the before–nudge model for all, but toilet with no cleaner, services. WTP for toilet with no cleaner was not statistically significant in the before-nudge model (Table 4).

The other two models (GMNL_X and GMNL_X_S) are estimated on the pooled sample, but they both include interaction effects between all attributes and the dummy variable denoting the nudge (Table 4), so as to identify the nudge effect on the mWTP estimates. Because the nudge can also have an effect on the scale parameter, the second model (GMNL_X_S) accounts for such effect on scale, but this does not bring a significant improvement in fit.

Both models with interactions perform significantly better than the pooled model without interactions (a likelihood ratio test has a p-value <0.001) in fitting the data (Table 4). Specifically, the interaction effects are highly significant for fenced market shed, veterinary clinic, holding shed, and watering trough, whereas the feed stall/shop by nudge interaction is marginally significant (Table 4). The nudge has a negative effect on the mean WTP for all these five services. This implies that all services with significant interaction effects had higher implicit prices when preferences were elicited without a nudge, probably because of the simplification strategies employed by respondents generated a systematic upward bias.

Table 4: Generalized multinomial logit estimation results [GMNL] in WTP space

	GMNL_pooled	GMNL_B	GMNL_A	GMNL_X	GMNL_X_S
Mean					
Opt-out	-40.951***	-45.351***	-45.916***	-44.436***	-45.173***
	(2.149)	(5.240)	(5.276)	(3.746)	(3.869)
Fenced market shed (SFEN)	5.506***	8.880***	4.758***	8.606***	8.817***
	(0.423)	(1.729)	(0.998)	(1.324)	(1.361)
Unfenced market shed (SUNF)	1.453***	1.585***	3.043***	1.580***	1.560***
	(0.311)	(0.582)	(0.800)	(0.568)	(0.578)
Veterinary clinic (VET)	6.758***	9.967***	5.889***	9.695***	9.885***
	(0.477)	(1.695)	(1.250)	(1.291)	(1.324)
Resting/holding shed (HLD)	4.101***	6.911***	4.051***	6.696***	6.846***
	(0.391)	(1.352)	(0.680)	(1.034)	(1.060)
Watering trough (WAT)	5.249***	7.718***	4.711***	7.484***	7.654***
	(0.380)	(1.421)	(0.887)	(1.062)	(1.091)
Toilet with cleaner (TCLN)	4.769***	8.398***	6.251***	8.105***	8.320***
	(0.393)	(1.923)	(0.756)	(1.509)	(1.548)

Toilet with no cleaner (TNCL)	2.618***	0.124	2.221**	0.209	0.152
	(0.338)	(0.879)	(1.131)	(0.794)	(0.809)
Feed stall/shop (FDSH)	4.672***	6.319***	5.149***	6.156***	6.275***
	(0.316)	(1.019)	(0.892)	(0.776)	(0.796)
Fee	-1.000	-1.000	-1.000	-1.000	-1.000
	(.)	(.)	(.)	(.)	(.)
<u>Interaction effects with nudge</u>					
Opt_out*Nudge				-2.537*	-1.055
				(1.492)	(1.874)
SFEN*Nudge				-3.714***	-4.015***
				(1.252)	(1.288)
SUNF*Nudge				1.494	1.480
				(0.991)	(0.984)
VET*Nudge				-3.595***	-3.958***
				(1.079)	(1.124)
HLD*Nudge				-2.546***	-2.773***
				(0.917)	(0.948)
WAT*Nudge				-2.632***	-2.910***
				(0.896)	(0.932)
TCLN*Nudge				-1.809	-2.060
				(1.578)	(1.612)
TNCL*Nudge				2.192	2.111
				(1.408)	(1.404)
FDSH*Nudge				-0.842	-1.076*
				(0.592)	(0.622)
<u>Heterogeneity in WTP parameters</u>					
Const	-2.567***	-2.709***	-2.657***	-2.685***	-2.716***
	(0.063)	(0.133)	(0.138)	(0.096)	(0.099)
After					0.056
					(0.043)
Tau					

_cons	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
N	34560.000	17280.000	17280.000	34560.000	34560.000
LL	-8243.390	-4405.077	-3820.024	-8225.138	-8224.294
AIC	16506.779	8830.154	7660.048	16488.275	16488.588
BIC	16591.284	8907.728	7737.621	16648.834	16657.597

Following the observations made from the conditional logit estimations above, we estimated mixed logit models in willingness to pay space. The mixed logit [MXL] models estimated with simulated maximum likelihood resulted in a comparable set of estimates with GMNL. The mean taste parameters in MXL estimations show the relative WTP values of the services and the standard deviations of the parameters show the heterogeneity around the mean WTP.

From the pooled data, we estimated three mixed logit model specifications: model MXL-1 is a standard mixed logit model; model MXL-2 is a mixed logit with all interactions with nudge included; model MXL-3 is a mixed logit with only the four consistently significant interaction terms included (Table 5).

All three models show that sample respondents are willing to pay for all the services at different levels. In all three specifications, veterinary clinics, fenced market sheds, watering troughs, and toilets with cleaners emerge as the four most important services in terms of the implicit prices. Veterinary clinics and fenced market sheds are, in order, consistently the two critically demanded services in the study areas (Table 5).

Model MXL_1 ignores the nudge effect, while models MXL_2 include all nine random parameter interactions between attributes and nudge. A likelihood ratio test shows that these 18 additional parameters cannot be jointly set to zero without a significant loss of fit (p-value <0.001). Model MXL_3 reduces the number of random parameter interactions to the most significant eight, with a similar conclusion in terms of restrictions when compared to MXL_1. We, hence, conclude that the nudge has an effect on the random distribution coefficients of the marginal WTPs. Model MXL_3 can also be compared to model MXL_2 as it includes only a subset of four of the nine possible interaction effects for a total of ten parameters restricted to zero (while it involves ten restrictions to zero when compared to MXL_1). All these joint restrictions emerge as rejected by the data, so MXL_2 is the best performing model. Note though that two attribute interactions with nudge are insignificantly different from zero in both mean and standard deviation (opt-out and TNCL).

All other interactions show, either significant effects only on the mean (SFEN and VET), but not on their spread, or only on the spread (TCLN and FDSH) and these imply and increase in dispersion of mWTP values, but the same mean as those elicited without nudge. Only for three attributes (HLD, WAT and SUNF) we observe significant differences from nudging on both mean and variance of the marginal WTP.

Interestingly, while in the models with interactions with fixed coefficients (GMNL_X and GMNL_X_S) all significant effects of nudging on mWTP estimates emerged as negative, in the random parameter models we observe one attribute (unfenced market shed, SUNF) with a significant and positive effect of nudging on the mean mWTP. The effect nearly doubles the magnitude of the mean estimated without nudge. Such attribute has an insignificant effect in the fixed parameter models. So, allowing for randomness of parameter in the nudge effects shows that such effects are mostly negative, but not always so.

The basic mixed logit model has revealed that there is unobserved heterogeneity in the mean WTP values across all services. In MXL-2, most of the nudge by service interactions also show presence of unobserved heterogeneity in mean WTP values. In MXL-3, only one [vet clinic * nudge] of the four interactions does not show any unobserved heterogeneity implying that the mean WTP explains the preference of the sample population uniformly (Table 5). Generally, the magnitude of the unobserved heterogeneity in the mean WTP values has decreased in the model with the selected interactions compared to the standard mixed logit model.

Table 5. Parameter Estimates of Mixed Logit Model in WTP Space

	MXL_1		MXL_2		MXL_3	
	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.
Mean WTP						
Opt-out	-57.937***	26.321***	-61.834***	28.711***	-56.187***	24.943***
	(3.852)	(2.362)	(5.877)	(3.303)	(3.706)	(2.226)
Fenced market shed (SFEN)	5.707***	4.428***	8.592***	4.688***	6.560***	4.188***
	(0.451)	(0.505)	(1.286)	(0.653)	(0.593)	(0.53)
Unfenced market shed (SUNF)	1.677***	3.219***	1.199**	3.431***	1.765***	3.096***
	(0.328)	(0.504)	(0.549)	(0.605)	(0.342)	(0.505)
Veterinary clinic (VET)	6.921***	3.410***	9.356***	3.638***	7.626***	3.276***
	(0.489)	(0.406)	(1.207)	(0.511)	(0.597)	(0.406)
Resting/holding shed (HLD)	4.302***	1.352**	6.220***	0.161	4.943***	0.102
	(0.394)	(0.557)	(0.927)	(0.781)	(0.491)	(0.877)
Watering trough (WAT)	5.266***	1.365***	7.249***	1.300**	5.791***	0.837
	(0.376)	(0.48)	(1.001)	(0.629)	(0.505)	(0.892)
Toilet with a cleaner (TCLN)	4.692***	2.216***	8.036***	0.673	5.597***	1.682**
	(0.394)	(0.529)	(1.452)	(1.114)	(0.522)	(0.701)
Toilet with no cleaner (TNCL)	2.622***	2.984***	0.561	3.566***	1.799***	3.314***
	(0.348)	(0.475)	(0.725)	(0.548)	(0.408)	(0.439)
Feed stall/shop (FDSH)	4.707***	2.378***	5.956***	2.228***	4.936***	2.384***
	(0.321)	(0.29)	(0.725)	(0.41)	(0.376)	(0.29)
Fee (negative)	-2.409***	0.249***	-2.499***	0.17	-2.392***	0.187**
	(0.065)	(0.065)	(0.094)	(0.11)	(0.066)	(0.074)
Interaction effects						
Opt_out*Nudge			-1.917	1.078		
			(2.053)	(5.264)		
SFEN*Nudge			-3.570***	1.758	-0.838	2.917**

		(1.245)	(1.778)	(0.618)	(1.241)
SUNF*Nudge		2.263**	2.646**		
		(1.008)	(1.213)		
VET*Nudge		-2.582**	0.429	-2.443***	0.015
		(1.043)	(1.433)	(0.828)	(1.272)
HLD*Nudge		-1.683**	3.129***	-1.211**	2.737***
		(0.826)	(0.622)	(0.526)	(0.492)
WAT*Nudge		-1.820**	2.438***	-1.804***	1.908**
		(0.852)	(0.734)	-0.656	(0.765)
TCLN*Nudge		1.894	3.552***		
		(1.559)	(0.784)		
TNCL*Nudge		2.15	0.009		
		(1.367)	(1.051)		
FDSH*Nudge		-0.675	2.747***		
		(0.597)	(0.651)		
N	34560	34560		34560	
LL	-7835.962	-7808.086		-7822.599	
AIC	15711.924	15692.172		15701.199	
BIC	15880.933	16013.29		15937.812	

Distributions of the marginal WTP values

To describe the effect on the distribution of the marginal WTP (mWTP) values, we derived individual level mWTP values using the HB-MXL Models. The focus of our discussion will be the services that showed considerable preference variations between before and after reminder.

Focusing on the four services whose WTP was observed to be affected by the nudge, the probability density function of the marginal WTP shows that the nudge has shifted the distribution to the left for the fenced market shed, veterinary clinic and watering trough (Figure 2). These are dominant services as observed in the GMNL and MXL estimations in WTP space and the nudge seems to have played a role in reducing the WTP across all the services. For holding shed, the distribution does not appear to be stable (Figure 2).

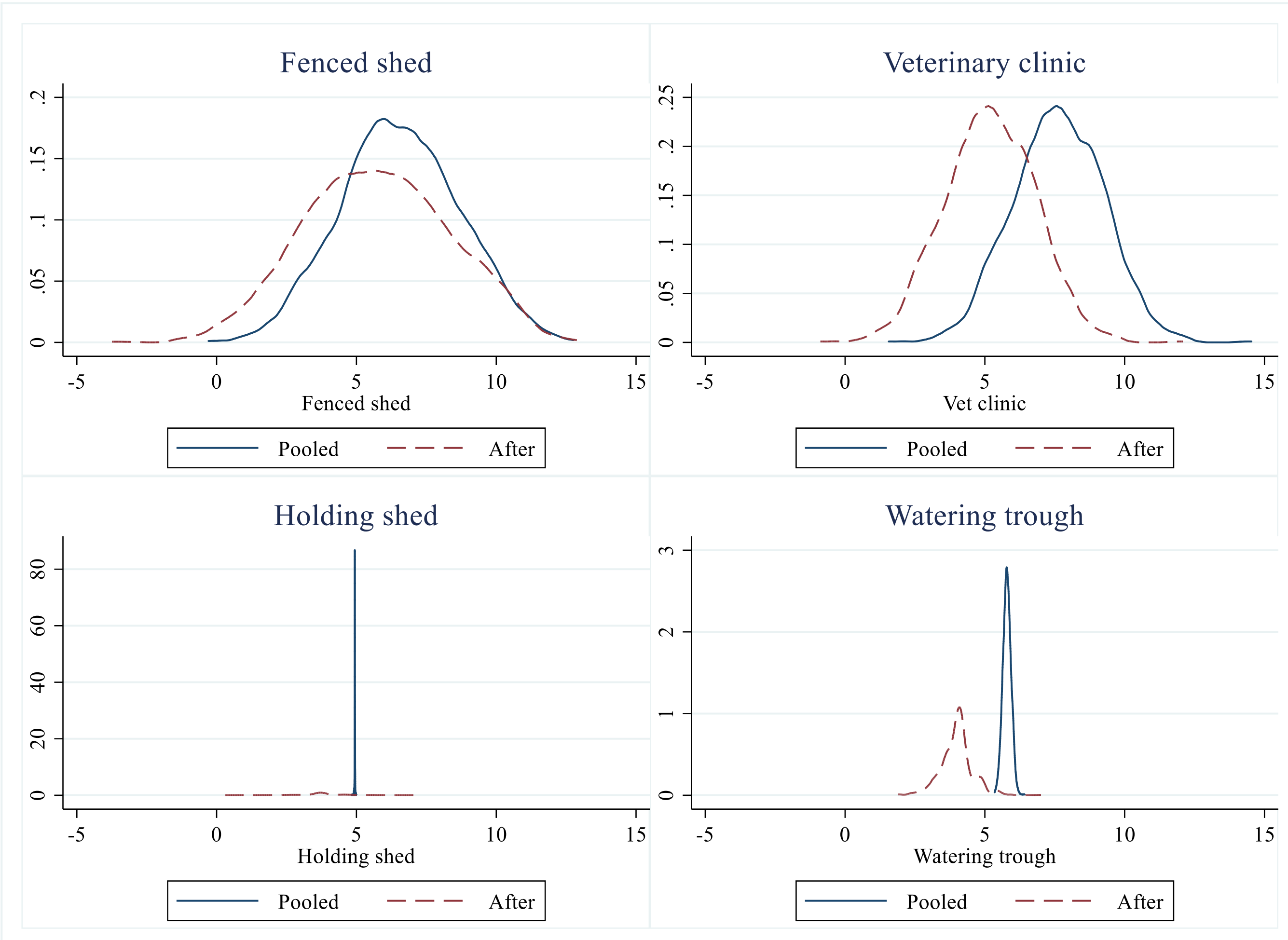

Figure 2: Posterior marginal WTP before and after reminder (10000 draws)

We have also estimated Bayesian mixed logit models with and without attribute by reminder-nudge interactions in WTP space. The simulated maximum likelihood and Bayesian estimators are employed to show the robustness of the results. The parameter estimates of the two estimation methods are not expected to be different especially for data with panel structure (Elshiewy, Zenetti, and Boztug 2016, Haan, Kemptner, and Uhlendorff 2015, Huber and Train 2001, Regier et al. 2009) and our results are no exception. Therefore, we are not going to present and discuss the coefficients of the mixed logit estimated using Bayesian estimator. Instead, we will briefly discuss the posterior distribution of the marginal WTP values using kernel density distributions.

The Bayesian estimation results of the mixed logit are included in the supplementary materials available on the journal's website. We estimated the MXL_1 and MXL_3 models using Bayesian procedures. We extracted the marginal WTP distributions from the MXL_3 where the WTP estimates took into account the nudge effect. Only the distribution of the marginal WTP for watering trough shows a considerable and negative effect of the nudge. The marginal effects on the veterinary clinic and holding shed are clearly leptokurtic with the mean close to zero (Figure 3).

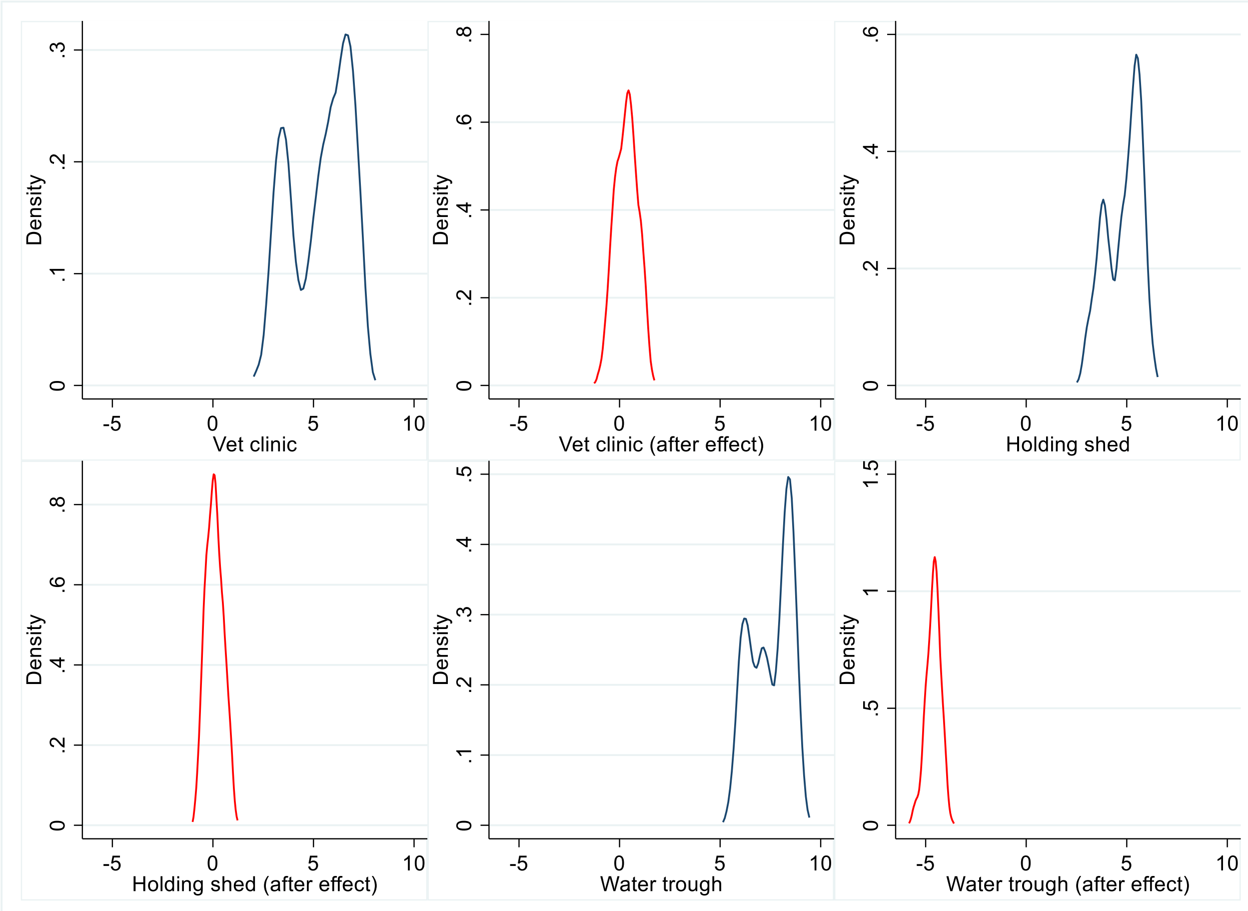

Figure 3: Posterior marginal WTP based on Bayesian mixed logit (10000 draws with 2000 burns)

The distributions mapped together in Figure 4 show that the attention reminder has considerably decreased [shifted to the left] the marginal WTP of water trough. Marginal WTP values for veterinary clinic and holding shed do not vary compared to the values for the estimation on the pooled data that ignored the nudge. Generally, it is clear that the nudge has affected the decision behavior of respondents and changed the distribution of their marginal WTP for the services in some cases considerably.

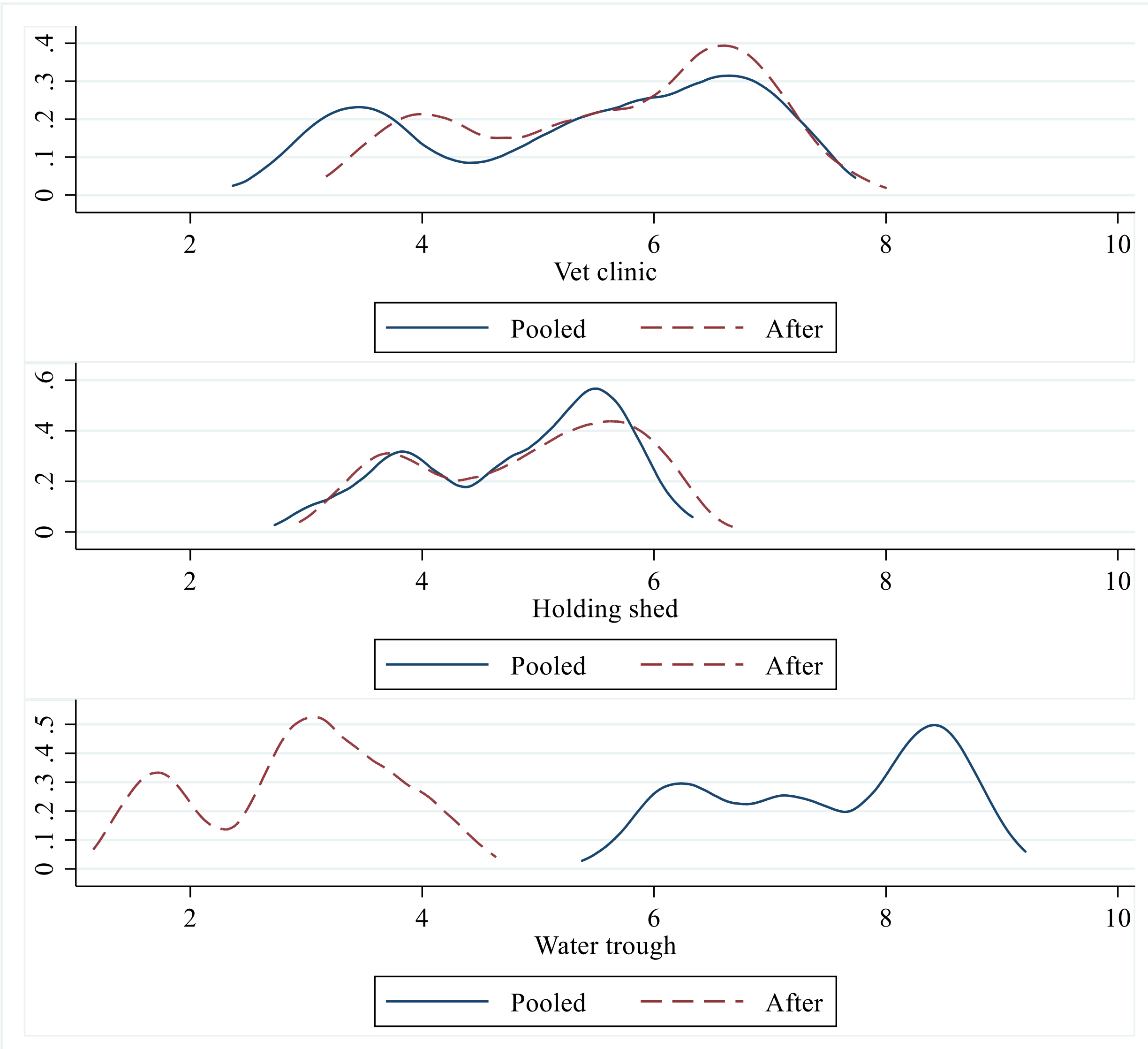

Figure 4: Posterior marginal WTP based on Bayesian mixed logit (10000 draws with 2000 burns)

Conclusion

Development of the livestock markets is an investment that Ethiopia needs to make as part of the effort to transform agrarian livelihoods. This investment needs to be evidence-based to ensure that the limited resources of the country are used efficiently. This study contributes in many ways towards the national agricultural growth and transformation agenda. We have shown that rural communities are willing to pay for the services they identified to be available in the livestock markets. The GMNL and MXL models we estimated consistently showed that veterinary clinic, fenced market shed, watering trough, toilet with cleaner, holding shed, and feed stall/shop, in order, are the services they are most interested and would like to have in the livestock markets. Prioritization of the investment that needs to be made to develop livestock markets and determination of the service charges need to take these preferences and WTP values into consideration.

These preferences were found to be consistent even after the introduction of a reminder nudge meant to influence the heuristics the respondents apply in the decision making process. A latent class modelling revealed considerable differences among respondents in attentions given to different attributes of the rural livestock markets due to the nudge. In particular, the attribute nonattendance latent classes estimated on before and after nudge data show that there is considerable difference in the membership probabilities of respondents in classes of non-attendance to market fee. The fact that respondents notice that they do not have to pay the specified amount could be the reason why they ignore it in the first place. When nudged to consider all attributes, they might therefore look into the fee attribute more seriously than otherwise implying increased compensatory decision-making behavior. The reminder nudge generally evened out attribute non-attendance in the decision making process.

We also showed the effect of the nudge on mean and marginal WTPs for the services through GMNL and MXL. The nudge has improved the goodness of fit of the econometric models. The different models estimated in WTP space show that the WTP for veterinary clinics, fenced sheds, water troughs, and holding shed varied considerably between the before-nudge and after-nudge estimations.

The probability density distributions of the coefficients estimated with mixed logit in WTP space with all interactions show that the nudge seems to have effect on the marginal WTP values of market sheds, veterinary clinic, holding shed, water trough, toilet with a cleaner, and feed stall/shop. The effect is positive [increasing the magnitude] only in the case of unfenced market and it has a negative effect on the other services.

Based on our results we argue that reminding respondents of the need for considering all attributes might not have any theoretical justification yet. However, it is apparent that the nudge has increased the concordance of the models to the underlying economic theory assumptions of the choice model. Our research has also shown that decision makers in very remote areas do behave just like any other consumers in adopting cognitive strategies, including attribute nonattendance, to simplify the choice process.

We believe that this paper addresses an interesting question with regard to the effect of a simple reminder nudge on attention and willingness to pay for attributes in a discrete choice experiment setup. However, there are a number of interesting questions that need to be addressed through a more focused research. First, empirical evidence needs to be generated on how nudges shall be designed and introduced in discrete choice experiments. We are not aware of any research in this line and the limited effort to address the decision making process in DCEs focused only on reducing hypothetical bias, e.g., (Bello and Abdulai 2016, Tonsor and Shupp 2011). Second, what are the implications of the manipulability of heuristics in stated choices for modeling and development/policy decision making? The limited effort in describing the level and causes of cognitive strategies to simplify choice decisions needs to be enhanced and evolve to identifying strategies to manipulate cognitive strategies of individuals.

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