Attribute-specific impacts of stated non-attendance in choice experiments

Attribute Specific Impacts of Stated Non-Attendance in Choice Experiments

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Abstract

In this paper, we generalize existing approaches to the treatment of stated attribute non-attendance data in discrete choice experiments by allowing attribute specific impacts. We implement this approach by employing an extended hierarchical Bayes logit model specification. To illustrate this approach, we consider data collected to examine Indian consumers' preferences for traditional aromatic rice varieties. Our results regarding stated attribute non-attendance reveal that, our new approach shrinks marginal utilities of non-attenders substantially compared to stated attenders, with significant differences in the shrinkage between some of the attributes. In addition, our results reveal the way in which non-attendance of attributes interact with each other and the impact that this has on the distribution of willingness to pay estimates.

JEL Classification: C81, D12, Q13.

Keywords: Discrete choice experiment, stated attribute non-attendance, aromatic rice

1 Introduction

Within the discrete choice experiment (DCE) literature it is implicitly assumed that a respondent will use all information presented to them in the form of attributes when arriving at a specific task choice. However, this assumption has been questioned by a growing number of researchers and there is increasing evidence indicating that the use of all information provided is far from the norm (see Scarpa et al., 2010, 2013, Kragt, 2013, and Chalak et al., 2016). The label given to this form of behaviour within the DCE literature is attribute non-attendance (ANA). ANA can either be viewed as a serious problem impacting model estimates derived from a DCE or it can be considered as a source of information on how an individual engages with a DCE that needs to be taken into account at the point of model estimation to improve model performance. Either way a number of approaches have emerged in the literature to examine, identify and take account of ANA. For example, Balcombe et al. (2016) and Caputo et al. (2017) consider how debriefing questions, referred to as stated ANA (SANA) can be used to assess and deal with this issue within econometric specifications. Alternatively, Balcombe et al. (2015) have examined how SANA relates to ANA as measured using eye-tracking data. There is also another strand of the literature that indirectly assesses the ANA by inferring it econometrically (see Scarpa et al., 2013, Kragt, 2013, and Caputo et al., 2017).

In this paper, we employ de-briefing questions to collect data on SANA. There are two methods that have gained traction for examining SANA: serial and task SANA. The first approach waits until all choice tasks have been completed before asking de-briefing questions about attribute use (e.g., Balcombe et al., 2015, 2016). The second approach asks de-briefing questions after each choice task (e.g., Caputo et al., 2017). We follow Balcombe et al. (2015, 2016) and employ the serial approach and collect SANA de-briefing data at the end of the choice task sequence.

There is now consensus that if somebody states they ignore a given attribute, this does not indicate that they have zero utility for that attribute, nor that they necessarily ignore it when completing tasks. However, a consensus is yet to emerge about how best to integrate this information into DCE model estimation. In this paper, we take the view that SANA is much more likely to capture attribute disengagement. This is not the same as absolute ANA. Therefore, we do not consider using a zero value for an attribute to be appropriate, an approach that has been criticised in the literature as it implies setting the marginal utility of a specific attribute to zero which may well give rise to biased model estimates (Chalak et al., 2016). Instead, we follow Balcombe et al. (2015, 2016) and use the de-briefing data to condition parameter estimates. However, we go beyond what has previously been implemented in the literature by conditioning each of our model attributes individually as opposed to at the model level. Like Balcombe et al. (2015, 2016) we employ a "shrinkage" parameter to condition all of our marginal utilities (or willingness to pay) for all attributes. But, unlike the earlier literature, we place a shrinkage parameter on each specific attribute whereas previous research has employed a common shrinkage parameter. To implement this approach, we adopt a hierarchical structure within a Bayesian framework that allows for the econometric identification of different levels of shrinkage across the attributes.[1]

To demonstrate this approach, we use a new DCE data set that has been collected in the Indian state of Odisha to examine consumers preferences for traditional aromatic rice varieties (TARVs). In general Indian aromatic rice varieties are categorized as Basmati or conventional aromatic rice varieties (CARVs), and non-Basmati indigenous traditional varieties (TARVs). CARVs are typically characterized as being slender, white and with a kernel length of more than 6mm. In contrast, TARVs differ on the basis of characteristics such as smaller kernel dimensions, as well as intensity of aroma, fluffiness and palatability (Singh et al., 2000). In addition, TARVs are typically cultivated without the use of chemicals and pesticides.

Currently, CARVs are the dominant aromatic rice of choice in India in large part because policy makers encouraged farmers to cultivate CARVs in order to increase production (Singh et al., 2000, Singh et al., 2006, Das, 2012). But, the increased importance of CARVs and associated increase in the use of chemical inputs and irrigation have resulted in negative environmental impacts (Das, 2012, Brainerd and Menon, 2014). The significant displacement of TARVs in rice production has in turn reduced the genetic diversity of rice, especially since TARVs have existed for many generations and have evolved and adapted to varying abiotic and biotic ecosystem constraints (Deb, 2014, 2017). There is, therefore, good reason to maintain the cultivation of TARVs as the genetic diversity they provide may prove important in the development of new varieties. Indeed, Choudhury (2017) reports that farmers in Odisha who grew TARVs withstood the effects of cyclones that hit the state in 2013 and 2014 better than the growers of CARVs.

Finally, although TARVs provide lower yield in comparison to CARVs, they can in principle yield greater economic returns for farmers because they may be sold at a significant price premium (Marothia et al., 2007). There is also evidence to suggest that TARVs may well offer consumers more desirable product characteristics. For example, an organoleptic study conducted in India by Bhonsle and Krishnan (2010) showed that size, shape, aroma, nutritional value and appearance are important characteristics for consumers and their results indicated that consumer demand would be strong for TARVs. Also, with increases in income levels, middle and high income consumers in India focus on the quality of their diet especially in relation to rice which may well favour an increase in consumption

[1] We implement our model using the open source program 'Stan' http://mc-stan.org/ which estimates models using Hamiltonian Monte Carlo (HMC) methods. HMC provides substantial advantages over competing Bayesian Algorithms, not least in that we are able to easily disseminate the code used to estimate the model in this paper.

of TARVs (Marothia et al., 2007, Calingacion et al., 2014, Custodio et al., 2016).

In an effort to better understand consumers' preferences for TARVs a DCE was designed and implemented using face-to-face interviews in Odisha. We employed a DCE because TARVs are currently sold unpackaged and unsorted in sacks or big containers without any effort to provide information to consumers about various aspects of the product. In contrast, CARVs are in sold using a brand and in packages which allow a higher price to be charged. Thus, although we can observe consumers purchasing TARVs, there is little understanding of what information, at the point of purchase or during cooking and consumption, drives their choice and what product information consumers would value if TARVs were to be sold in a manner that is similar to CARVs. Thus, our DCE aims to reveal consumer preferences for specific attributes of TARVs that can be used to enhance marketing, for example used as information on labels on packaged TARVs, and lead to increases in demand.

Our DCE makes three contributions to the literature. First, as already explained, we introduce an extension to the existing literature with regard to how we econometrically deal with SANA data. Second, we contribute to a small but growing literature examining DCE ANA in a developing economy context e.g., Nguyen et al., (2015), Bello and Abdulai (2016), and Ortega and Ward (2016). Third, our DCE is the first study to examine consumer preferences for attributes of TARVs.

2 Choice Experiment Design

2.1 Identification of Attributes

Identification of the attributes relating to consumers' preferences for TARVs began with a review of the DCE literature on rice in general. This was then followed by a series of qualitative studies including focus group discussion, in-depth interviews and verbal protocol analysis (Green, 1995).

There are no existing DCE studies examining consumer preferences for rice TARVs specifically. Existing studies of consumers' preferences for rice have a rather eclectic focus, resulting in substantial variation in the type of attributes used. For example, Ujiie (2014) considered consumer preferences for eco-labelled rice in Japan, Aoki et al. (2017) examined consumer choices when offered rice from two countries, Su et al. (2017) studied attitudes towards marketed rice subject to improved insect control as well as storage management and Qing et al. (2017) examined how the use of an eco-label on rice products changed consumer willingness to pay (WTP) for specific products. In all of these cases price is the only common attribute which is not surprising as the focus of each piece of research is different: country of origin, storage management and eco-labels.

The study of most relevance to ours is a study of rural and urban consumers in Brunei by Galawat and Yabe (2010) who focused rice as a product to be consumed, employing the following attributes: colour; grain size; texture; taste; smell; health hazard awareness; origin and price. Galawat and Yabe (2010) found that urban consumers preferred white, long grain, non-glutinous, aromatic and organic attributes whereas rural consumers preferred white, glutinous, sweet and organic attributes. The hedonic study of rice grain quality study by Cuevas et al. (2016) discusses and empirically examines consumer choice based on rice product characteristics employing attributes at the point of purchase such as such as grain size and grain shape.

There are also non-DCE studies that have examined consumer preferences for rice. For example, aroma is considered to be the most preferred attribute for rice in India followed by taste, shape, size, tenderness, colour and chemical use in production (Rani et al. 2006, Srivastava and Jaiswal, 2013). Within the literature aroma is typically classified as semi-aromatic, aromatic and highly aromatic, whereas size is classified as medium and short grained and shape as normal, slender and round (Das 2012).

This brief review highlights that most studies indicate that consumer preferences for rice depend upon a mix of price, physical appearance, post-cooking characteristics and production.

We assess the actual attributes considered by consumers when purchasing TARVs, using three qualitative techniques to uncover latent dimensions of consumer preferences.

We first used in-depth interviews using questions relating to preferences for rice attributes as well as aspects of buying, store format, and knowledge of use of chemicals and pesticides during cultivation. We then employed focus groups to ask respondents general questions with discussions of respondents' preferences for attributes, consumption frequency and their perception about the absence of chemicals and pesticides during cultivation. Finally, we used verbal protocol analysis (i.e., thinking aloud) where participants verbalized their thoughts about their decision

The recruitment of respondents started inside various retail outlets after observing respondents purchasing aromatic rice.[2] Recruitment continued for two weeks with those who consented to participate in the survey, contacted later by telephone for a suitable date, time and place for interview, discussion or observation. We recruited 22 respondents and they where allocated on the basis of a lottery to a specific research method.[3]

The verbal protocol analyses, showed that respondents evaluated physical attributes by touching, feeling and smelling TARVs consistent with the result of focus group discussion and in-depth interviews, where the respondents revealed the same evaluation process to determine the quality of TARVs. In summary, the qualitative analysis revealed that respondents consider price, age, colour, cleanliness, size, shape, aroma, tenderness and the use of chemicals.

Based on these findings, we constructed a set of nine attributes and levels shown in Table 1.

Table 1: DCE Attributes and Levels

Attribute	Levels of Attribute
Grain Size	Medium, Short
Grain Shape	Normal, Slender, Round
Cleanliness	Very Clean, Clean, Little Unclean
Age	Old (more than 6 months), New (less than 6 months)
Colour	White, Off-White
Aroma	Highly Aromatic, Aromatic, Semi-Aromatic
Tenderness	Moderately Soft, Soft, Very Soft
Chemicals	Used only for processing after cultivation, Not used at all
Price	45,50,55,65,75 Rupees (US$ Approx, 0.75,0.83,0.92,1.08,1.25) per kg

This set of attributes describing TARVs is more comprehensive than in existing DCEs examining rice. Although the number of attributes might be considered large, our decision to employ this set attributes reflects the fact that our DCE focuses on a product which is very familiar to our survey

[2]Prior oral permission was gained from all retail outlets to allow us to observe customers from a distance.

[3]For more details on the qualitative analysis see Mohanty (2016).

participants. While it could be imagined that the variety might be included in this list, there are more than 50 TARVs and variety is not commonly known to consumers.

As already noted, TARVS are not grown with the use of chemical inputs. As the survey was conducted in India prices were given in Rupees to respondents. The price range of rice for sale in a wide range of retail outlets was initially found to be between 24 and 100 Rupees per kg respectively. However, once we had taken account of the reasons for the variation in the price, we arrived at a slightly narrower price range that adequately covered the price variation of the vast majority of TARVs on sale at the time the survey was conducted (between February and June 2014). Finally, we note that in our analysis, we convert these to US dollar equivalents since the value of the US dollar is more familiar to the majority of readers than the value of the Rupee (the exchange rate at the time the study was conducted was 60 Rupees to 1 US dollar).

2.2 Experimental Design

In this study, a baseline alternative commonly available in all stores was considered as the appropriate form for a 'status quo' option. As noted all respondents in the study were selected because they were observed to be purchasers of TARVs. Therefore, we did not consider it necessary to include an 'opt-out'/'no choice' option. Our selection of attribute levels for the status quo option was determined by examining how TARVs are currently sold and remained fixed across all choice cards.

Given the set of attributes and levels presented in Table 1, a d-optimal experimental design was used (Huber and Zwerina, 1996) for the construction of choice sets. The experimental design was standard in that we followed Scarpa and Rose (2008) assuming a Multinomial Logit utility specification with uninformative priors (i.e. null priors) on all attributes. The design, generated using GAUSS, had 32 choice sets with each containing the status quo option plus two other unlabelled options. We divided the 32 cards into four blocks of eight choice cards. In each choice set, 'option 1' was the 'status quo' option. The final version of the questionnaires was developed after corrections and a pilot study.

In order to help respondents to become familiar with the nature of the task, an example of a choice set was given to them before they undertook the choice tasks. An example of a choice set given to the respondents is shown in Figure 1.[4]

[4] As noted by a referee, it is not uncommon for DCE in developing countries to employ graphics within choice cards to help participants understand the choice being made. However, given the specific nature of the choice task and the sample of respondents employed, this was not considered to be necessary in this study.

Figure 1: Example Choice Card

Table 2: An example of a choice set in the CE

Attributes	Option 1	Option 2	Option 3
Price (Per kilogram)	50 INR	65 INR	75 INR
Aroma	Semi - Aromatic	Aromatic	Highly Aromatic
Cleanliness	Little Unclean	Clean	Very Clean
Color	Off - White	White	White
Size	Medium	Medium	Short
Shape	Normal	Slender	Round
Age of the Rice	New	New	Old
Tenderness	Moderately Soft	Soft	Very Soft
Chemicals	Used for processing after cultivation	Not used at all	Not used at all
I would Choose	☐	☐	☐

2.3 Survey Data

Our DCE was implemented in Odisha a major rice growing and consuming state in India. In Odisha rice is a staple food item and people typically eat aromatic rice on weekends, festivals and special occasions. To implement our DCE, we recruited respondents from two major cities Bhubaneswar (population of 838,000) and Cuttack (population of 665,000) from different income groups categorized by the National Council of Applied Economic Research (http://www.ncaer.org/): lower income, middle income and higher income groups.

As with the qualitative survey work, survey participants were approached after they were observed purchasing aromatic rice at supermarkets, hypermarkets, wet markets or local grocery stores. Their contact details were collected to arrange an interview on a day, time and place convenient for the participants. Out of 328 consumers approached for the survey, 77% agreed to participate giving a total sample of 252 participants (132 from Bhubaneswar and 120 from Cuttack).

Given our experimental design, we then assigned participants evenly across the four blocks for both cities with reference to several key parameters so as to minimise sampling bias e.g., household size, education, age, gender. Participants were subsequently contacted for a face-to-face interview in order to explain the survey instrument. The survey contained questions asking about socioeconomic characteristics, the DCE choice sets plus follow up questions relating to attribute attendance and rankings of attribute importance. Given the nature of the sampling process, it is not the purpose of this study to claim that this sample is representative of all consumers in these cities or the state. Instead, we are interested in preferences of existing buyers of TARVs to see what is driving choice. A summary of the socioeconomic characteristics of the sample respondents is given in Table 2.

Table 2: Sample Descriptive Statistics

Variable	Participants (%)	Variable	Participants (%)
Employment Status		**Educational Level**	
Government Service	70 (27.8)	High School	16 (6.3)
Private Service	53 (21.0)	Higher Secondary	25 (9.9)
Own Business	28 (11.1)	Diploma	25 (9.9)
Student	6 (2.4)	Bachelor's Degree	96 (38.1)
Unemployed	3 (1.2)	Master's Degree	79 (31.3)
Homemaker	72 (28.6)	PhD	11 (4.4)
Any other	20 (7.9)		
Age Range (Years)		**Martial Status**	
Less than 25	9 (3.6)	Married	237 (94.0)
25 to less than 35	52 (20.6)	Single	10 (4.0)
35 to less than 45	76 (30.2)	Widowed	5 (2.0)
45 to less than 55	67 (26.6)		
55 to less than 65	31 (12.3)		
65 and over	17 (6.7)		
Income Groups (Rupees)		**Household Size**	
15,001-25,000	13 (5.2)	Small (1-3)	60 (23.8)
25,001-35,000	34 (13.5)	Medium (4-6)	161 (63.9)
35,001-45,000	33 (13.1)	Large (7-9)	25 (9.9)
45,001-55,000	20 (7.9)	Very Large (10 or more)	6 (2.4)
55,001-65,000	32 (12.7)		
65,001-75,000	31 (12.3)	**Gender**	
75,001-85,000	17 (6.7)	Female	146 (57.9)
85,001-95,000	16 (6.3)	Male	106 (42.1)
95,001 onwards	56 (22.2)		

Average household size of the participants is approximately five, with a minimum of two and a maximum of 14 members compared with an average household size of 4.3 reported in the 2011 Census of India (Indian Government, 2014). Almost all participants belong to the middle class as they have monthly household income of above 15,000 Rupees given the existing distribution of income within the state (Odisha State Government, 2016). In terms of gender the survey has more females than males although at the state level the percentage of females is 49.5% (Indian Government, 2014) reflecting the fact that women are often the shoppers. The age range of participants corresponds reasonably closely to that reported in the 2011 Census although there is an under-representation of the less than 25 years of age cohort.

Finally, during the survey, participants were briefed about the difference between TARVs and CARVs. In addition, they were furnished with an information sheet before the DCE was administered. The specific information provided is reproduced in Box 1:

Box 1: Information on CARVs and TARVs given to survey participants

Explanation Sheet: The Attributes of TARV Each consumer will be given an explanation sheet, which describes the difference between CARV and TARV, before responding to the choice experiments. **CARV:** The CARV are long in size and normal or slender in shape. These varieties are synonyms with Basmati. CARV are cultivated by farmers in Northern India states such as Punjab, Haryana, Uttar Pradesh and Uttaranchal. Farmers use chemicals and pesticides for the cultivation of these varieties. Examples of these varieties are Basmati, Pusa Basmati and Dehradun rice. **TARV:** The TARV are short and medium in size and normal, slender or round in shape. These varieties are grown without any use of chemicals and pesticides. Examples of these varieties are 'Govind Bhog', 'Gopal Bhog', 'Kalajeera', 'Lilavati, and 'Pimpudibasa'.

The information presented in Box 1 is important as it places the type of rice that is the subject of this DCE within context. This is important as TARVs are much less widely consumed than CARVs and as noted there are significant differences in these categories of rice.

3 Model Specification and Estimation

This study uses a 'mixed logit' for estimation because it can approximate a wide range of random utility models, and allows for respondent heterogeneity when making choices. The mixed logit can be implemented within a Classical or Bayesian statistical framework, and within the latter framework the mixed logit is commonly referred to as the Hierarchical Bayes Logit (HBL). In this study, we employ a form of the HBL.

As is standard in the DCE literature, we assume that the utility (U_{ijs}) for the jth person from the ith option in the sth choice set is:

$$U_{ijs} = u\left(x_{ijs}, \beta_j\right) + e_{ijs} \tag{1}$$

where the subscripts are $(option) : i = 1, ..., N; (person) : j = 1, ..., J;$ and, $(choice\ set) : s = 1, ..., S$, x_{ijs} is a $(K \times 1)$ vector of known attributes, z_j is a vector of observed characteristics for the jth respondent (potentially including stated non-attendance information) and $\beta_j = b_j\left(z_j\right)$ is a $(K \times 1)$ vector of marginal utilities for the jth respondent that is conditioned on z_j. As is standard, we also assume an extreme value error e_{ijs} that is independent across, i, j and s implying that the probability of choosing option i for the jth person in the sth choice set is

$$p_{ijs}\left(\beta_j\right) = \frac{e^{u\left(x_{ijs}, \beta_j\right)}}{\sum_i e^{u\left(x_{ijs}, \beta_j\right)}} \tag{2}$$

The form of the utility function specified in this paper is:

$$u\left(x_{ijs}, \beta_j\right) = \sum_{k=1}^{K} \beta_{kj} x_{k,ijs} \tag{3}$$

where the vector $z_j = (m_j, \delta_{1j}, ...\delta_{K,j})$ includes m_j which is the income of the jth individual and $\delta_{kj} = 1$ if the jth individual states that they ignored the kth attribute and zero otherwise.

3.1 Stated Attribute Non-Attendance

The SANA information is integrated into the model by defining:

$$\rho_{kj} = \left(1 - \frac{1}{1+e^{\tau_k}}\delta_{kj}\right) \tag{4}$$

where τ_k is the parameter that is estimated directly and ρ_{kj} is bounded between 0 and 1 by design.

We further define δ_{kj} at $\delta_{kj} = 1$ as

$$\rho_k = \frac{e^{\tau_k}}{1+e^{\tau_k}} \tag{5}$$

In the model that follows, the first attribute will be $-price$ so that in common with much of the literature, we specify a coefficient that is bounded in the positive domain. The parameter ρ_{kj} then becomes a multiplicative parameter for each of the marginal utilities in the following way:

$$\begin{aligned} \beta_{1j} &= \exp\left(\alpha_{1j} - \alpha_0 \ln\left(\frac{m_j}{\bar{m}}\right)\right)\rho_{1j} \\ \beta_{kj} &= \rho_{kj}\alpha_{kj} \text{ for } k = 2, 3, ..., K \end{aligned} \tag{6}$$

where the α_{kj} parameters are assumed to be normally distributed and $\bar{m}$ is sample average income.

Next, we can express our model as follows:

$$\begin{aligned} u\left(x_{ijs}, \beta_j\right) &= \sum_{k=1}^{K} \beta_j x_{k,ijs} = \beta_{1j}x_{1,ijs} + \sum_{k=2}^{K} \beta_{jk}x_{k,ijs} \\ &= \exp\left(\alpha_{1j} - \alpha_0 \ln\left(\frac{m_j}{\bar{m}}\right)\right)\rho_{1j}x_{1,ijs} + \sum_{k=2}^{K} \rho_{kj}\alpha_{kj}x_{k,ijs} \end{aligned} \tag{7}$$

The effect of this model structure is that any stated non-attender has a distribution for the non-attended parameter that is "shrunk" towards zero, in the sense that its mean is moved towards zero, and the parameter distribution is more dense around the mean than compared to the attenders. Importantly, as ρ_{kj} is bounded between 0 and 1, this parameter allows for a range of behaviours. For example, when $\rho_{kj} = 1$ SANA for the kth parameter is irrelevant to the jth respondent's marginal utility for the kth attribute, and at the other extreme when $\rho_{kj} = 0$ this implies that a non-attender has zero marginal utility for the kth attribute.[5]

The approach described extends the existing literature in that earlier models imposed $\rho_k = \rho$ for all k. Although this is in principle an obvious modeling extension it raises model estimation issues. In particular, by allowing ρ_k to vary across attributes, parameter estimation in a unrestrictive (non-hierachical) way is not generally possible, because for many models respondents may have little (or even no) SANA for some of the attributes. In such circumstances estimating ρ_k will be non-identified (in the sense that the likelihood function will be invariant to its value). However, by estimating ρ_k using a hierarchical structure the distribution for ρ_k for attributes where there is little or no SANA poses no problem since the posterior distribution of ρ_k for these parameters will be defined by the hierarchical distribution on which it depends. Importantly, Monte Carlo studies confirmed that if we

[5] The advantages of this multiplicative approach relative to an additive one is discussed in Balcombe et al. (2015).

have values for ρ_k that lead to alternative extremes in behaviour within one data set (i.e., $\rho_k = 1$ and $\rho_k = 0$ for $k \neq k^*$) then such behaviours will lead to posterior distributions for ρ_k, and ρ_{k^*} that are at the respective edges of the unit interval.

The full hierarchical structure is as follows:

$$\begin{aligned} \alpha_{jk} &\sim N\left(\mu_k, \theta_k^{-1}\right) \text{ for } k = 1, 2, ..., K \\ \tau_k &\sim N\left(\tau, \eta^{-1}\right) \end{aligned} \tag{8}$$

along with:

$$\begin{aligned} \alpha_0 &\sim N\left(\bar{\mu}_0, \bar{\sigma}_0^2\right) \\ \mu_k &\sim N\left(\bar{\mu}_k, \bar{\sigma}_k^2\right) \text{ for } k = 1, 2, ..., K \\ \theta_k^{-1} &\sim G\left(\bar{a}_\theta, \bar{b}_\theta\right) \\ \tau &\sim N\left(\bar{\tau}, \bar{\theta}^{-1}\right) \\ \eta^{-1} &\sim G\left(\bar{a}_\eta, \bar{b}_\eta\right) \end{aligned} \tag{9}$$

where a bar above the parameter (e.g. $\bar{\mu}_0$) denotes a value is set by the user and $G(.)$ is the Gamma distribution and $N(.)$ the Normal Distribution.

Finally, the WTP for the kth parameter is:

$$WTP_{kj} = \frac{\beta_{kj}}{\beta_{1j}} = \beta_{jk} \exp\left(-\alpha_{1j} + \alpha_0 \ln\left(\frac{m_j}{\bar{m}}\right)\right) \rho_{1j} \tag{10}$$

Since the WTP is linear in logs with respect to income (m), the parameter α_0 represents the sample average income elasticity of the WTP, which is held constant over attributes and respondents. This is restrictive in the sense that a potential extension of the model could allow for different impacts of income on WTP. However, it is a parsimonious approach to the incorporation of income effects, when the majority of DCE studies do not incorporate income effects at all. The level of income used for each respondent was the mid-point of the respective interval.

Finally, the exact priors used in the empirical model were $\left(\bar{\mu}_0, \bar{\sigma}_0^2\right) = (0, 1)$, $\left(\bar{\mu}_k, \bar{\sigma}_k^2\right) = (0, 9)$, $\left(\bar{a}_\theta, \bar{b}_\theta\right) = \left(\bar{a}_\eta, \bar{b}_\eta\right) = (1, 1)$ $\left(\bar{\tau}, \bar{\theta}^{-1}\right) = (0, 25)$.[6] We experimented with moderate changes in these priors, and obtained relatively small changes in the underlying WTPs and parameter estimates that we report.[7]

4 Results

Our results are presented in the following order. First, we examine the SANA data to see how survey respondents engaged with the set of attributes employed in the DCE. Then, we present model

[6] These priors are relatively diffuse and allowed for the data to dominate. For example, if each of the mean parameters lay on the edge of one standard deviation (3) and the price parameter is 0, then given the design the mean minimum probability of choosing any particular option (over choice sets) is nearly zero (i.e., for nearly all choice sets one of the options will be excluded with near certainty), and the mean maximum probability (over all choice sets) is around 90% (i.e., one of the options is preferred 90% of the time for most choice sets). And, if the price parameter increases, the choices become even more definite.

[7] Additional results are available on request for model specifications employing more diffuse priors.

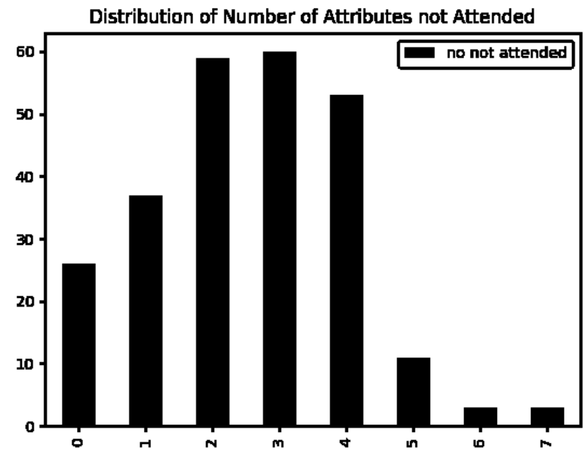
comparison statistics that support the use of the model we report. Third, we examine what the SANA data means in terms of shrinkage parameters. We then consider how this has impacted model specific WTP estimates.

The estimates produced here used the results from 10 chains each with 20,000 iterations, with a warm-up (or burn-in) phase of 15,000 with thinning of 5 to leave 10,000 draws from which to summarise the posteriors. The length of the warm-up phase, which is relatively longer than compared to the collection phase allows the tuning of the underlying sampler to achieve a high degree of efficiency. Thus, although Gibbs Sampling and/or Metropolis Hastings can be implemented with considerably shorter warm-up runs relative to HMC because of the nature of algorithms, once HMC is appropriately tuned it is many times more efficient than these algorithms in most circumstances. Overall our results converged well according to tests that examine the divergence within and across chains.[8]

4.1 Analysis of SANA

We first examine the nature and patterns of SANA. The responses collected are summarised in Figure 2.

Figure 2: Distribution of SANA



As illustrated by Figure 2, most respondents state that they do not attend at least one attribute with many stating that they do not attend multiple attributes. Approximately 10% (27 out of 252) of respondents indicated that they attended all the attributes. In contrast a few respondents stated that they ignored 7 out of 9 attributes. In this case respondents stated that they only choose according to Aroma.

The rates of SANA with respect to each of the attributes are given in Table 3. These values show that the tenderness, chemicals and age attributes were ignored to a much higher degree than the other attributes. Price and colour are very similar with SANA being just below 30% of respondents. Size, shape and cleanliness are ignored by a relatively small proportion of respondents (around 10%).

[8]The Stan code developed will work irrespective of the platform on which Stan runs (R, Python, etc.). Although this data set required quite a high number of iterations to satisfy convergence, it was still many times faster than that required by other code such as the Gauss routines supplied by Train (2009). The computational benefits of using Stan are several: 1) it is compiled in C which is very fast; 2) it uses Hamiltonian Monte-Carlo (HMC) which can be much quicker than Gibbs Sampling and/or Metropolis Hastings algorithms; and, 3) it is able to run multiple chains simultaneously using multiple cores.

The most striking result is that no respondents in the sample claimed to have ignored aroma. This is perhaps unsurprising given the nature of the sampling process in that all survey participants were purchasing aromatic rice. However, as we shall see, this connection does not necessarily mean that just because respondents focused on this attribute, this extended to considering or valuing this attribute as being more important than the others.

4.2 Model Selection

The choice of model we report is based on the comparison of several models. Specifically, we considered a model that contains no SANA data, a model that assumes that impact of SANA is common to all attributes and finally a model in which SANA is used at the attribute specific level. To undertake our model comparison we employed the Deviance Information Criterion (DIC) (Spiegelhalter et al., 2014). Our results revealed that the lowest DIC was recovered for the model that employs the attribute specific SANA specification (as described above). Specifically, our results are: SANA Attribute Specific 790.5; Model Without SANA 888.1; and Common SANA Common 800.3. For this reason, we focus on the model with attribute specific SANA estimates.[9]

4.3 Model Estimates: Shrinkage Estimates

We now examine some of the key parameters of interest, with the SANA shrinkage parameters presented in Table 3.

Table 3: Percentage Stated Attribute Non-Attendance and Shrinkage Estimates (ρ_k)

Attribute	SANA (%)	$\rho_{k,mean}$	$\rho_{k,stdv}$	$\rho_{k,\mathbf{10\%CI}}$	$\rho_{k,90\%\mathbf{CI}}$
Price	28.9	0.35	0.07	0.27	0.44
Aroma	0.0	.	.	.	.
Clean	9.9	0.21	0.07	0.12	0.30
Colour	29.3	0.24	0.06	0.17	0.32
Size	10.7	0.26	0.10	0.14	0.40
Shape	15.4	0.27	0.10	0.16	0.40
Age	43.2	0.21	0.05	0.14	0.27
Tender	61.0	0.26	0.07	0.17	0.35
Chemicals	55.0	0.14	0.03	0.10	0.17

Note: $\rho_{mean} = 0.23$, $\rho_{stdv} = 0.05$

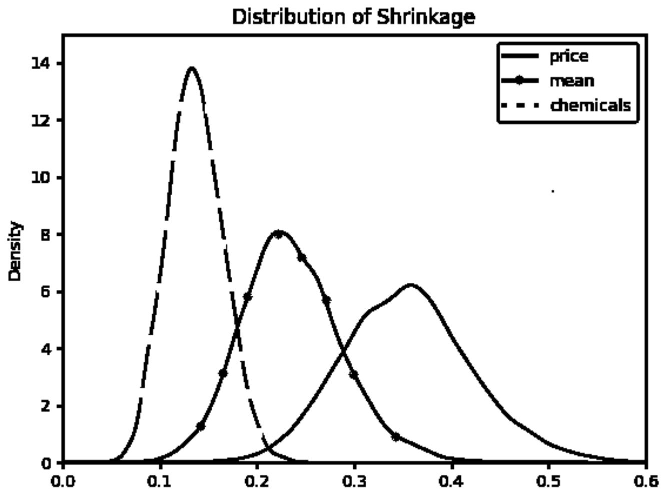
Since all respondents claim to use aroma in making their choices, there is no shrinkage parameter identified for this attribute. The mean and standard deviation for $\rho(\tau)$ as calculated by $\left(\frac{e^{\tau}}{1+e^{\tau}}\right)$, this is the estimate of shrinkage without allowing it to vary by attribute, is as also reported at the bottom of Table 3. It reflects that on average, non-attenders have their marginal utility scaled down to around 23.5% of those for attenders.

Turning to the attribute specific estimates, the attributes clean, colour, size, shape, age and tenderness, all have individual attribute shrinkage values close to the average. However, for the attributes

[9] Results for all model specifications are available on request.

price and chemicals there is a significant divergence, and we also have confidence intervals that do not overlap (by quite a margin). This point is further illustrated by the kernel density plots within Figure 3 which show the posterior densities of estimates of ρ_{price} and $\rho_{chemicals}$ along with the posterior density of ρ which is labelled as the mean.

Figure 3: Distribution of Shrinkage Parameters for Chemical, Price and On Average



The evidence with regard to the extent of SANA therefore reflects our understanding from the majority of previous studies in that SANA does not actually mean that respondents' act in accordance with having zero utility for those attributes that they state they ignore (i.e., they do not ignore those attributes). However, there is a gap between the attributes in this respect, with price SANA having the least shrinkage, and chemical SANA the most. The chemical finding is all the more interesting given that more than half the respondents say that they ignored this attribute. It points to a very large split between consumers with regard to their attitudes towards chemicals. Over half the respondents say they ignore this attribute, and those that state this have only around 14% of the marginal utility for this attribute compared to those that say that they pay attention to this attribute.

4.4 Consumers' WTP for TARVs

For brevity, we concentrate on the posterior distributions for WTP rather the subsidiary latent variables that underpin them. Unlike the majority of studies that report WTPs, we do not simulate these using ex-post simulation. Instead, we take the sampled parameters/WTPs for each individual, thus constructing the estimates using the 252×10,000 values collected from the sampler. Since the WTPs are the ratio of the parameters the moments are not finite even given the log-normal transformation of the price parameter. Therefore, the collected values used the truncated distributions eliminating draws that had WTPs for attributes that were 50% larger than the range of prices used for the study (i.e., with a range of prices of approximately US 50c, draws were excluded if they exceeded a WTP of 75c for a any singular attribute).[10]

[10] Note, this is an entirely legitimate way of imposing inequality restrictions within a Bayesian methodology. Alternatively, rejection steps can be placed within the sampler only accepting draws within the specified range of admissible values.

The WTP estimates for our model are presented in Table 4.

Table 4: Model Specific WTP Estimates With and Without SANA in US $ for 1 kg of Rice

	WTP With SANA		**WTP Ignoring SANA**	
Attributes	*Mean* (*Stdv*)	10, 50 and 90%	*Mean* (*Stdv*)	10, 50 and 90%
Aroma				
Aromatic v Semi	0.19 (0.09)	0.08, 0.18, 0.31	0.16 (0.08)	0.07, 0.15, 0.27
Highly v Semi	0.32 (0.13)	0.16, 0.32, 0.50	0.28 (0.11)	0.14, 0.27, 0.42
Cleanliness				
Quite v Unclean	0.36 (0.16)	0.12, 0.38, 0.57	0.34 (0.12)	0.18, 0.33, 0.50
Very v Unclean	0.45 (0.19)	0.15, 0.47, 0.68	0.42 (0.14)	0.23, 0.41, 0.61
Colour				
White v Off-White	0.27 (0.18)	0.05, 0.27, 0.52	0.29 (0.12)	0.14, 0.28, 0.45
Size				
Short v Long	0.20 (0.11)	0.05, 0.19, 0.35	0.18 (0.09)	0.08, 0.17, 0.29
Shape				
Slender v Normal	0.06 (0.08)	-0.02, 0.05, 0.17	0.06 (0.07)	-0.03, 0.05, 0.16
Round v Normal	0.18 (0.12)	0.04, 0.17, 0.34	0.17 (0.09)	0.06, 0.16, 0.30
Age				
>6 months v <6	0.24 (0.20)	0.03, 0.17, 0.56	0.32 (0.17)	0.11, 0.31, 0.56
Tenderness				
Soft v Moderate	0.16 (0.14)	0.03, 0.10, 0.37	0.24 (0.11)	0.11, 0.23, 0.39
Very v Moderate	0.21 (0.17)	0.05, 0.14, 0.48	0.33 (0.12)	0.17, 0.32, 0.50
Chemicals				
None v Used	0.29 (0.26)	0.04, 0.14, 0.69	0.49 (0.17)	0.25, 0.50, 0.70
Status Quo	0.08 (0.15)	-0.11, 0.07, 0.27	0.07 (0.13)	-0.10, 0.06, 0.24

In Table 4, we give the mean and standard deviations associated with the 10, 50 and 90% percentiles (50% representing the median). Our results are for our preferred model estimated with and without (ignored) the SANA data taken into account. The model was specified such that all of the parameters were *a priori* expected to be positive for the majority of consumers, and indeed this turns out to be the case. For the WTP estimates, in general, the median estimates are slightly smaller than the mean estimates but for most of the attributes they are comparable.

If we begin by concentrating on the WTP estimates that take account of the SANA responses the mean estimate for cleanliness is highest indicating that consumers have a WTP on average of 45c extra to have very clean rice over unclean rice. This is a very large WTP given that the cost of 1kg of rice is around $1 US dollar. One may inquire whether this is realistic, however, we believe that it is as rice does not constitute a large proportion of total expenditure on food and this is reflected in the relatively large WTPs across the board. Moreover, respondents have a high WTP for clean rice because rice does not get cleaned simply by being washed in water. The process is often cumbersome, time consuming and painstaking, and it is boring to segregate from raw rice (paddy), small sandstones, and other outside materials that will not be found in TARVs sold in retail stores.

With regard to the other attributes, we see that the value of clean rice is followed by highly aromatic rice over semi aromatic, followed by lack of chemicals and colour, which in turn are followed by tenderness, size and shape. Interpreting these results in a "classical" sense, we would infer these WTPs to be significantly different from zero. Custodio et al. (2016) suggest that although consumers' preferences for different attributes of rice vary across the culture and country, varying levels of attributes such as; 'tenderness', 'size', 'shape', 'aroma' and 'texture' are usually important.

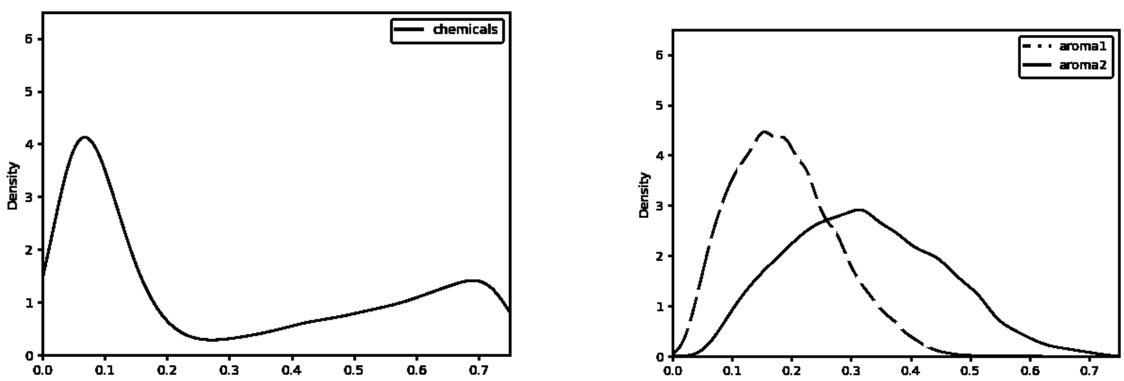
Next, as part of the estimation process, we have also estimated the mean and standard deviation for income elasticity. The mean (standard deviation) income elasticity is approximately 0.56 (0.095) meaning that with every 1% increase in income, we would expect respondents WTP for each of the attributes in question to increase by around 0.5%. While this is technically inelastic this still demonstrates a reasonably large propensity for consumers to demand more of the desirable attributes associated with TARVs as incomes rise. These income responsiveness results are in keeping with those reported by Cuevas et al. (2016) who note that income response depends on income class.

Turning to the WTP estimates that ignored the SANA data we see some interesting changes in the WTP estimates. Most importantly the WTP estimates for chemicals, tenderness, age and colour have all increased by varying amounts. Unsurprisingly, the attributes with the highest level of SANA have seen the biggest changes in WTP i.e., tenderness and chemicals. However, focusing on the means of the WTP distributions only gives a limited understanding of our estimated consumer preference distributions. By examining other quantiles, we can gain a better understanding of the nature of preferences along with an understanding of the interaction between SANA and WTP. What we observe is that SANA of attributes has two distinct effects on WTP depending on the interactions of price SANA and SANA with regard to non-monetary attributes.

In the case of price SANA this tends to extend the tails of the WTP distributions. In contrast SANA of a non-monetary attribute tends to decrease the WTP for that attribute (unless the respondent has also not-attended price). We illustrate these effects with respect to the attributes chemicals and aroma where the WTP distributions are presented in Figure 4.

Figure 4: WTP Distributions

Chemicals (None v Conventional) **Aroma (Aromatic v Semi Aromatic)**



To begin with, the no use of chemicals has both a very large level of non-attendance (55%) and an associated shrinkage estimate that is very low (0.137). In contrast, and as already noted aroma had no SANA. Accordingly, the plot of the WTPs for aroma on the right hand panel of Figure 4 gives a skewed WTP with a long tail to the right. This, in part, reflects the fact that a number of respondents (nearly 30%) said they ignored price, leading to these respondents having very large WTPs. In contrast, the chemical WTP distribution is bimodal, with a group of chemical SANA respondents having very low WTPs, but with another group of chemical attenders but price SANA having very large WTPs to avoid chemicals. Our view is that this result is not simply an artifact of the model. We would contend that both in the market place and in the laboratory, some attributes will invoke polarised responses by respondents. Understanding the potential for this polarisation is an important component for understanding consumer responses in general, but should not be confused with respondents actually ignoring these attributes completely and/or being unwilling to make any tradeoffs with respect to them.

5 Discussion and Conclusions

We present a Discrete Choice Experiment (DCE) examining Indian consumers preferences for traditional aromatic rice varieties (TARVs) and employ an extended approach to stated attribute non-attendance (SANA) to treat data collected from survey respondents, using a Hierarchical Bayesian approach. The significance of ANA in general is well established within the DCE literature and the use of SANA is one of the main approaches to identifying this issue. Our results reveal relatively small but substantive differences between the way non-attendance was related to utility, and that this in turn influences the estimates and distributions of WTP for attributes. Thus, our extension of the existing approaches with how to deal with SANA has not only illustrated how ANA between attributes matters, but that in virtually all cases SANA does not mean actual non-attendance, but rather a "discounted" use of an attribute when making choices. These results further strengthen the view that setting marginal utility of an attribute to zero is methodologically inappropriate.

In terms of the product examined in this study, we have found quite large WTPs for the set of TARVs' attributes. This suggests that consumers are prepared to pay reasonable amounts of money for TARVs, as has previously been suggested in the literature. In addition, the estimates we produced suggested that with increases in income, there will be associated increases in the WTP of consumers to pay for the attributes associated with TARVs.

It has been noted that with the growth in adoption of conventional aromatic rice varieties (CARVs) and other HYVs that there is a need to actively conserve the germplasm of many TARVs. Without these efforts there is an increasing probability that many TARVs may be lost over time (Singh et al., 2000). Furthermore, the cultivation of TARVs can contribute to the conservation of the environment in India as they do not require the same level of chemical input during production as CARVs (Shiva 2016). Indeed, the fact that TARVs are typically cultivated without the use of chemicals can be used to differentiate TARVs from CARVs as a positioning strategy to attract consumers of aromatic rice both nationally and internationally. This can be made a unique selling proposition for TARVs and can be viewed as a comparative advantage of TARVs over CARVs. Thus, there are reasons in terms of supply and demand that strengthen the case for facilitating farmers continued use of or transition towards the production of TARVs (Deb, 2017). Finally, the benefits that could flow to farmers using TARVs are, however, subject to several challenges. As noted by Giraud (2013) the marketing of rice by type is sometimes subject to deception in that highly aromatic rice varieties are mixed with less aromatic varieties. In an effort to avoid this problem and to ensure that consumers are getting legitimate TARVs it may well be appropriate to consider the introduction of quality certification of TARVs. The certification can be used as a differentiation strategy in order to signal to consumers interested in purchasing non-CARVs.

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