Evaluating Preferences for Organic Product Attributes in Nigeria: Attribute non-attendance under explicit and implicit priming task

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Abstract

In this paper, we employ a framework that allows us to jointly model the response to the stated choice component as well as the response to the attribute processing questions for organic product attributes among consumers in Nigeria. The model allows us to make use of respondent reported information on processing strategies and conditions attribute parameters on underlying latent attribute importance ratings, while avoiding the potential endogeneity bias and measurement error problems arising with traditional methods. Using between-sample design, we compare the welfare estimates from respondents under cheap talk and honesty priming treatments. Our results suggest that the HP task leads to lower WTP values by a factor of two relative to cheap talk task, for three of the four attributes identified. Our findings also reveal some modest impacts on implied WTP patterns, with a more realistic difference between the valuations for the attributes, and lower overall heterogeneity relative to the commonly used mixed multinomial logit model.

Keywords organic products, cheap talk, honesty priming, attribute non-attendance, hybrid model

JEL code C18, C25, D12

1. Introduction

Food security remains an issue of growing concern in sub-Saharan Africa (SSA), and in the drive to overcome this challenge, the tendency of governments in the region have been to formulate policies and design programmes to draw farmers into high-input technology (UNEP-UNCTAD, 2008). As a result of this, the use of agrochemicals is now becoming an obvious part of current agriculture production systems in SSA (Sosan et al., 2008). In Nigeria, for instance, an estimated 125,000 to 130,000 Mt of pesticides are applied annually for agricultural pest control, the highest in West Africa (UNSD, 2012). Further, the country's import bill on synthetic fertilizer totaled about USD 2 billion between 2006 and 2010 (UNSD, 2012).

A wide array of agrochemicals exist, all of which are potentially harmful and have been linked to adverse human health conditions and environmental problems (WHO, 1990; FAO, 2004). In developed countries, stringent laws and regulations on agrochemical use exists, and adherence is strictly enforced (e.g., European Union's Food Regulation EC/178 (EC, 2009); United States Environmental Protection Agency (EPA, 1997)). On other hand, in most SSA countries these laws are either non-existent or ineffective and, environmental pollution and other associated problems seem to continue unabated (Sosan et al., 2008). This is particularly true in the context of Nigeria, where the extent of pollution of the agrarian communities (which constitute over 60 percent of the population) by agrochemicals cannot be accurately estimated, as there are neither detailed research on the extent of environmental and health impact nor any effective monitoring process in place (Oruonye and Okrikata, 2010).

In light of these uncertainties, scholars and non-governmental organizations (NGOs) in Nigeria have being advocating for organic agriculture (OA) as a sustainable alternative farming system (Philip and Dipeolu, 2010). OA is considered as one of the approaches that meet the objectives of sustainable agriculture. It is a holistic production management system that avoids the use of synthetic chemicals, growth hormones, antibiotics and gene manipulation, while promoting improved precise standards of production that are socially and economically sustainable (IFOAM, 2008).[1] According to the United Nations Conference on Trade and Development (UNCTAD) and United Nations Environment Program (UNEP) (2008), OA has the potential to offer a range of local and national sustainable development opportunities for Africa in that it integrates traditional farming methods, uses inexpensive locally available natural resources and has positive economic effects on farmers' productivity and income.

Although the Organic Agriculture initiative was introduced almost a decade ago in Nigeria, certified organic farming remains undeveloped, with very low adoption amongst farmers.[2] Many studies have indicated that the potential for the development of certified OA in many African countries is significantly constrained by the general lack of domestic markets and the sole reliance on export (e.g., IFOAM, 2012; UNEP-UNCTAD, 2008). Some recent studies suggest that many supplying countries and farmers of organic produce face huge challenges in entering and benefitting from organic exports in a sustainable way (e.g. Kleeman et al., 2014; Oelofse, et al, 2010).

It is in this context that the need to diversify and explore domestic markets for organic products is now been considered in Nigeria to complement the international market access

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[1] Although in Nigeria, as in other SSA countries, there are a number of traditional farming systems that practice some organic techniques, these systems do not fully meet the production standards for organic farming. Organic products are grown under a well-defined and unique set of certification procedures that give consumers quality assurance and guarantee the products' integrity in the market (IFOAM, 2008).

[2] Currently, of the 11,987 hectares of land under OA less than 60 hectares are recorded as fully certified organic farms and virtually all the organic products are for export (IFOAM, 2012).

(FAO, 2011). The availability of domestic market for certified organic products has the potential to open up more opportunities to farmers already in the business, as well as facilitate the adoption by others. Presently, the market features of organic products in the country shows that it is still in the introductory stage and the product attributes are not well familiar to consumers (Philip and Dipeolu, 2010). The identification of market potentials of the organic product is important, given that future development of the sector will to a large extent depend on consumers' acceptance and demand. Market potentials for organic products are determined by consumers' preferences for the attributes; as reflected by the price premiums (or discounts) they are willing to pay (Chowdhury et al., 2011).

Discovering the right niche market is a complicated task, since preferences highly vary among consumers (Loureiro and Hine, 2001). Studies on consumers' preferences in matured organic markets in Europe and North America are well documented in the literature (e.g. Krystallis et al., 2006; Janssen and Hamm, 2012; Van Loo et al., 2010). However, little information is available in the context of SSA where the organic markets are basically at early stages of development, or even non-existent. Few studies have investigated preferences for attributes of organic products among urban consumers in SSA and have used hypothetical stated preference (SP) approaches. Specifically, contingent valuation methods (CV) have been predominantly employed (e.g. Coulibaly et al., 2011; Philip and Dipeolu, 2010). Although the results from these studies provide some insight into the valuation of organic products, the underlying assumption of taste homogeneity has limited the validity of the estimated models (Train and Weeks, 2005).

Arguably, the hypothetical CE is now the most widely used method in valuing consumer demand for attributes of nonmarket products (de-Magistris et al., 2013). Concerns, however, persist that the willingness-to-pay (WTP) values obtained from this nonmarket valuation technique overstate individuals' true values of the good (Harrison 2006). Hypothetical bias is a well-known shortcoming of CE approach, and studies have focused on the development of different *ex-ante* mitigation strategies.[3] For example, de-Magistris et al., (2013) proposed a new type of *ex ante* calibration approach termed "honesty priming'' (HP), along the same line as Jacquemet et al., (2011). In particular, the authors compare the effect of cheap talk script (CT) (Cumming and Taylor, 1999)[4] and HP on consumer's WTP for sustainability-related labels (''organic'' and ''food miles'') under hypothetical and non-hypothetical CE. The results indicate that the CT script had no effect on triggering sincere bidding, but that the HP improve the disclosure of true preference in hypothetical CE, but not in non-hypothetical settings. Although, there is general agreement that hypothetical bias exists, there is little consensus on the best mitigation strategy to adopt.

Meanwhile a growing body of empirical evidence suggests that accounting for respondents' attribute processing strategy is of significance for both market share prediction and welfare estimates (e.g., Scarpa et al., 2013). In particular, findings show that respondents may follow a large variety of decision rules to simplify otherwise complex decisions (Hensher 2006). Many of these simplified decision rules, or "heuristics," result in non-attendance to certain attributes (ANA). Within the contributions to date, some surveys include self-reported statements on ANA (e.g., Hensher 2006; Carlsson, et al., 2010); others infer ANA behavior from the data through advanced model specifications (e.g., Hess and Hensher, 2010). Empirical

[3] Broadly, two strategies have been developed to attenuate bias in hypothetical settings, namely: (i) an *ex ante* mitigation approach; and (ii) an *ex post* certainty scale calibration approach. The latter allows respondents to express their confidence about WTP with follow-up questions (e.g., Fifer et al., 2014). However, Ready et al., (2010) reveal that this approach is highly complex in CEs having more than two options per choice scenario; which is the case in our study. Thus, the focus in this paper is on the *ex-ante* mitigation approach.

[4] Several studies demonstrate its usefulness by finding a lower marginal WTP in the cheap talk version of a survey (e.g. Cummings and Taylor, 1999; Chowdhury et al., 2011). Other studies suggest that, the script does not have any effect (e.g., Brummet, et al., 2007), or it actually increases the bias, depending on its context, length, structure, and the amount paid (Aadland and Caplan, 2003).

evidence show that there is no one-to-one correspondence between stated processing strategies and actual (i.e. revealed) processing strategies (e.g. Hess and Hensher 2010). Drawing inference of ANA on observed choice responses represents a valuable alternative and is the focus of many studies (e.g. Hess and Hensher, 2013; Scarpa et al., 2013). The motivation for steering clear of stated attribute processing strategies during model estimation is guided by three main reasons. First, there are arguably issues with endogeneity; that is, by conditioning the modeled choice process on stated processing strategies, a correlation between respondent reported processing strategies and other unobserved components could lead to biased parameter estimates. Second, collecting additional data on stated non-attendance complicates survey design and lengthens survey duration and hence cost. Finally, such statements might be affected by respondent inaccuracies (measurement error) in perception and recall, and eventually be both uninformative and invalid.

However, Hess and Hensher (2013), argued that the respondent reported data on processing strategies may still contain valuable information, but that such data should not be used deterministically as an error free measure of ANA. Rather, one should recognize that such data are simply a function of respondent-specific perceived attribute importance. In this respect, Hess and Hensher (2013) proposed a hybrid model framework which still allows the use of respondent reported information on processing strategies, while avoiding the risks arising from traditional methods. In particular, respondents' answers to information processing questions are treated as dependent rather than explanatory variables, that way preventing risks of endogeneity bias as well as avoiding the use of the answers as error free explanatory variables.

In this paper, we use recent survey data from Nigeria on consumers' preferences for organic products to test whether there exist a statistically significant difference in welfare value estimates obtained from two *ex-ante* calibration methods: CT, which is considered an explicit approach and HP, an implicit technique. Specifically, we employ the hybrid model framework to explicitly address the potential endogeneity bias that arises from correlation between respondent processing strategies and other unobservable components in ANA treatments, while exploring the effect of priming tasks on delivering WTP values for organic product attributes. Our study builds on previous studies in two major ways. First, it expands on de-Magistris et al., (2013) in that in addition to observed choice responses, we also take into account respondents' attribute processing strategies. To our knowledge, with the exception of Hess and Hensher (2013) in transportation discipline, we are not aware of any study that has examined the implications of the use of this adaptive decision strategy within the choice modeling structure, whilst systematically addressing the issue of concordance between stated and inferred ANA. Yet this seems an important question to answer, as it has implications for survey design and operation. Second, in contrast to de-Magistris et al., (2013), we examine respondents' valuation of both environment- (public) and health-related (private) attributes of organic food products. This information is especially relevant to producers in identifying target markets and product pricing, particularly in SSA.

The rest of the paper is structured as follows. The next section gives an outline of the econometric framework. This is followed in section 3 by a description of the survey design and the data. Section 4 outlines the empirical specification, while section 6 presents the results of the empirical analysis. The final section briefly summarizes the key findings of the study.

2. Econometric Framework

As indicated earlier, the empirical approach employed in this study follows the model proposed by Hess and Hensher (2013). In a standard specification of random utility model, the utility of alternative *i* for respondent *n* in choice scenario t is given as:

$$U_{int} = V_{int} + \varepsilon_{int} \tag{1}$$

where V_{int} is the deterministic component of utility and ε_{int} is the random component of the utility. With *J* alternatives *(j = 1… J),* the probability of alternative *i* being chosen is given as:

$$P_{int}(\beta) = P\left(V_{int} + \varepsilon_{int} > V_{jnt} + \varepsilon_{jnt}, \forall j \neq i\right) \tag{2}$$

The deterministic component of the utility is given by a function of observed attributes x and estimated taste parameters β, i.e $V_{int}(\beta) = f(x_{int}, \beta)$, where typically, a linear in parameters specification is adopted.

In the Mixed Multinomial Logit (MMNL) model, we accommodate random variations across respondents in β, and with a type I extreme value distribution for the remaining error term ε, this is specified as:

$$P_{int}(\Omega) = \int_{\beta} \frac{e^{V_{int}(\beta)}}{\sum_{j=1}^{J} e^{V_{jnt}(\beta)}} h(\beta|\Omega)d\beta = \int_{\beta} P_{int}(\beta)h(\beta|\Omega)d\beta \tag{3}$$

where $\beta \sim h(\beta|\Omega)$, with Ω representing a vector of parameters to be estimated, for example the mean and standard deviation. This model collapses back to a standard multinomial logit (MNL) structure (i.e. $P_{int}(\beta)$), if no random heterogeneity is retrieved. We work with repeated choice data, and under an assumption of intra-respondent homogeneity, the likelihood of the actual observed sequence of choices for respondent n is then expressed as:

$$L_n(\Omega) = \int_{\beta} \left[\prod_{t=1}^{T} P_{i^*nt}(\beta)\right] h(\beta|\Omega)d\beta, \qquad (4)$$

where i^*nt refers to the alternative chosen by respondent n in choice situation t.

As part of the survey, we collected information on the choices made by the respondent, i.e. i^*nt, $\forall\, n, t$. We also captured answers to questions relating to information processing strategies. In particular, with K different attributes (and hence K different associated β parameters), we elicit data on respondents' stated ANA for each of these attributes, say $NA_{nk}, k = 1, \ldots.., K$, where NA_{nk} is equal to 1 if respondent n states that he/she ignored attribute x_k in making choices, while A_{nk} equal to 1 if respondent n attend to x_k. Therefore, let us further define $A_{nk} = 1 - NA_{nk}\, \forall\, k$ as answers to respondents' attribute attendance.

In a simplistic modeling approach, answers to questions relating to information processing strategies would normally be used as explanatory variables, where β_k would be replaced by $A_{nk}\beta_k$. This means that the parameter β_k is set to zero for any respondent who indicated that attribute x_k was ignored. However, other studies have suggested that stated attribute non-attendance may simply equate to lower sensitivity (e.g., Hess et al., 2013), and rather than imposing a zero coefficient value for such respondents, separate coefficients are estimated, whereby β_k is replaced by $NA_{nk}\beta_{k,na} + A\beta_{k,a}$. In this framework, $\beta_{k,a}$ is used for respondents who stated that they attended to attribute k, while $\beta_{k,na}$ is used for the remaining respondents. According to Hess and Hensher (2013), while this second approach departs from the assumption of absolute correctness of the stated non-attendance data, possible issues with endogeneity still arise. Specifically, there is likely to be correlation between the respondent reported processing strategies and other factors not accounted for in the deterministic part of utility, hence leading to potential correlation between V_{int} and ε_{int}.

Therefore, to address the endogeneity problem, we follow Hess and Hensher (2013). First, we treat answers to information processing as dependent variables which are a function of the true underlying, and unobserved, processing strategies. Second, we focus on the notion of attribute importance, hypothesizing that for every attribute k, each respondent has an underlying rating of attribute importance.[5] This attribute importance rating is unobserved, and is thus given by a latent variable α_{nk} for respondent n, with:

$$\alpha_{nk} = \varphi_k z_n + \eta_{nk} , \qquad (5)$$

where z_n represents characteristics of the respondent, and η_{nk} a random disturbance assumed to follow a standard normal distribution across respondents and across the K different attributes. The vector φ_k explains the effect of z_n on α_{nk}.

Third, we hypothesize that the answers to the attribute non-attendance questions can be modeled as a function of these latent variables. In particular, we use a binary logit specification, where, conditional on a given value for the latent variable α_{nk}, the probability of the actually observed value for NA_{nk} is modeled as:

$$L_{NA_{nk}}(\kappa_k, \zeta_k | \ \alpha_{nk}) = \frac{NA_{nk} e^{\kappa_k + \zeta_k \alpha_{nk}} \ + \ A_{nk}}{1 + \ e^{\kappa_k + \zeta_k \alpha_{nk}}} , \qquad (6)$$

where κ_k and ζ_k are parameters to be estimated, with the former relating to the mean value of NA_{nk} in the sample population, and the latter giving the impact of the latent variable α_{nk} on the probability of stated non-attendance. We then group the various latent variables

[5] It should be emphasized here that this is somehow different from a marginal sensitivity, as it does not relate to the actual value of the attribute in question.

together in $\alpha_n = <\alpha_{n1}, \ldots., \alpha_{nk}>$, with the same definition for κ and ζ. With K different indicators, Equation 6 can be re-specified as:

$$L_{NA_n}(\kappa, \zeta|\alpha_n) = \prod_{k=1}^{K} \frac{NA_{nk}e^{\kappa_k+\zeta_k\alpha_{nk}} + A_{nk}}{1 + e^{\kappa_k+\zeta_k\alpha_{nk}}} . \quad (7)$$

In addition to using the latent variables to explain the answers to the non-attendance questions, we also employ them as shrinkage factors inside the choice model component of the hybrid model, thus allowing for a continuous measure of importance (instead of a simple discrete complete attendance/non-attendance approach). In other words, we employ the latent variable scaling approach, whereby rather than setting the coefficient of the latent variable to zero at a certain threshold, the coefficient is scaled. In particular, we replace the parameter β_k by $e^{\lambda_k\alpha_{nk}}\beta_k$, where we estimate the attribute-specific scaling parameters $\lambda = <\lambda_1, \ldots., \lambda_K>$. Likewise, to capture heterogeneity, we use two separate components α_{nk} and β_k to permit for the absence of a strict relationship between attribute importance and marginal sensitivities, thus accommodating any unrelated random heterogeneity in the β_k term. Conditional on given values of α_n and β, and assuming linearity in attribute specification, the probability that respondent n chooses alternative i, in choice situation t is given as:

$$P_{int}(\beta, \lambda|\alpha_n) = \frac{e^{\sum_{k=1}^{K} e^{(\lambda_k\alpha_{nk})}\beta_k x_{k,int}}}{\sum_{j=1}^{J} e^{\sum_{k=1}^{K} e^{(\lambda_k\alpha_{nk})}\beta_k x_{k,jnt}}} , \quad (8)$$

where $x_{k,int}$ is the kth component in x_{int}. Here, a positive estimate for λ_k means that as the importance rating α_{nk} increases in value, so does the marginal sensitivity to attribute x_k .

Equation 7 is dependent on a given value of α_n, while Equation 8 is dependent on given values for β and α_n. Given that, both are random components, integral of the conditional probability in Equation (8) over all their possible values is required. This is carried out at the level of the combined likelihood for respondent n, which relates to the stated choice component as well as the answers to the non-attendance questions, and is specified as a product of *T* discrete choice probabilities:

$$L_n\,(\Omega, \lambda, \kappa, \zeta, \varphi) = \int\limits_{\beta} \int\limits_{\alpha_n} \left[\prod_{t=1}^{T} P_{i^*nt}\,(\beta, \lambda|\alpha_n)\right] L_{NA_n}(\kappa, \zeta|\alpha_n) h(\beta|\Omega) \mathrm{g}(\alpha_n|\varphi, z_n) \mathrm{d}\beta \mathrm{d}\alpha_n, \qquad (9)$$

where α_n follows a K-dimensional normal distribution with an identity matrix used for the covariance matrix, and with the mean for α_{nk} being given by φz_n. The maximization of the log-likelihood (*LL*) for the hybrid model across the *N* respondents given by $\sum_{n=1}^{N} \ln(L_n(\Omega, \lambda, \kappa, \zeta, \varphi))$, entails the estimation of the following components: Ω the vector of parameters of the multivariate distribution of β; λ the vector of parameters explaining the scaling of marginal utilities as a result of the latent variables; κ the vector of constants in the probabilities for the observed responses to non-attendance questions; ζ the vector of parameters explaining the response to non-attendance questions as a result of the latent variables; and φ the vector of parameters linking the latent variables to socio-demographic characteristics of the respondents.

From our survey, we also collected information from respondents on attribute rankings.[6] Let the mutually exclusive rankings for the K attributes be given by R_k, $k = 1, \ldots, K$, where $1 \leq R_k \leq K, \forall\, k$. Hence, we then make use of a rank exploded MNL model. In particular, let us define:

$$\gamma_{nk} = \varsigma_k + \tau_k \alpha_{nk}, \forall k, \qquad (10)$$

where, for normalization, we set $\varsigma_1 = 0$. We then write:

[6] The model specification in Equation (9) is applicable to any dataset collecting additional respondent-reported information, such as, on attribute non-attendance, attribute ranking, etc (Hess and Hensher, 2013).

$$v_{nr} = \sum_{k=1}^{K} \delta_{(R_{k,r})} \gamma_{nk}, r = 1, \ldots., K, \tag{11}$$

where $\delta_{(R_{k,r})}$ is equal to 1 if $R_k = r$, i.e. if attribute k has ranking r, and 0 otherwise. With ς and τ grouping together the individual elements ς_k and $\tau_k \forall k$, respectively, the probability for the response to the ranking question is then specified as:

$$L_{Rn}(\varsigma, \tau, \alpha_n) = \prod_{r=1}^{K-1} \frac{e^{v_{nr}}}{\sum_{s=r}^{K} e^{v_{ns}}} \tag{12}$$

Therefore, the values of the attribute ranking from Equation 12 is also jointly modelled with values of non-attendance $L_{NA_n}(\kappa, \zeta|\alpha_n)$ and the likelihood of the observed sequence of choices $P_{int}(\beta, \lambda|\alpha_n)$ from Equation 9. In combination, the LL function for the hybrid model integrates the choice models with the measurement (latent variable) models. Thus, Equation 9 can be rewritten as:

$$L_n(\Omega, \lambda, \kappa, \zeta, \varphi, \varsigma, \tau)$$
$$= \int_{\beta} \int_{\alpha_n} \left[\prod_{t=1}^{T} P_{int}(\beta, \lambda|\alpha_n) \right] L_{NA_n(\kappa, \zeta|\alpha_n)} \, L_{R_n} \, (\varsigma, \tau|\alpha_n) h(\beta|\Omega) \mathrm{g}(\alpha_n|\varphi, z_n) \mathrm{d}\beta \mathrm{d}\alpha_n \tag{13}$$

In comparison with Equation 9, we now also need to estimate the two vectors, ς and τ, from the attributes rankings in Equation 12.

It is worth mentioning that in Equation 8 in the choice model component, the five λ parameters essentially play the role of attribute-specific scale parameters. As recently discussed by Hess and Rose (2012) in relation to the G-MNL model, disentangling random scale heterogeneity from random heterogeneity in individual coefficients in discrete choice models is not possible. This would be even more relevant in the case of attribute specific scale parameters. Indeed, any increases in magnitude for the marginal utility for attribute k could be accommodated in either the random distribution of β_k, or the $e^{\lambda_k \alpha_n}$ scaling term. However, a key distinction arises in the present work. The latent variable component which is interacted with λ_k in the utility function is also used inside the additional component, to model the response to the attribute non-attendance questions. For this reason, the two components, λ and β, can both be identified, remembering also that the variance of the random component in α_{nk} is normalized to 1.

3. Survey Design and Data Description

As indicated previously, market data for sales of organic products are unavailable in SSA, as certified organic products are yet to be generally introduced in the domestic markets. We therefore, elicit primary data on consumer preferences using hypothetical CE. The data were drawn from a recent household survey conducted between July and October, 2013 in Kano State, North-Western Nigeria. The location occupies a strategic economic position as a commercial nerve centre and second most populous state in the country. The high population density, coupled with the socio-demographic heterogeneity and ethnic mix characterizing the location allowed for high degree of cross-sectional variation and representation in the dataset.

In our survey, we conducted face-to-face interviews with questionnaire, and ensured that subjects were generally representative, and had experience with buying food items. The target population was therefore the primary food buyers in the households. However, unlike previous studies on organic food choice in SSA which were limited to urban centres, we sampled participants randomly from both urban and rural areas, using a multistage sampling approach. First, two highly heterogeneous local government areas (LGAs) were selected, each from urban and rural locations (i.e., based on national census data; NPC, 2006). Second, twelve districts were randomly selected, that is, three from each LGA. Finally, we sampled a proportionate number of households across socio-demographic strata from these districts, constituting 900 respondents.

Our questionnaire focused on three areas of variation: individual socio-demographic data; choice experiment; and follow up questions on attribute processing strategies and attribute importance. As a tailpiece to the socio-demographic questions, we also probed respondents on their level of awareness of organic agriculture, and based on a common understanding of organic production, we proceeded with the CE task. As an initial step in implementing the CE, we selected tomatoes as the organic product to analyze. The selection of vegetable, in particular tomato, is guided by previous methodological and empirical suggestions on SSA (e.g., Coulibaly et al., 2011) and the acceptance by respondents as realistic. Further, the attributes and their corresponding levels were also identified through detailed review of the literature, discussions with scientific experts, focus groups, and pre-testing.

The choice sets, comprised of two experimentally-designed organic profiles and a 'status-quo' option. The organic profiles were created following Scarpa et al. (2007), using a three stage Bayesian sequential approach. A preliminary pilot study based on an orthogonal fractional factorial design (Hensher et al., 2005), was carried out to test the questionnaire and to provide Bayesian priors for the main design. Then, using the procedures described by Scarpa et al., (2013),[7] the design involved 36 choice tasks orthogonally arranged in four blocks of nine choice scenarios each to reduce the probability of respondent fatigue. An even number of respondents were randomly assigned to each of these groups. As shown in Figure 1, each organic alternative is described by four quality attributes and a price. The price attribute in

[7] The final design was generated using the Ngene software (version 1.0) and we accounted for uncertainty of priors by employing normally distributed Bayesian priors. The final design with the lowest Bayesian D-error (0.2534) was attribute-level balanced.

the choice sets were the prices for 1kg basket of tomatoes, with three different price levels. The lowest price level represents the base price, which reflects the average retail market price; collected from the local marketplaces immediately prior to the experiment. The remaining price levels reflect possible premium prices associated with the organic tomato products. It is important to mention that, given that certified organic tomatoes are unavailable in the market, the pricing was derived base on local market experts' opinion and focus group discussions.

Another attribute relates to the origin of the certifier of the organic product. Private voluntary certification of organic products has been shown to be an important aspect of the OA initiative in developing countries (e.g., Kleeman et al., 2014). Therefore, in this study we identified three organic certification scenarios. The first level corresponded with the scenario in which the organic tomato is certified by both foreign and indigenous third party certifiers. While, second and third levels correspond to the scenarios with foreign certifiers only and indigenous certifiers only, respectively. The remaining three quality-attributes of the organic choice options concern: higher vitamin A content; lower soil erosion and lower pesticide residues, and each were described by high, medium and low attribute levels. Several studies have indicated that organic farming leads to lower usage of pesticide relative to conventional farming (Dangour et al., 2009). The first level (100% reduction) is related to the absence of residues, the second level (25% reduction) implies traces of residues from one component (<0.01mg/kg), and the third level (5% reduction) comprises residues (>0.01mg/kg) from more than one components. Some studies have found a higher amounts of carotenoid content in organic vegetables, which are precursor and good source of vitamin A. Vitamin A can strengthen eye vision and the immune system (Chowdhury et al. 2011). Hence, the vitamin A content could be 5%, 25%, or 100% higher in organic tomato than in the conventional counterpart. Similarly, OA contributes positively to the process of encountering soil degradation, as it improves soil organic matter content. Studies show that water retention capacity on organic farming plots are higher than on conventional plots (e.g., Azadi, et al., 2011). Thus, soil erosion could be 5%, 25%, or 100% lower on organic plots relative to conventional farms.

Following Lusk and Schroeder, (2004) in the CE procedure, we implemented different treatments and used a between-subject approach, whereby each respondent was randomly assigned to participate in only one of the three hypothetical CE treatments. In the first treatment, participants were not exposed to any of the *ex-ante* mitigation strategies. This treatment represents the baseline (N), and it corresponds with the conventional and frequently applied hypothetical CE. The second treatment (CT) consisted of a CE with a cheap talk script, which was described to participants before responding to the CE questions. We used a generic, short, and neutral CT script, (Cummings and Taylor, 1999; Silva et al., 2011), which were modified and developed in English and the local dialects. We refer to this as the cheap talk (CT) treatment. The third treatment (HP) consisted of a CE survey with an honesty priming script, which we also placed immediately before the CE questions. The HP script was the same as the one used by de-Magistris et al, (2013), although we translated and implemented minor modifications after the validation exercise. Following Pashler et al., (2013), we further included questions to ascertain true activation of honesty and manifestation of the priming effect.

After completion of the nine choice tasks (instead of the entire survey), respondents were immediately presented with follow-up questions capturing information on attribute processing. In particular, each respondent was asked to rank the five attributes in order of importance, and then to indicate whether they had ignored any of the five attributes in making their choices.

Table 1 reports the socio-demographic characteristics of the participants in the three treatments. In order to allow for comparison of the results, there is a need to ensure similarity of characteristics across treatments, as such we employed stratified random sampling technique to select our participants in the sublocations as described above. We then used a chi-square test to determine if there were significant differences in socio-demographic profiles across treatments. The results of the tests show that the null hypothesis of equality between the socio-demographic characteristics across treatment samples cannot be rejected at the 5% significance level for gender, age, education, income, and household size. Likewise, similar test results was obtained for the perceptual indicators: whether participants have previous awareness of organic products and whether there is any known recent incidence of food-related disease among relatives and friends. These results suggest that our randomization was successful in equalizing the characteristics of participants across the two treatments.

Results on respondent-reported ANA information is also presented on Table 1. The results show that the rate of stated ANA varies across the treatments in general, with respondents under the HP treatment reporting lowest ANA rates followed by CT, and then N treatments. There are also significant differences in ANA rates between respondents exposed to the mitigation strategies (HP and CT) and the baseline (N) group. In particular, the price attribute in the HP and CT treatments has the lowest ANA rate, while it is second highest in the N treatment.

4. Empirical Specification

Each respondent was faced with up to nine choice tasks, and for the analysis, we made use of a sample of 2,700 observations from 300 respondents, each in the HP, CT and N treatments, as well as a pooled sample of 8,100 observations from the 900 respondents. Eight different models were estimated on the data, four mixed multinomial logit models (MMNL) and four hybrid models (HYBRID) shown in Equation 13. All eight models were coded in Biogeme (Bierlaire, 2003), using 250 Halton draws per respondent and per random term in simulation based estimation (Halton, 1960). For the hybrid model, simultaneous estimation of all model components was used (Hess and Hensher, 2013).

In both the MMNL and hybrid models, constants were included to capture the conventional alternatives. All five marginal utility coefficients were specified to vary randomly across respondents, where a correlated lognormal distribution was used for marginal utility coefficients. Specifically, with $\psi_k, k = 1, \dots, 5$ giving five standard normal variates that are distributed independently and identically across respondents. Draws for the five marginal utility coefficients are specified as:

$$\beta_{Price} = e^{\mu_{ln(\beta_{Price})} + s_{ln(\beta_{Price})}}$$

$$\beta_{Pesticide} = e^{\mu_{ln(\beta_{Pesticide})} + s_{ln(\beta_{Pesticide}),\ln(\beta_{price})} + s_{ln(\beta_{Pesticide})}} \tag{14}$$

$$\beta_{Certification} = e^{\mu_{ln(\beta_{Certification})} + s_{ln(\beta_{Certification}),\ln(\beta_{Price})} + s_{ln(\beta_{Certification}),\ln(\beta_{Pesticide})} + s_{ln(\beta_{Certification})}}$$

$$\beta_{Vitamin} = e^{\mu_{ln(\beta_{Vitamin})} + s_{ln(\beta_{Vitamin}),\ln(\beta_{Price})} + s_{ln(\beta_{Vitamin}),\ln(\beta_{Pesticide})} + s_{ln(\beta_{Vitamin}),\ln(\beta_{Certification})} + s_{ln(\beta_{Vitamin})}}$$

$$\beta_{Erosion} = e^{\mu_{ln(\beta_{Erosion})} + s_{ln(\beta_{Erosion}),\ln(\beta_{price})} + s_{ln(\beta_{Erosion}),\ln(\beta_{Pesticide})} + s_{ln(\beta_{Erosion}),\ln(\beta_{Certification})} + s_{ln(\beta_{Erosion}),\ln(\beta_{Vitamin})} + s_{ln(\beta_{Erosion})}},$$

where $s_{kl}\ (with\ l \leq k \leq 5)$ relate to the Cholesky terms of the underlying normal distribution, e.g., $s_{\ln(\beta_{Price}),\ln(\beta_{Pesticide})}$ and $s_{\ln(\beta_{Price})}$ giving the two components of the Cholesky matrix relating to the price coefficient, the first being off-diagonal, the second being the diagonal element, while e.g. $\mu_{ln}(\beta_{Price})$ gives the mean for the underlying normal distribution for the price coefficient.

In all the MMNL models, we assume full attribute attendance and thus do not use the respondent reported processing strategies, and no attempts was made to additionally incorporate deterministic effects linked to the respondent reported attribute rankings. These (MMNL) models are primarily included for illustrative purposes, given its past use in the previous studies (e.g. de-Magistris et al., 2013).

In the hybrid model, we make use of the non-attendance data as well as the ranking data, with likelihood contributions given in Equations 7 and 12, and the overall log-likelihood being defined as in Equation 13. We also extend on Hess and Hensher (2013) model by including socio-demographic interactions in the latent variable specification in Equation 5. In comparison with the MMNL models, the hybrid models (HYBRID) make use of 30 additional parameters, 5 of them in the choice model component (the λ terms), with the remaining 25 used in the measurement model. This latter model is appropriately normalized and this is the most parsimonious suitable specification, such that there is no risk of over-fitting.

The five λ parameters quantify the effect of the latent variables inside the choice model, as shown in Equation 8. With α following a standard normal distribution, we can see that the β parameters in the hybrid model still follow a lognormal distribution, just as in the base model. For example, for the price coefficient, this is represented as:

$$\beta_{n,Price} = e^{\lambda_{Price}\alpha_{n,price}}, e^{\mu_{ln}(\beta_{Price})+s_{ln(\beta_{Price})}} \tag{15}$$

The remaining sets of parameters $(\kappa, \zeta, \varsigma \; and \; \tau)$ follow the approach set out in Equations 7 and 10 to 12, with ς_{Price} normalized to zero.

5. Empirical Results

We first tested the hypothesis of equality across treatments using the likelihood ratio test. Table 2 reports the likelihood values for the pooled and segmented samples (treatments).

The results indicate that the null hypotheses of equality between the pooled and segmented treatments cannot be accepted, suggesting that comparing the estimated parameters from the various treatments is appropriate when estimating the models separately.

The maximum likelihood estimates for the choice models are summarized in Table 3.[8] They relate to model statistics and the estimates of the discrete choice component of the six models. First, it is important to note that the fit of the hybrid model cannot be compared to that of the MMNL models given that the latter are estimated on the stated choice data alone, while the hybrid structure also models the responses to the non-attendance questions and the attribute ranking questions. This is reflected in the greater null log-likelihood (LL) for the hybrid model.

The magnitudes and (negative) signs of the constants indicate some inertia towards the conventional (or status quo) alternative, along with some reading left-to-right effects. The five mean parameters for the underlying normal distributions are all statistically significant across all four models, with the expected negative signs for parameters of price attributes, and the high preference for increase in the remaining four attributes of the organic profile. Further, from the Cholesky matrix, we observe that majority of the estimates of the diagonal elements are statistically significant, indicating heterogeneity in preferences for the identified organic attributes among respondents.

The next set of estimates shown in Table 3 relate to the λ parameters, which have the role of a scaling parameter on the marginal utilities. Here, we see that for all five attributes, consistent with Hess and Hensher (2013), increases in the associated latent variable lead to increases in sensitivity for the concerned attribute. This is in line with the interpretation of the five latent variables as underlying importance ratings for the attributes. In addition, we extend

[8] As mentioned above, the model was estimated using Biogeme (Bierlaire, 2003).

on Hess and Hensher (2013) framework, by establishing the impact of socio-demographics parameter φ_k on the latent attribute importance ratings. The estimates reveal that participants with higher importance ratings for the identified attributes (in both treatments) are more likely to be older and more educated, and with previous awareness of organic products. Moreover, in the HP treatments, this group are more likely to have experienced a food-related disease within the last 24 months.

We next turn to the two additional measurement components of the hybrid model that allow the use of the $e^{\lambda_k \alpha_{nk}}$ term, namely the model for the response to the non-attendance questions, and the model for the response to the ranking question. All the estimates for the κ parameters are negative, reflecting the fact that the stated non-attendance rates were lower than 50 % for each of the five attributes. . The ς terms for the ranking component play a similar role, with ς_{Price} normalized to zero. The remaining negative estimates reflect the overall highest ranking for the price attribute, followed by low pesticide and then soil attributes in the HP treatment. Low pesticide attribute is ranked highest among participants in the CT treatment, ahead of price and certification attributes.

For the remaining parameters, the rule of thumb is that a negative estimate for ζ_k implies that as the latent variable α_{nk} increases, the probability of respondent n indicating that he/she ignored attribute k decreases. Similarly, a positive value for τ_k implies that as α_{nk} increases, the probability of respondent n ranking attribute k highly is increased (Hess and Hensher, 2013).

Although $\zeta_{pesticide}$ in the CT treatment is not statistically significant, we observe the expected signs for the ζ and τ parameters for price, low pesticide residue and certification attributes in the two treatments. For each attribute, an increase in the associated latent variable is associated with a lower probability of stated non-attendance for that attribute, and an increased probability of higher ranking for the attribute. At the same time, the estimates for the λ parameters (all being positive and significant) in the choice model component show that such increases in the latent variables also lead to higher sensitivity to the associated attributes in the utility functions. This indicates consistent results across the three model components (λ ,ζ, ς) for these three attributes (i.e., price, pesticide residue and certification), and as such justifies the interpretation of the latent variable as an underlying attribute importance rating.

A different view however unfolds for vitamin A and erosion attributes. For instance, in the CT treatment, while the estimate for $\zeta_{Vitamin}$ and $\zeta_{Erosion}$ are positive, and the estimate for $\tau_{Vitamin}$ and $\tau_{Erosion}$ are negative, the estimate for $\lambda_{Vitamin}$ and $\lambda_{Erosion}$ in the choice model is once again positive, implying that increases in the latent variable lead to increased marginal disutilities for higher vitamin A and low soil erosion attributes. In other words, this indicates that increases in the latent variables $\alpha_{n,Vitamin}$ and $\alpha_{n,Erosion}$, which lead to higher marginal utility for vitamin A and erosion attributes, also counter-intuitively result in a higher probability of stated non-attendance for these attributes, and increased probability of a lower ranking for the attributes. Similarly, in the HP treatment, even though, $\lambda_{Erosion}$ and $\lambda_{Vitamin}$ are both positive as expected, we observe contrasting signs for $\zeta_{Vitamin}$ and $\zeta_{Erosion}$ as well as for $\tau_{Erosion}$ estimates.

The findings for vitamin A and soil erosion attributes are consistent with the results of Hess and Hensher (2013), who also reported lack of consistency between the behaviour in the stated choice components and the respondent provided information on attribute non-attendance and attribute ranking. It also further highlights and confirm the usefulness of the modelling framework proposed by Hess and Hensher (2013), since it allows for such discrepancies to be identified without relying on deterministic approaches treating respondent provided information as error free measures of attribute non-attendance and attribute rankings.

Table 4 summarizes the results from the estimation of trade-off between the attribute coefficients. The results here relate to sample population level distributions, taking into account the distributions of latent variables α and parameter of the attributes β. In particular, we calculate the monetary valuations for the four attributes. In the MMNL models, the β_k parameters all follow lognormal distributions, with the same applying to the $e^{\lambda_k \alpha_{nk}} \beta_k$, product in the hybrid model. As a result, all trade-offs follow lognormal distributions. The results show that potential market for organic products exists in Nigeria, as respondents are willing to pay a premium for the certifications as well as the health- and environment-related attributes of organic products identified, especially with lower pesticide residue attracting the highest value in both treatments. The results in the Table 3 also show the implied coefficient of variation (or noise-to-signal ratio). While the calculation of the mean and standard deviation accounted for correlation between individual distributions, they are again applied to estimate the noise-to-signal ratio. The hybrid models exhibit lower noise relative to the MMNL models.

We also test whether there exist a statistically significant difference in welfare value estimates obtained from the two alternative priming tasks (HP and CT) applied in the hypothetical CE. Based on the results of both the t-test and complete combinatorial test (CC) (Poe et al., 2005), the null hypotheses of differences in WTP estimates cannot be rejected in all four cases, indicating that hypothetical CE under different priming task gives different WTP values. In our case, the HP task leads to lower WTP values by a factor of two relative to CT task, for three of the four attributes identified. Further, in comparison to the WTP values obtained from the baseline treatment (N), the results reveal that the HP task is better able to mitigate potential upward bias in WTP values in hypothetical CE relative to CT treatment. Thus, the low values for HP task might reflect a more realistic valuation of the attributes. This findings is consistent with de-Magistris et al., (2013).

Overall, the differences between the hybrid models ($HYBRID_{HP}$ and $HYBRID_{CT}$) are relatively modest. However, we observe lower (and arguably more realistic) differences between the monetary valuations of attributes in the hybrid models than is the case in MMNL models. Also noteworthy is the fact that for the majority of trade-offs, we see reduced heterogeneity in the hybrid model. This low and more realistic level of heterogeneity is arguably a reflection of greater ability by this model to accommodate the heterogeneity across respondents by linking the values to underlying attribute importance ratings. This is not possible in MMNL models, since they do not make use of the additional information about the attribute processing. These findings also highlight the underlying flaws in models that condition choice models on the assumption of respondents' full attendance to the presented attributes.

6. Conclusion

The need to diversify and explore domestic markets for organic products is now been considered in Nigeria to complement the international market access. Discovering the right niche market is a complicated task, since preferences vary among consumers. The identification of market potentials for organic food product is important, given that future development of the sector will to a large extent depend on consumers' acceptance and willingness to pay for the products.

Progress has been made in developing techniques to estimate values of nonmarket goods through stated hypothetical CE. Concerns, however persist that the monetary values obtained from such nonmarket valuation techniques overstate individuals' true values of the good. A well-known alternative in the literature to overcome this limitation is the non-hypothetical CE. However, due to the practical challenges of adopting this non-hypothetical version of CE, a number of authors have identified and proposed different mitigation strategies for hypothetical bias in CE (e.g., de-Magistris, et al., 2013). Similarly, the valuation of specific product characteristics hinges on respondents' ability to understand and process various attributes simultaneously, making the issue of attribute non-attendance (AN-A) critical in understanding agent behavior and deriving accurate estimates of utility parameters.

In this paper, we employ a framework that allows us to jointly model the response to the stated choice component as well as the response to the attribute processing questions. We used a recent survey data from Nigeria to compare the welfare value estimates obtained from two *ex-ante* calibration methods: cheap talk script, which is considered an explicit approach and honesty priming, an implicit technique. We explicitly address endogeneity issues raised by typical ANA treatments, while exploring the effect of priming task on delivering WTP values for organic product attributes.

Our empirical results show that the honesty priming model ($HYBRID_{HP}$) obtains a highly significant improvement in log-likelihood by 158.95 units over cheap talk model ($HYBRID_{CT}$). Our findings also reveal that there are significant differences in welfare value estimates obtained from the two alternative priming tasks (HP and CT) applied in the hypothetical CE, confirming that hypothetical CE under different priming task gives different WTP values. Although, since a monetary incentive is missing in this study, we are unable to assess the effect in real CE settings, nevertheless, the introduction of the priming tasks provides us with information about the effectiveness of the HP task to mitigate potential upward bias in WTP values in hypothetical CE relative to the CP script. Similarly, variations in WTP values under the three treatments in the hypothetical context was also established.

Third, the findings in this paper are consistent with earlier results, as it highlights the lack of consistency between the behaviour in the stated choice components and the respondent provided information on attribute non-attendance and attribute ranking. Fourth, from the results we observe that participants with higher importance ratings for the identified attributes (in both treatments) are more likely to be older and more educated, and with previous awareness of organic products. Moreover, in the HP treatments, this group are more likely to have recently experienced a food-related disease. Finally, our analysis reveal that the hybrid model framework had better impacts on implied WTP patterns, with a more realistic difference between the valuations for the attributes, and lower overall heterogeneity relative to the MMNL models used in previous work.

Overall, the results show that potential market for organic products exist in Nigeria, as respondents are willing to pay a premium for the certification attribute as well as the environment- and health-related attributes of organic products identified, especially with lower pesticide residue attracting the highest value in both treatments. This finding highlights participants' inclination towards health concerns and could serve as an important entry point for marketing. Further, since consumer's previous awareness effectively advances the potential demand for organic products, the adoption of effective sensitization program would be imperative for the successful development of sustainable organic sector in Nigeria. Similarly, given consumers' valuation of the certification attributes, institutionalizing third party certification for organic food products would be an appropriate policy strategy. A consumer-oriented approach to understanding organic agriculture in Nigeria is important not only in its own right, but also in terms of response to the increasing significance of organic food products and the anticipated growth in the future market for such products.

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TABLE 1: Sample Characteristics, Percentages

Variable Definition	Neutral	Honesty priming	Cheap talk
Gender			
Female	18.41	18.67	17.67
Male	81.59	81.33	82.33
Chi-Square (2) = 0.9749			
p-value = 0.614			
Age			
Between 18-40 years	24.07	24.0	23.33
Between 41-60 years	59.59	59.67	59.67
More than 60 years	16.33	16.33	17.0
Chi-Square (4) = 0.8625			
p-value = 0.930			
Level of Education			
None	10.89	12.0	12.0
Primary	20.44	18.33	18.33
Secondary	65.33	66.0	66.33
Tertiary	33.33	3.67	3.33
Chi-Square (6) = 6.9180			
p-value = 0.329			
Ave. Monthly Income (₦)			
Low income (≤ 30,000)	14.56	13.67	14.56
Medium income (30,001 – 150,000)	57.67	58.0	57.67
High income (> 150,000)	27.78	27.33	27.78
Chi-Square (4) = 0.6985			
p-value = 0.952			
Awareness of organic			
Aware	21.96	22.33	22.33
Unaware	78.04	77.76	77.76
Chi-Square (2) = 0.1429			
p-value = 0.931			
Food-related Disease			
Incidence	13.07	13.67	13.33
No-incidence	86.92	86.33	86.67
Chi-Square (2) = 0.4117			
p-value = 0.814			
Household size			
Less than 4 persons	29.11	29.33	28.67
Between 4 – 10 persons	55.07	54.33	54.0
More than 10 persons	15.82	16.33	17.33
Chi-Square (4) = 2.4645			
p-value = 0.651			

Table 1: Distribution of Stated Attribute Non-attendance across Treatment (continued)

	Neutral	Honesty priming	Cheap talk
Pesticide	20%	3%	9%
Certification	15%	5%	9%
Vitamin	23%	4%	10%
Price	23%	2%	8%
Erosion	17%	3%	11%

Table 2: Hypothesis Tests of Equality across Treatments

Hypothesis Tests of Equality	Number of Observations	MMNL Models	HYBRID Models
		LL	*LL*
Pooled[a]	8,100	-4.684.443	-11,771.204
Neutral (Baseline)	2,700	-1,334.180	-3,845.301
Honesty priming	2,700	-1,193.733	-3,754.168
Cheap talk	2,700	-1,992.791	-3,913.119
H_0 = Test of equality across treatments		327.478***	517.232***

***p<0.01

[a] Indicates all treatments

TABLE 3: Maximum likelihood estimates for neutral, honesty priming and cheap talk treatments

	$MMNL_N$		$HYBRID_N$		$MMNL_{HP}$		$HYBRID_{HP}$		$MMNL_{CT}$		$HYBRID_{CT}$	
Respondents	300		300		300		300		300		300	
Observations	2,700		2,700		2,700		2,700		2,700		2,700	
LL(0)	-3,376.557		-4,330.199		-3,157.503		-4,092.202		-3,452.158		-4,213.039	
LL	-1,334.180		-3,845.301		-1,193.733		-3,754.168		-1,992.791		-3,913.119	
Par.	11		41		11		41		11		41	
Variable	Est.	*t*-Ratio	Est.	*t*-Ratio	Est.	*t*-Ratio	Est.	*t*-Ratio	Est.	*t*-Ratio	Est.	*t*-Ratio
β_{price}	-6.4866	-17.21	-0.9335	-14.73	-3.1568	-9.16	-1.2527	-18.34	-3.8294	-16.33	-0.7161	-13.33
$\beta_{pesticide}$	1.1302	17.89	0.6985	17.10	2.1025	12.50	1.0201	21.94	0.6772	12.10	0.4372	12.10
$\beta_{certification}$	0.0046	0.12	-0.1102	-2.36	0.4273	7.46	0.0997	2.43	0.2147	6.50	0.0624	1.88
$\beta_{vitamin}$	0.4376	9.95	0.3761	1.25	0.3270	5.44	0.2420	5.43	0.2170	5.41	0.2321	6.46
$\beta_{erosion}$	0.5133	11.75	-0.4366	-0.51	0.4857	7.98	0.3241	7.28	0.2807	7.94	0.2785	7.63
Constant	-17.6277	-16.32	-2.0057	-16.90	-16.4829	-8.72	-2.5313	-17.88	-16.3698	-16.23	-1.3033	-15.70
$S_{(\beta_{Price})}$	-0.2014	-2.44	0.0142	0.56	0.6681	2.52	-0.0099	-4.40	0.2888	2.16	-0.0030	-6.22
$S_{(\beta_{Pesticide}),(\beta_{price})}$	-0.3611	-1.86	0.2333	1.82	-0.1773	-1.64	0.0140	1.47	0.6299	0.52	0.0192	0.88
$S_{(\beta_{Pesticide})}$	-0.4529	-5.95	-0.0407	-1.67	1.1966	8.43	0.0416	1.64	0.3440	3.29	0.0137	1.01
$S_{(\beta_{Certification}),(\beta_{Price})}$	-0.4771	-1.77	-0.0378	-0.73	-0.2721	-1.75	-0.0496	-0.09	-0.6905	-1.09	-0.0183	-0.99
$S_{(\beta_{Certification}),(\beta_{Pesticide})}$	-0.2395	-4.11	-0.0176	-1.06	0.2580	7.37	-0.0525	-1.91	-0.7205	-1.57	-0.0360	-0.08
$S_{(\beta_{Certification})}$	0.0269	0.69	-0.0075	-3.41	0.1582	2.28	-0.0125	-1.09	0.0721	0.88	0.0125	1.63
$S_{(\beta_{Vitamin}),(\beta_{Price})}$	0.1200	4.41	0.1007	0.59	0.1590	3.42	-0.0230	-8.10	0.5672	4.33	-0.0336	-0.55
$S_{(\beta_{Vitamin}),(\beta_{Pesticide})}$	0.1608	7.89	0.1052	2.15	-0.1392	-8.73	0.0407	1.23	0.6142	6.15	0.1032	1.29
$S_{(\beta_{Vitamin}),(\beta_{Certification})}$	0.1150	2.83	0.1180	1.35	-0.1422	-3.85	0.0432	0.20	-0.6021	-1.70	0.0807	1.35
$S_{(\beta_{Vitamin})}$	0.2556	4.77	0.0352	1.25	-0.2292	-3.61	-0.0061	-2.20	-0.1945	-2.08	-0.0168	-3.81
$S_{(\beta_{Erosion}),(\beta_{price})}$	-0.0339	-5.32	0.1690	0.84	0.0603	3.57	0.2711	0.22	-0.6280	-4.91	0.2695	1.91

$S_{(\beta_{Erosion}),(\beta_{Pesticide})}$	-0.1765	-7.39	-0.1995	-0.63	-0.3030	-8.59	-0.1987	-1.30	0.5514	6.04	-0.0672	-10.99
$S_{(\beta_{Erosion}),(\beta_{Certification})}$	0.2720	4.19	0.2141	0.24	0.1077	4.99	0.0630	0.15	-0.5594	-1.92	0.0796	1.21
$S_{(\beta_{Erosion}),(\beta_{Vitamin})}$	-0.0684	-1.09	-0.0015	-1.23	-0.2250	-0.62	0.1130	6.28	0.5673	0.34	0.0137	1.88
$S_{(\beta_{Erosion})}$	0.3447	5.91	-0.0147	-0.51	-0.2914	-4.47	-0.0178	-2.53	-0.2243	-2.42	0.0401	1.81
λ_{Price}	-	-	0.6461	10.02	-	-	0.5678	11.65	-	-	0.9489	8.69
$\lambda_{Pesticide}$	-	-	0.9014	11.01	-	-	0.5142	14.42	-	-	1.0071	8.19
$\lambda_{Certification}$	-	-	-0.2713	-0.90	-	-	1.7056	2.25	-	-	3.3604	1.84
$\lambda_{Vitamin}$	-	-	0.1322	1.74	-	-	0.3873	2.64	-	-	0.4747	2.68
$\lambda_{Erosion}$	-	-	0.3091	3.59	-	-	0.4781	4.62	-	-	0.6278	4.74
φ_{Age}	-	-	0.0566	1.03	-	-	0.3213	6.91	-	-	0.2717	5.37
φ_{Male}	-	-	0.4186	8.70	-	-	0.5945	13.01	-	-	0.3279	6.09
φ_{Educ}	-	-	0.3502	11.90	-	-	0.3014	11.10	-	-	0.1633	5.59
$\varphi_{H/hsize}$	-	-	0.0087	2.71	-	-	0.0132	5.08	-	-	-0.0902	-3.81
$\varphi_{Disease}$	-	-	-0.2101	-4.25	-	-	0.0948	1.66	-	-	-0.2128	-4.36
φ_{Aware}	-	-	0.6407	12.59	-	-	0.6288	14.95	-	-	0.5486	10.98
κ_{Price}	-	-	-2.2257	-3.80	-	-	-1.1221	-18.20	-	-	-1.8554	-3.18
$\kappa_{Pesticide}$	-	-	-2.1482	-4.80	-	-	-2.4568	-4.48	-	-	-2.5823	-6.30
$\kappa_{Certification}$	-	-	-3.8785	-7.59	-	-	-3.6238	-5.90	-	-	-3.3259	-6.45
$\kappa_{Vitamin}$	-	-	-3.4855	-5.14	-	-	-4.0187	-8.08	-	-	-3.6021	-8.24
$\kappa_{Erosion}$	-	-	-3.2621	-7.32	-	-	-3.7787	-7.81	-	-	-3.6343	-1.86
ζ_{Price}	-	-	-0.8736	-3.81	-	-	-0.5765	-23.07	-	-	-0.6206	-23.33
$\zeta_{Pesticide}$	-	-	-0.3480	-10.88	-	-	-0.1085	-4.01	-	-	-0.0447	-1.50
$\zeta_{Certification}$	-	-	0.3266	7.33	-	-	-0.5151	-14.68	-	-	-0.6357	-16.42
$\zeta_{Vitamin}$	-	-	0.6401	24.19	-	-	0.8940	30.57	-	-	0.8671	25.51
$\zeta_{Erosion}$	-	-	0.2550	9.37	-	-	0.3061	8.92	-	-	0.4339	12.82

ς_{Price}	-	-	0	-	-	-	0	-	-	-	0	-
$\varsigma_{Pesticide}$	-	-	0.2384	3.21	-	-	-0.1931	-1.95	-	-	0.4260	6.81
$\varsigma_{Certification}$	-	-	-0.7354	-10.17	-	-	-0.8131	-10.24	-	-	-0.6853	-11.73
$\varsigma_{Vitamin}$	-	-	-2.3133	-23.94	-	-	-2.3151	-20.67	-	-	-1.0475	-18.77
$\varsigma_{Erosion}$	-	-	-1.3722	-18.92	-	-	-0.6433	-6.72	-	-	-2.5194	-27.11
τ_{Price}	-	-	0.6382	20.85	-	-	0.9579	29.08	-	-	0.4068	11.09
$\tau_{Pesticide}$	-	-	0.4163	8.34	-	-	0.2496	3.89	-	-	0.3793	7.25
$\tau_{Certification}$	-	-	-0.2429	-4.04	-	-	0.2043	3.87	-	-	0.2608	5.18
$\tau_{Vitamin}$	-	-	0.0178	0.38	-	-	0.3075	5.94	-	-	-0.2706	-5.72
$\tau_{Erosion}$	-	-	0.2286	4.83	-	-	-0.0764	-1.82	-	-	-0.5170	-7.10

Table 4: Implied trade-offs and monetary valuations

	Neutral		Honesty priming		Cheap talk		ΔWTP [a]		
	$MMNL_N$	$HYBRID_N$	$MMNL_{HP}$	$HYBRID_{HP}$	$MMNL_{CT}$	$HYBRID_{CT}$	(HP-N)	(CT-N)	(HP-CT)
Mean									
Lower Pesticide residue	19.72	13.05	14.49	7.93	16.58	7.57	-5.11**	-5.48*	0.37*
Certification	9.82	7.26	15.97	3.16	9.08	5.20	-4.10***	-2.06**	-2.05*
Higher Vitamin A content	9.55	9.45	11.22	3.64	8.52	6.16	-5.81*	-3.29**	-2.52*
Lower Soil Erosion	10.40	10.03	12.81	3.95	9.06	6.46	-6.08*	-3.57*	-2.51*
Coefficient of variation									
Lower Pesticide residue	2.56	1.50	13.30	3.25	7.10	1.15			
Certification	17.43	1.03	10.08	2.29	3.74	1.04			
Higher Vitamin A content	5.40	8.08	4.63	1.64	9.46	2.50			
Lower Soil Erosion	14.37	2.36	3.91	2.84	6.40	3.07			

***p<0.01, **p<0.05,*p<0.1

[a] ΔWTP denotes a complete combinatorial (CC) method for overlapping of two WTP distributions (Poe, et al., 2005) for the HYBRID models.

Products	Organic Tomato A	Organic Tomato B	Conventional Tomato C
Pesticide Residues	Chemical usage is reduced by **25%**	Chemical usage is reduced by **5%**	
Nutritive Content	Vitamin A in Tomato is increased by **5%**	Vitamin A in Tomato is increased by **5%**	
Environmental Conservation	Soil erosion is reduced by **100%**	Soil erosion is reduced by **25%**	
Origin of Certifier(s)	Foreign label	Foreign & indigenous labels	
Price	₦ 60/Kg	₦ 80/Kg	₦ 60/Kg
I will buy…	○	○	○

Figure 1: A sample of the choice set