Identification of consumer segments and market potentials for organic products in Nigeria: A Hybrid Latent Class approach

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Abstract

Given the growing interest in the potential of organic agriculture to correct environmental externalities in sub-Saharan Africa, we use data from a hypothetical stated preference survey conducted in Nigeria to determine the market potentials of organic products as well as show how the relative importance that consumers attach to organic attributes varies strongly as a function of underlying attitudes. We specify a latent class structure that allows us to jointly analyze responses to stated choice and assignment to latent classes, while avoiding measurement error problems. Our results reveal that consumers are willing to pay premium for both environmental and health gains achieved through organic production systems, although their quantitative valuation is higher for the health concerns. Furthermore, we note that individuals with stronger preferences for organic products tend to attach a global value to the third party organic certification program attributes, whereas the valuation tends to be more restrictive among respondents that prioritize the status quo option (conventional alternative). We also observe that differences in respondents' geographic location and level of awareness of organic food production characteristics (prior to the survey) have significant impact on consumers' choices.

JEL code D12, Q13, Q18, Q56

Keywords organic products, consumer segments, environmental and health attitudes, hybrid latent class

1. Introduction

Land degradation is a far-reaching biophysical problem that threatens food production systems in developing regions of the world (particularly sub-Saharan Africa), where about 10 million hectares of crop land are lost annually (e.g., Azadi *et al.* 2011). Available empirical evidence stress the role played by resource-poor farmers in human-induced natural resource degradation (e.g., Reardon and Vosti 1997). This situation has generated concern over which environmental externalities of agricultural production should be encouraged and which should be corrected. The prevailing economic explanation for the continuing trend toward resource degradation is that economic incentives often encourage degradation and discourage conservation (e.g., Heath and Binswanger 1996).

In light of this challenge, there is a growing interest in the potential of organic agriculture (OA) to correct environmental externalities in sub-Saharan Africa (SSA). OA is one of the approaches that meet the objectives of sustainable agriculture. 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. Furthermore, like other ''green'' labelling initiative, OA is considered a mechanism for the private provision of public goods.[1] This is premised on the notion that the joint production of public and private characteristics in a good might mitigate the crowding-out effect in the private provision of public goods (e,g,, Cornes and Sandler 1984). Implying that the capacity of consumers' acceptance and demand for the attributes of organic products could redress the failure of the market to provide public goods. However, the current state of organic markets in various parts of SSA reveal that many consumers are unfamiliar with the concept of certified OA (e.g., Philip and Dipeolu 2010). Hence, the identification of market potentials of the organic product is important for the future development of the sector.

Although studies on seasoned organic markets in Europe and North America have shown that consumers are concerned with the environment when making consumption decisions (e.g., Carlsson, Frykblom and Lagerkvist 2007), the degree of concern differs among individuals. On one hand, most consumers choose organic products because of a perception that the products have unique (and in some cases superior) attributes compared to the conventional alternatives (Vindigni, Janssen and Jager 2002). For example, some consumers prefer organic products for self-interest motives such as health risk avoidance, while others select organic due to ethical and altruistic concerns about biodiversity, climate, or animal welfare. Similarly, many individuals with external orientation tend to respond to the social benefits of organic farming, and choose to reward local farmers for using environment-friendly production methods (e.g., Davis 1994).

On the other hand, a major reason for not selecting organic products by some consumers is linked to a perception that conventionally produced alternatives are better, especially given that organic quality attributes are intrinsic (i.e., credence good) and may be difficult to identify by visual inspection alone (e.g., Jolly *et al.* 1989). Likewise, it is argued that modern OA appears to be showing more signs of increasing intensification and specialization, similar to trends in conventional agriculture (e.g. Guthman 2004). Generally, these findings lend support to the idea of heterogeneity in preferences for organic products within the population. It is reasonable to hypothesize that preferences are not unique to the individual, but rather a group of individuals (e.g., Hu *et al.* 2004), thus in the present study we are the first to employ a hybrid latent class (HLC) approach (e.g., Hess, Shires and Jopson 2013; Mariel, Meyerhoff and Hess 2015), that controls for heterogeneous class-specific preferences in the context of organic products in SSA.

A number of studies have researched preferences for attributes of organic products among urban consumers in SSA and have used hypothetical stated preference (SP) approaches (e.g., Philip and Dipeolu 2010; Probst *et al.* 2012). Using contingent valuation method, Philip and Dipeolu (2010) investigated consumers' preferences for organic vegetable in Nigeria, whereas Probst *et al.* (2012) employed mixed multinomial logit model (MMNL) to explore the existence of heterogeneity in preferences for organic products among urban consumers in Ghana, Benin and Burkina Faso. However, none of these studies employed a joint latent class specification that identify different market segments (classes) based on consumers' socioeconomic and attitudinal data, as well as on observed choice behavior and product characteristics, potentially making the classes more directly relevant to management decision-making.[2]

The integration of choice data with attitudinal data to shed light on taste differences go back to McFadden (1986), Swait (1994), and Ben-Akiva *et al.* (1999). It is worth noting that several studies making use of answers to attitudinal statements often directly incorporate the individual's responses as explanatory variables in the utility specification (e.g., Bechtold and Abdulai 2014).[3] However, proponents of HLC approach (e.g., Ben-Akiva *et al.* 1999) query whether responses to attitudinal statements should be included directly as error free explanatory variables in a model. The authors argue that respondents' answers are mainly indicators of true underlying latent attitudes, hence incorporating these responses directly to a model could potentially lead to measurement error and endogeneity bias problems.[4]

In this study, we examine heterogeneous preferences for organic products attributes among consumers' in Nigeria using household survey data from a discrete choice experiment (CE). Specifically, we use HLC model to investigate how the relative importance that consumers attach to organic products' attributes varies strongly as a function of underlying attitudes.[5] This model framework allows us to jointly examine the response to the stated choice component as well as the response to the attitudinal questions, without risk of exposure to measurement error and endogeneity bias problems. Given that organic products are quasi-public goods, we account for both environment (public) and health-related (private) attitudes of respondents. Thus, we incorporate all sources of heterogeneity, including socioeconomic and attitudinal data. To the extent that the markets for organic products have shown potentials for growth, our study is formulated to provide more insight into heterogeneous consumers' preferences for organic products in Nigeria as well as to draw implications for future development of the sector.

The rest of the paper is organized as follows. The next section presents the econometric specification of the general CE framework, followed by a description of the design of our survey and the data in the third section. The empirical specification and results from the analysis are then reported in sections four and five, respectively. The final section provides concluding remarks and implications.

2. Econometric Framework

We employ the hybrid latent class (HLC) approach presented by Hess, Shires and Jopson (2013), in which a latent class model (LC) is used within the hybrid choice modeling framework. The framework explains the effect of respondent's attitudes on observed sequence of choices through the class allocation probabilities, such that responses to attitudinal questions are specified as functions of the underlying latent attitudes to avoid the risk of endogeneity bias (e.g., Ben-Akiva *et al.* 1999). The HCL is composed of two parts. The structural equation component explains both the latent variable and utility function in terms of observable exogenous variables and attributes, respectively. The measurement component links the latent variable to responses to the attitudinal questions (i.e., the indicators). In addition, the HLC model also has a class allocation model which itself has structural equations highlighting utility of the various classes.

The main structural equations component is based on the random utility theory, thus utility of respondent n for alternative i in choice situation t is presented as:

$$U_{int} = V(z_{int}, m_n, \beta) + \varepsilon_{int} \quad (1)$$

where $V(z_{int}, m_n, \beta)$ is the deterministic part of utility function, with z_{int} as the vector of attributes of alternative i (including the conventional alternative dummy), m_n a vector of socio-demographic characteristics and β a vector of parameters. The term ε_{int} is a random component assuming an i.i.d. EV (0, 1) and it accounts for unobserved attributes and characteristics.

Latent class models assume that discrete segments C (classes) of the population have different choice behaviors and each class, c is characterized by a unique class-specific utility parameter (β_c). Given membership to a class c, the conditional probability that respondent n chooses alternative i in choice situation t is expressed as:

$$P_n = \Pr(y_{nt}|c, z_n) = \prod_{t=1}^{T_n} \frac{e^{(\beta_c z_{int})}}{\sum_{j=1}^{J} e^{(\beta_c z_{jnt})}}, \quad (2)$$

where y_{nt} denotes the sequence of choices for respondent n over T_n choice tasks. Equation (2) is a product of MNL probabilities and for identification reasons we fix the scale parameter to 1. The LC approach also hypothesizes that respondent’s actual class assignment is probabilistic, since the classes are unobservable. Thus, let the class allocation probability ($\theta_{n,c}$) for respondent n be modeled using a logit structure, which is given as:

$$\theta_{n,c} = \frac{e^{(\delta_{0,c} + \gamma_c m_n)}}{\sum_{c=1}^{C} e^{(\delta_{0,c} + \gamma_c m_n)}}, \quad (3)$$

where utility of a class is a function of socio-demographics (m_n), with γ_c and $\delta_{0,c}$ denoting the vectors of parameters and constant for class c, respectively. For normalization reasons, we fixed the constant to zero for one of the classes. Therefore, the unconditional probability over sequence of observed choices is derived by taking the expectation over all classes, C. This is specified as:

$$P_n = \Pr(y_{nt}|z_n) = \sum_{c=1}^{C} \theta_{n,c} \prod_{t=1}^{T_n} \frac{e^{(\beta_c z_{int})}}{\sum_{j=1}^{J} e^{(\beta_c z_{jnt})}}, \qquad (4)$$

For the measurement equations component, studies have shown that the deterministic inclusion of responses to attitudinal statements (as direct measures of respondent's underlying attitudes) in a model may result in measurement error and endogeneity bias problems. In line with Hess, Shires and Jopson (2013), we account for these issues in the specifications. First, we consider respondent's attitude as a latent variable, which is defined as:

$$\alpha_n = f(M_n, \lambda) + \eta_n, \qquad (5)$$

where $f(M_n, \lambda)$ is the deterministic part of α_n, with $f(.)$ specified as linear. The vectors M_n and λ denotes the socio-demographic variables of respondent n and the estimated parameters, respectively. The random term (η_n) is assumed to be normally distributed with a zero mean and standard deviation, σ_η. Next, we use the values of the attitudinal indicators as dependent variables. Specifically, the value of the kth indicator for respondent n is specified as:

$$I_{kn} = h(\alpha_n, \zeta) + \omega_n, \qquad (6)$$

where the indicator I_{kn} is a function of latent variable (α_n) and vector of parameters (ζ). The random term, ω_n is normally distributed with a mean 0 and standard deviation, σ_{I_k}. To avoid the estimation of unnecessary parameters, we centered the indicators on zero. The indicators are responses to attitudinal questions, with a finite number of possible values (i.e., scale 1-5). As such, we use ordered logit structure for the five indicators (I_1-I_5). The measurement equation component consists of threshold functions, such that for a discrete indicator (I_{kn}) with strictly increasing R levels $(i_1, i_1 \ldots . i_R)$, we compute the threshold parameters, $\tau_1, \tau_2 \ldots \ldots \tau_{R-1}$.

The likelihood of specific observed value of $I_{kn}(k = 1,2, \ldots .5)$ is expressed as:

$$L_{I_{kn}} = I_{(I_{kn}=i_1)} \left[\frac{e^{\left(\tau_{k,i_1} - \zeta_k \alpha_n\right)}}{1+e^{\left(\tau_{k,i_1} - \zeta_k \alpha_n\right)}} \right] + \sum_{r=2}^{R-1} I_{(I_{kn}=i_r)} \left[\frac{e^{\left(\tau_{k,r} - \zeta_k \alpha_n\right)}}{1+e^{\left(\tau_{k,r} - \zeta_k \alpha_n\right)}} - \frac{e^{\left(\tau_{k,(r-1)} - \zeta_k \alpha_n\right)}}{1+e^{\left(\tau_{k,(r-1)} - \zeta_k \alpha_n\right)}} \right] +$$

$$I_{(I_{kn}=i_R)} \left[1 - \frac{e^{\left(\tau_{k,(R-1)} - \zeta_k \alpha_n\right)}}{1+e^{\left(\tau_{k,(R-1)} - \zeta_k \alpha_n\right)}} \right], \tag{7}$$

where ζ_k measures the impact of the latent variable (α_n) on indicator I_{kn} and $\tau_{k,1}, \tau_{k,2} \ldots \ldots \tau_{k,R-1}$ are a set of estimated threshold parameters. In application, the threshold parameters are estimated using a set of auxiliary parameters, $(\mu_{k,1}, \mu_{k,2} \ldots \ldots \mu_{k,(R-2)})$, in the threshold functions, such that $\tau_{k,r} = \tau_{k,r} + \mu_{k,r}$; where $\mu_{k,r} \geq 0, \forall\, r$. The auxiliary parameters are specified to guarantee that threshold parameters are strictly increasing; $\tau_{k,1} < \tau_{k,2} \ldots < \tau_{k,(R-1)}$. For identification, we constrained one of the threshold to 0 and the scale parameter to 1.

The latent variable (α_n) is linked to the remaining part of the model through the class allocation probabilities specified in Equation (3). In our test for the class allocation specification, we were unable to retrieve any significant socio-demographic interactions other than those captured through the latent variable specified in Equation (5). Thus, following Mariel, Meyerhoff and Hess (2015) we re-write Equation (3) as:

$$\theta_{n,c} = \frac{e^{\left(\delta_{0,c} + \delta_{1,c}\alpha_n\right)}}{\sum_{c=1}^{C} e^{\left(\delta_{0,c} + \delta_{1,c}\alpha_n\right)}}, \tag{8}$$

where $\delta_{0,c}$ and $\delta_{1,c}$ are parameters to be estimated. The sign of $\delta_{1,c}$ describes the effect of the latent variable (α_n) in determining the probability of belonging to a specific taste class.

The log-likelihood (LL) function for the HLC model integrates the choice models with the measurement models (attitudinal variables) over η_n, conditional on a specific realization of the latent variable (α_n). Hence, the joint model is specified as:

$$LL(\beta, \delta, \lambda, \zeta, \tau) = \sum_{n=1}^{N} ln \int_{\eta} \left(P_n \prod_{k=1}^{8} L_{I_{kn}} \right) \mathrm{g}(\eta) d\eta, \qquad (9)$$

where P_n is defined in Equation (4), but with class allocation probabilities $\theta_{n,c}$ as in Equation (8) and $L_{I_{kn}}$ as expressed in Equation (7) for $k = 1, 2, \dots, 5$. For identification reasons, the standard deviation (σ_η) of the random component (η) is set to1.

3. Survey Design and Data Description

Our analysis makes use of consumer preferences data collected in Kano State, northwestern Nigeria. This location is densely populated and highly diverse socio-demographically, thus allowing for high representation in our dataset.

Interviews were conducted with questionnaire, and a total of 600 primary food buyers in the households were sampled using a multistage sampling approach. Our questionnaire centered on choice experiment, respondent's socio-demographic and attitudinal data. Initially we elicited respondents' level of awareness of OA, and based on common understanding regarding the meaning of organic concept, we proceeded with the CE task.

The choice sets, consist of two generated organic alternatives and a 'status-quo' option. We generate the organic alternative profile using a three stage Bayesian sequential approach (Scarpa, Campbell and Hutchinson 2007). In the CE, respondents were randomly assign to nine choice scenarios each. As presented in Table 1, each organic alternative is illustrated by four quality attributes and a price. The price attribute in the choice sets were the prices for 1kg basket of tomatoes, with three different price levels. Attribute relating to the origin of the certifier of the organic product is also identified. We recognize three organic third party certification scenarios namely: when the organic tomato is certified by foreign certifiers only, scenario with both foreign and indigenous third party certifiers, and indigenous certifiers only. 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. [6]

Furthermore, our questionnaire elicit basic information on socio-demographics characteristics and some attitudinal statements - such as questions about the respondent's household buying habits, their attitudes and beliefs. Table 2 presents the attitudinal statements used in the HLC model specification. These statements covered a wide range of aspects that are of both health and environmental concerns. These questions were scored on a five-point Likert scales ranging from *completely disagree* (1) to *completely agree* (5). From an a priori perspective, the third column shows the signs describing the expected tendency of responses from proponents of OA. For example, a positive sign for the fair payment statement implies that proponents would more probably choose higher values on the response scale for the specified indicator on incentivizing environment-friendly food production.

We present information on the socioeconomic characteristics of the sample households used in the econometric modeling in Table 3. The results indicate that most households have an average size of about 10 members, and their mean monthly income was estimated at nearly ₦ 47,000. Majority of the household-heads have less than 8 years of formal education. Moreover, level of awareness of organic products is low among the respondents, as only 25 percent indicated previous knowledge of certified organic farming. Moreover, 46 percent of the respondents practice some environmental conservation, such as food waste recycling.

4. Empirical Specification

Each respondent was faced with up to nine choice tasks, and for the analysis, we made use of a sample of 5,400 observations from the 600 respondents. Two different models were estimated on the data, a standard latent class model (LC) and the hybrid latent class model (HLC) as shown in Equation (4) and (9), respectively. The LC model is primarily included for illustrative reasons, given their past use in the previous studies (e.g., Bechtold and Abdulai 2014). The two models were coded in Biogeme (Bierlaire 2003), and for the HLC model, we simultaneously estimate the structural and measurement model components (e.g., Ben-Akiva *et al.* 1999).

As indicated previously, the LC structure assume that discrete segment of the population have different choice behavior and taste, and that the heterogeneity can be linked to individual’s attitudes and perceptions. In discrete choice analysis, this translates into class-specific choice model and class-membership model specifications. To allow for some comparisons, the class-specific choice and class-membership components were treated consistently across the two models, ensuring that the base structure of the LC model equate to reduce form version of the hybrid structure (HLC) (e.g., Mariel, Meyerhoff and Hess 2015). For the class-specific choice model, in both the LC and HCL models, we consider the four quality attributes and price, and allow their effects to vary across classes. The quality attributes were all dummy coded, with the base levels set to zero.[7] Next, for the class-membership probabilities, we consider the constant ($\delta_{0,c}$) and parameter of the latent variable ($\delta_{1,c}$) in the logit structure. The sign of $\delta_{1,c}$ determines whether increases in the value of the latent variable (α_n) lead to an increased or decreased probability for a specific taste class. Generally, the specification at this stage corresponds to a standard LC structure which forms the basis of the developments in this paper.

The final component of the hybrid model is given by the measurement equations for the attitudinal indicators. To make use of the answers to the five attitudinal statements reported in Table 2, we hypothesize that the responses together with respondents' actual choices are driven by the underlying latent attitudes. The latent variable (α_n) is linked to the remaining part of the hybrid structure through the class allocation probabilities as specified in Equation (8). It is important to note that we mainly consider respondents' answers to the four environment-related attitudinal statements ($I_1 - I_4$) and a health-related statement (I_5). In other words, the answers to these statements are assumed to be likely dependent on the underlying health and environmental attitudes of the respondents.

We employ an ordered logit specification (in Equation 7) to estimate the thresholds for each of the five ordered indicators, although the specific distribution of the responses led to our merging of the first three and last two levels for all indicators. We also simplify the model further by constraining the estimates of the indicators in Equation (7) to 1. As such, any differential impact of the latent variable on the indicators was plugged into the estimates for the thresholds.

As described in section 2, the combine LL function for the HLC model is composed of two components. The first component is P_n as specified in Equation (4) which gives the likelihood of observed choices, this is obtained by taking the expectation over all C classes (i.e., the product of the logit probabilities). Whereas the second component, $L_{I_{kn}}$ denoting the probability of responses to the attitudinal questions, is a product of five ordered logit terms (for I_1–I_5) as defined in Equation (7). We use a simultaneous estimation with integration over η (as shown in Equation (9)), and also reflect the repeated choice nature of our data. The distribution of the random latent variable, g(η), is univariate normal, with zero mean and a standard deviation of one. Likewise, we estimate the LC model simultaneously, although without the $L_{I_{kn}}$ component and the integration over η (Hess Shires and Jopson 2013).

5. Empirical Results

In this section, we first discuss the results of the identification of the number of latent classes, before we proceed to present the maximum likelihood estimates for the best-fitting LC and HLC models. Finally, we present the class-specific WTP values for the identified attributes.

Models with two through five classes were estimated using Biogeme software (Bierlaire 2003). For each model, we determine the optimal number of latent classes (Boxall and Adamowicz 2002) using the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). We present the estimates for these models in Table 4. The log-likelihood values at convergence (LL) reveal improvement in the model fit as classes are added to the procedure up to the three class model. Inspection of the AIC and BIC values suggests that the three class model is the optimal solution, given that the minimum BIC and AIC statistics are clearly associated with three classes. We therefore estimate a three-class model for both LC and HLC specifications.

The maximum likelihood estimates for the LC and HLC models are reported in Tables that follows, and then the respective welfare measures. Foremost, we focus on the estimates derived from standard LC model on Tables 5 and 7, and then discuss results from the HLC model on Tables 5, 6 and 9. Generally, our results indicate existence of considerable heterogeneity in preferences across latent classes, as revealed by the differences in magnitude and significance of the utility function estimates. We observe that the class membership probabilities are significantly related to the consumers' attitudes. Similarly, as expected, we note that across models the price coefficient is negative and statistically significant in all classes, suggesting that respondents' utility decreases with increase in price. Furthermore, the results show that a decrease in pesticide residue increases respondents' preferences for organic tomatoes, as the attribute is positive and statistically significant in all the classes, across models.

From the LC model in Table 5, we observe that although members of class 1 exhibit lower utility for the conventional alternatives as shown by the negative and significant conventional alternative variable, they are more likely to be termed as *indifferent* to certified organic food. This is because the coefficient estimates for three of the four organic quality attributes identified are not statistically significant from zero, implying that the reduction of pesticide residues is the only relevant quality attribute for members of this class. For class 2, we find that all the organic quality attributes are positive and significant, suggesting that members of this class are likely to be associated with being *advocates* of organic products. In particular, our results show that members derive significantly higher utilities from the certification program, increase in vitamin A contents, reduction in pesticide residues and lower soil erosion, and also obtain distinct disutility from the conventional alternative.

On the other hand, consumers who are likely to be members of class 3 prefer to maintain the status quo, as shown by the positive and statistically significant conventional alternative dummy. Members of this class also express significant disutility for the certification program attribute. However, based on available evidence, a product can only be correctly qualified as 'organic' when it is grown under a well-defined and unique set of certification procedures (IFOAM 2012)[8]. Therefore, members of class 3 are more likely to be labelled as *conservatives*. In general, our results reveal that of the respondents participating in the CE about 33% have a fitted probability to belong to class 3, while 22% and 45% will likely belong to classes 1 and 2, respectively. This finding suggests that organic products have considerable potential for growth in Nigeria, since the bulk of respondents (about 67 %) are more likely to belong to either class 1 (indifferent segment) or class 2 (advocates).

Table 7 presents WTP measures corresponding to significant attributes in the three classes of the LC model. The WTP measures are computed from the LC model estimates giving the implied monetary valuation of different changes in attribute levels. A positive WTP value in our results show how much the respondents would be willing to pay for a change of the given attribute from its base level, whereas a negative WTP suggests the amount they are willing to pay to prevent this change. For example, in the class 2, members are willing to pay a premium of ₦ 11.03, ₦ 8.97 and ₦ 8.46 for lower pesticide residues, reduction in soil erosion, and certification attributes, respectively.

Next, we focus on the results on the HLC model in Table 5. Foremost, it is worth noting that although the log-likelihood of HLC structure cannot be directly compared to the LC model fit[9], the estimated coefficients from both models are very similar. Also, given that we incorporate supplementary behavioral information in HLC choice specification, the accuracy of most of the coefficients increase, as expected (e.g., Mariel, Meyerhoff and Hess 2015). This finding confirms our hypothesis that the identified underlying health and environmental attitudes influence respondents' class allocation probabilities, as all relevant coefficients are statistically significant at the 10% level.

Moreover, from the measurement components presented in Table 6, our results show that the latent variable actually inform assignment to latent classes in the HLC model. The latent variable has a significant impact on all five attitudinal indicators (ζ) identified. Similarly, the signs of the indicators suggest that proponents of organic products are more likely to be associated with higher latent variable. Thus, consistent with *a priori* expectation, we observe that the *advocates* of organic products assign higher values (positive signs) to both attitudinal statements relating to fair payment of environment-conscious farmers and the objections to cloning, while the remaining three indicators attract lower values (negative signs). Furthermore, from the estimates of the class allocation model, we observe that respondents with a lower latent variable are more likely to be in class 3, and least likely to fall into class 2, given that the signs of $\delta_{1,3}$ and $\delta_{1,2}$ are positive and negative, respectively. These findings conform to our earlier identification of class 3 as being characterized by strong opposition to organic products, while members of class 2 are identified as *advocates* of organic products.

To further describe the consumer segments (i.e., *advocates* and *conservatives*), we employ the socio- demographic variables (λ). The signs of the characteristics indicate that the latent variable is higher among older and more educated respondents, who are environment-conscious (recycle food waste) and have previous awareness of the concept of organic agriculture. Similarly, this segment of consumers are more likely to be resident in the urban areas and have modest household sizes. [10]

As specified in Equation (8), the class allocation probability is respondent-specific, and a function of the random latent variable (α), which implies that the allocation probabilities also follow a random distribution. Thus, we simulate the class allocation probabilities using 10,000 Halton draws for the random latent variable and for each respondent, as in Equations (5) and (8). Here, we integrate the parameter estimates (λ) with the associated values of socio-demographic variables and the random errors, η (e.g., Mariel, Meyerhoff and Hess 2015). The class allocation probabilities are shown in Figure 1, where the estimated distributions suggest that there is a higher likelihood of respondents belonging to classes 2 and 3 relative to class 1. Moreover, given that the latent variable (α) is a function of socio-demographic variables, in Table 8, we report the simulated allocation probabilities for two opposing groups, *advocates* and *conservatives*. In this case, unlike the LC model, the subgroups are characterized by socio-demographic variables, the values in the first column define *conservatives* as being below the 25th percentiles of the corresponding variables; age, years of education, household size, and being unaware of organic concept and located in rural centers. The second column uses the 75th percentiles of these variables to define *advocates* that present a diametrically opposing values of the different characteristics.

Clearly, the relative advantage of using the HLC is that it enables us to consistently examine the role played by respondents' underlying attitudes in explaining preferences for organic attributes. While the LC model has structural equation that explains preference function in terms of observable attributes, the HLC model has in addition to the structural aspect a measurement component for the endogenous (latent) variables that provide more behavioral insight. In other words, for the LC model, we identify consumer segments based on the choices of observable quality attributes, whereas in the HCL model, latent classes are consistently determined based on both the preferences for observable quality attributes as well as the underlying attitudes that explain respondents' preferences.

Turning next to the implied trade-off for the organic attributes derived from HLC model. In Table 9, we report the welfare measures and confidence intervals for the two subgroups. We calculate 95% confidence intervals using the Krinsky–Robb parametric bootstrapping method. Also, we simulate the WTP values for the sample population by computing weighted means of the WTP values in each class (e.g., Mariel, Meyerhoff and Hess 2015). We merged the values across respondents to obtain sample level distributions (pooled). A comparison of the WTP estimates for the attributes across the latent classes reveal notable differences in preference structure. Based on the WTP measures, our findings confirm the interpretation of the segments as mentioned above (i.e., *advocates* and *conservatives*). Although statistically significant differences exist between the premiums for the attributes across subgroup, the simulated welfare values show that the reduction in pesticide residues attribute attracts highest premium followed by lower soil erosion, and then higher vitamin A content and certification attributes. Similarly, corresponding simulated distribution of both the segmented and pooled implied trade-off for each attribute is also represented in Figures 2 and 3 respectively, illustrating the reported respondents' preference ordering.

Respondents that are identified as *conservatives* appear to show preference for food products with reduced pesticide residues, although relative to *advocates*, the price premiums for this subgroup tends to be lower. This implies that members of the conservative subgroup are price sensitive and more likely to partly base their purchasing decision on price as well. Meanwhile, individuals that *advocate* for organic food have been shown to express significant preferences for all the organic quality attributes identified with the highest value placed on lower pesticide residues, followed by certification, and then lower soil erosion and increased vitamin A content. For example, respondents in this segment are willing to pay ₦ 5.53 more for reduced soil erosion and even more for lower pesticide residues (₦ 6.74) and certification program (₦ 6.53). However, they obviously derive disutility from conventionally-produced tomatoes and would be willing to accept up to ₦ 5.77 as compensation.

On the other hand, in the *conservative* subgroup, the conventional alternative is more highly valued relative to the identified organic quality attributes. The high valuations of conventional tomatoes, may be attributed to the fact that members of this class perceive organic food products with skepticism. Moreover, the certification attribute is negative and statistically significant, suggesting that the quality of organic traceability network is not important for members of this class.

Generally, we observe that respondents (*advocates*) are willing to pay an additional ₦ 20 for organic tomatoes over the base retail price (₦ 60) for one kilogram basket of conventional tomatoes. This value corresponds to more than 30% premium when compared to the typical market prices results for conventional tomatoes during the peak seasons in Nigeria.[11] The simulated WTP values reveal that respondents are in favor of reducing the pesticide residues in food products, regardless of whether they are categorized as indifferent, advocates or opponents of organic products. However, the valuation of certification attribute differs strongly between the two opposing groups, as the proponents would prefer tomatoes produced in accordance with the specifications of organic third-party certifiers that guarantee compliance with the production standards, as well as adequate inspection of the processes within the supply chain.

6. Conclusion

In this study, we examine the existence of preference heterogeneity for organic products, as well as the sources of heterogeneity for consumers in Nigeria. We use a hybrid model framework to jointly analyze the response to the stated choice component as well as the response to the attitudinal questions, without exposure to risks of endogeneity bias and measurement error.

Our results reveal that market for organic products exists in Nigeria, as consumers are willing to pay a premium for both health and environmental gains realized through organic production systems, although their quantitative valuation is higher for the health concerns. This finding reflects public opinion in Nigeria toward food safety and health concerns. Given that organic foods are recognized as products capable of generating health benefits, and considering the fact that older people are more concerned with health than younger people, this finding is in line with expectations. Likewise, our result is consistent with earlier research demonstrating that age seems to increase health-related concerns and also attractiveness of products with health claims (e.g., Bechtold and Abdulai 2014).

Furthermore, we note that individuals with stronger preferences for organic products tend to attach a global value to the certification program, whereas the valuation tends to be more restrictive among respondents that prioritize the status quo option (conventional alternative). Another interesting issue that emerges from our study, is the issue of regional heterogeneity. We observe that difference in geographic location has significant impact on consumers' choice of organic products. Similarly, while across market segments willingness to pay for health improvement increases significantly, we found that advocates of organic products are more likely to be resident in the urban areas. These result suggest that to sustain organic production on the demand for healthier food, it is important to improve the frame conditions (that is, the distribution and sale systems) for the marketing of organic foods as part of a policy strategy.

In addition, we find that respondents' level of awareness of organic food production characteristics (prior to the survey) is a relevant and significant factor in increasing their WTP for the organic quality attributes, predominantly, better-informed respondents demonstrate higher WTP. Thus, the idea that environment-conscious consumers tend to seek information, and the notion that information may shift preferences for environmental conservation appear to be supported by our results.

Overall, our findings contribute to the debate on the potential of organic certification to correct environmental externalities in agricultural production. We find that respondents display a range of different preferences and that the behavioral asymmetry may be reflecting differences in underlying attitudes. More so, we observe that in order to drive the market for organic produce, a key element in the strategy to reach consumers would be to facilitate access to the products (via urban sale outlets). Moreover, actions to better inform the public in general is cardinal to promote concern for the health and environment as well as a shift in preferences while also driving the demand for organic products. Furthermore, despite the fact that WTP is higher for the private attributes of organic production systems relative to the public attributes, environmental preferences also provide a feasible foundation for the development of the organic market in Nigeria.

References

Azadi, H., S. Schoonbeek, H. Mahmoudi, B. Derudder, P. De Maeyer, and F. Witlox. 2011. Organic Agriculture and Sustainable Food Production System: Main Potentials. *Agriculture, Ecosystems and Environment* 144(1): 92–94.

Bechtold K., and A. Abdulai. 2014. Combining Attitudinal Statements with Choice Experiments to Analyze Preference Heterogeneity for Functional Dairy Products. *Food Policy* 47: 97–106.

Bello, M., and A. Abdulai. 2016. Measuring heterogeneity, survey engagement and response quality in preferences for organic products in Nigeria. *Applied Economics* 48 (13): 1159-1171.

Ben-Akiva M, J. Walker, D. McFadden, T. Gärling, D. Gopinath, and D. Bolduc. 1999. Extended Framework for Modeling Choice Behavior. *Marketing Letter* 10 (3):187–203.

Bierlaire M. 2003. BIOGEME: A Free Package for the Estimation of Discrete Choice Models. In: Chevroulet T, Sevestre A, (eds.), Proceedings of the 3rd Swiss Transportation Research Conference, Monte-Verita, Ascona, Switzerland.

Boxall, P. and W. Adamowicz. 2002. Understanding Heterogeneous Preferences in Random Utility Models: A Latent Class Approach. *Environment Resource Economics* 23 (4): 421–46.

Carlsson, F., P. Frykblom, and C. J. Lagerkvist. 2007. Consumer Benefits of Labels and Bans on GM Foods – Choice Experiments with Swedish Consumers. *American Journal of Agricultural Economics* 89 (1): 152–61.

Collins, A. T., Rose, J. M. and Hess, S. 2012. Interactive Stated Choice Surveys: A Study of Air Travel Behavior. *Transportation* 39:55–79.

Cornes, R., and T. Sandler. 1984. Easy Riders, Joint Production, and Public Goods. *Economic Journal* 94, 580–98.

Coulibaly, O., T. Nouhoheflin, C.C. Aitchedji, A.J. Cherry, and P. Adegbola. 2011. Consumers' Perceptions and Willingness-to-Pay for Organically Grown Vegetables, *International Journal of Vegetable Science* 17: 349-62.

Davis, J.J. 1994. Consumer Response to Corporate Environmental Advertising. *Journal of Consumer Marketing* 11(2): 25-37.

Guthman, J. 2004. Back to the Land: The Paradox of Organic Food Standards. *Environmental and Planning* 36: 511–28.

Heath, J., and H. Binswanger. 1996. Natural Resource Degradation Effects of Poverty and Population Growth are Largely Policy-Induced: The Case of Colombia. *Environment and Development Economics* 1:65–84.

Hess S., J. Shires, and A. Jopson. 2013. Accommodating Underlying Pro-Environmental Attitudes in a Rail Travel Context: Application of a Latent Variable Latent Class Specification. *Transportation Research Part D* 25:42–8.

Hu, W.Y., A. Hunnemeyer, M. Veeman, W. Adamowicz, L. Srivastava. 2004. Trading Off Health, Environmental And Genetic Modification Attributes in Food. *European Review of Agricultural Economics* 31: 389–408.

IFOAM 2012. Global Organic Farming Statistics and News. Research Institute of Organic Agriculture (FiBL) and International Federation of Organic Agriculture Movements (IFOAM): www.organic-world.net/statistics-data-tables-dynamic.html

Jolly, D.A, G.H. Schutz, K.V. Diaz-Knauf, and J. Johal. 1989. Organic Foods: Consumer Attitudes and Use. *Food Technology* 1:60-6.

Kleemann, L. and A. Abdulai. 2013. Organic Certification, Agro-Ecological Practices and Return on Investment: Evidence from Pineapple Producers in Ghana. *Ecological Economics* 93:330-41.

Krinsky, I. and A. L. Robb. 1986. On Approximating the Statistical Properties of Elasticities. *Review of Economics and Statistics* 68(4): 715–19.

Mariel, P., J. Meyerhoff, and Hess, S. 2015. Heterogeneous Preferences toward Landscape Externalities of Wind Turbines – Combining Choices and Attitudes in a Hybrid Model. *Renewable and Sustainable Energy Reviews* 41:647–57.

McFadden, D. 1986. The Choice Theory Approach to Market Research. *Marketing Science*. 5: 275–97.

Philip, B. and A.O. Dipeolu. 2010. Willingness-to-Pay for Organic Vegetables in Abeokuta, Southwest Nigeria. *African Journal of Food Agriculture Nutrition and Development* (AJFAND) 10 (11): 4364-78.

Poe, G. L., K. L. Giraud, and J. B. Loomis. 2005. Computational Methods for Measuring the Difference of Empirical Distributions. *American Journal of Agricultural Economics* 87(2): 353–65.

Probst, L., Houedjofonon, E., Ayerakwa, H.M., and Haas, R. 2012. Will They Buy It? The Potential for Marketing Organic Vegetables in the Food Vending Sector to Strengthen Vegetable Safety: A Choice Experiment Study in Three West African Cities. *Food Policy* 32: 296-308.

Reardon, T., and S. Vosti. 1997. Poverty-Environment Links in Rural Areas of Developing Countries. S.A. Vosti and T. Reardon (eds.) *Sustainability, Growth, and Poverty Alleviation: A Policy and Agroecological Perspective*. Baltimore: John Hopkins University Press.

Scarpa, R., D. Campbell, and W.G. Hutchinson. 2007. Benefit Estimates for Landscape Improvements: Sequential Bayesian Design and Respondents' Rationality in a Choice Experiment Study. *Land Economics* 83(4): 617–34.

Swait, J. 1994. A Structural Equation Model of Latent Segmentation and Product Choice for Cross-Sectional Revealed Preference Choice Data. *Journal of Retailing and Consumer Services* 1: 77–89.

UNEP-UNCTAD. 2008. Organic Agriculture and Food Security in Africa. United Nations Conference on Trade and Development; United Nations Environment Programme, UNCTAD/DITC/TED/2007/15.

Vindigni, G., M.A. Janssen, and W. Jager. 2002. Organic Food Consumption: A Multi-Theoretical Framework of Consumer Decision Making. *British Food Journal* 104(8): 624-42.

Yiridoe, E.K., S. Bonti-Ankomah, and R.C. Martin. 2005. Comparison of Consumer Perceptions and Preference toward Organic Versus Conventionally Produced Foods: A Review and Update of the Literature. *Renewable Agriculture and Food System* 20: 193– 205.

Table 1: Attributes and attribute levels in the choice experiments

Attributes	Description	Attribute Levels
Pesticide	Reduction in the level of pesticide residues content	5%, 25% ,100% lower
Certification	Organic certification scenarios	Foreign, Foreign plus indigenous, Indigenous labels
Vitamin	Increase in vitamin A content	5%, 25%, 100% higher
Price	Purchase price (in Naira)	₦ 60, ₦ 80, ₦100
Erosion	Reduction in the level of soil erosion	5%, 25%, 100% lower

Table 2: Attitudinal statements and tendency of response

Indicators	Definition	Hypothesis
I_1	It is fair to pay farmers more for producing environment-friendly food	+
I_2	Environmental problems are highly exaggerated	-
I_3	My actions are too small to affect any environmental quality	-
I_4	Government is doing enough to control environmental pollution	-
I_5	Scientists are going too far with cloning	+

Note: response scale ranges from ‘’completely disagree (1)’’ to ‘’completely agree (5)’’

Table 3: Sample Socio-demographics

Variables	Definition	Mean	S.D.	Min	Max
Age	Age of household head in years	43.34	11.7	17	75
Gender	Dummy(1=if household head is male, 0 otherwise)	0.82	0.39	0	1
Education	Years of formal education of the household head	7.29	4.13	0	26
Income	Average monthly income in Naira (₦ '000)	47.73	75.42	9	800
Household Size	Number of members of the household	9.88	2.66	4	15
Awareness	Dummy(1=if previously aware of organic products, 0 otherwise)	0.24	0.42	0	1
Disease	Dummy(1=if incidence of food disease in 24months, 0 otherwise)	0.17	0.38	0	1
Region	Dummy(1=if urban dweller, 0= if rural dweller)	0.52	0.50	0	1
Recycling	Dummy(1=if food waste is often recycled, 0 otherwise)	0.46	0.49	0	1

Table 4: Criteria for number of classes

Number of latent classes (C)	Observations (N)	Number of Parameters (P)	Log-likelihood (LL)	AIC	BIC
2	5,400	38	-7,741.1	15,558.1	7,904.39
3	5,400	44	-7,659.4	**15,406.9**	**7,848.47**
4	5,400	50	-7665.8	15,431.6	7,874.25

Note: Bold figures indicate that the optimum number of latent classes is three under both AIC and BIC.

Table 5: Maximum likelihood estimates from LC and HLC models - choice component

	LC model						HLC model					
Respondents	600						600					
Observations	5,400						5,400					
LL	-3,181.648						-7,659.443					
Parameters	20						44					
	Class 1		Class 2		Class 3		Class 1		Class 2		Class 3	
Class Prob.	0.218		0.452		0.330							
Variable	Est.	*t*-Ratio	Est.	*t*-Ratio	Est.	*t*-Ratio	Est.	*t*-Ratio	Est.	*t*-Ratio	Est.	*t*-Ratio
Utility function												
β_{price}	-2.185	-5.56	-0.204	-3.82	-0.491	-5.47	-1.460	-18.79	-0.169	-6.23	-0.504	-7.58
$\beta_{pesticide}$	1.232	4.14	0.690	5.35	0.773	10.21	1.108	6.58	0.694	5.12	0.797	11.91
$\beta_{certification}$	-0.490	-0.74	0.730	6.75	-0.109	-5.57	-0.523	-1.53	0.762	6.91	-0.113	-6.23
$\beta_{vitamin}$	0.206	0.53	0.491	4.90	0.247	6.85	0.374	1.57	0.531	4.89	0.258	8.27
$\beta_{erosion}$	-0.162	-0.60	0.688	6.28	0.227	9.26	0.067	0.37	0.748	6.75	0.230	10.31
$\beta_{conventional}$	-1.577	-6.92	-3.733	-8.05	-0.549	-7.96	-1.250	-4.00	-3.399	-9.37	-0.568	-9.90
Class allocation function												
$\delta_{0,2}$	0.479	1.80					-0.133	-4.04				
$\delta_{1,2}$							0.412	5.44				
$\delta_{0,3}$	-0.547	-3.08					-0.275	-0.38				
$\delta_{1,3}$							-0.899	-1.92				

Table 6: Maximum likelihood estimates from HLC model- structural and measurement components 2

Variable	Est.	*t*-Ratio
Structural Equation (LV specification)		
λ_{Age}	0.401	9.89
$\lambda_{Recycling}$	2.515	6.24
λ_{Educ}	0.186	8.47
$\lambda_{H/hsize}$	-0.021	-0.08
$\lambda_{Disease}$	-1.358	-3.00
λ_{Aware}	4.461	12.50
λ_{Region}	0.525	2.40
Measurement Equation (effects of LV)		
ζ_{I_1}	0.737	18.39
ζ_{I_2}	-0.536	-11.57
ζ_{I_3}	-0.495	-19.54
ζ_{I_4}	-0.050	-2.37
ζ_{I_5}	0.344	7.54
Measurement Equation (thresholds)		
$\mu_{I_1,1,2\&3}$	-1.115	-6.72
$\mu_{I_1,4\&5}$	0.022	1.16
$\mu_{I_2,1,2\&3}$	-1.214	-5.46
$\mu_{I_2,4\&5}$	0.027	2.14
$\mu_{I_3,1,2\&3}$	-0.912	-6.87
$\mu_{I_3,4\&5}$	0.055	2.02
$\mu_{I_4,1,2\&3}$	-0.290	-7.69
$\mu_{I_4,4\&5}$	-0.015	-2.55
$\mu_{I_5,1,2\&3}$	-0.055	-2.98
$\mu_{I_5,4\&5}$	-0.033	-3.86

Table 7: Implied trade-offs and monetary valuation from the LC model

	Class 1	Class 2	Class 3
Lower Pesticide residues	4.49	11.03	6.46
	(3.52, 5.58)	(9.69, 11.36)	(4.47, 8.54)
Certification	NS	8.46	-7.94
		(7.43, 9.53)	(-8.88, -7.04)
Higher Vitamin A	NS	5.90	3.76
		(4.54, 7.44)	(3.32, 4.22)
Lower Soil Erosion	NS	8.97	4.04
		(7.04, 11.15)	(3.38, 4.72)
Conventional alternative	-6.42	-7.13	7.69
	(-7.42, -5.45)	(-8.05, -6.22)	(3.58, 8.60)

Note: 95% confidence intervals calculated using the Krinsky and Robb (1986) method in parentheses. The CIs are based on 10, 000 replications.
NS: means attribute is not statistically significant.

Table 8: Description of the opposing latent segments, from the HLC model

	Conservatives	Advocates
Age (in years)	< 26	>38
Education (in years)	<14	>20
Household size	>6	<5
Recycling	No	Yes
Disease	No	Yes
Region	Rural	Urban
Aware	Unaware	Aware

Note: The simulated allocation of probabilities presented is for the 25 and 75 percentiles.

8 Table 9: Implied trade-offs and monetary valuation from the HLC model

	Pooled	Advocates	Conservatives
Lower Pesticide residues	4.91 [a, g]	6.74	2.41
	(3.52, 5.58)	(4.31, 7.21)	(1.98, 3.72)
Certification	1.83 [b, f]	6.56	-2.97
	(1.48, 3.19)	(6.09, 7.25)	(-1.88, -4.04)
Higher Vitamin A	2.83 [c, f]	3.55	2.01
	(1.96, 3.17)	(3.09, 4.21)	(1.79, 2.25)
Lower Soil Erosion	4.46 [d, g]	5.53	3.00
	(3.03, 5.17)	(4.58, 6.89)	(1.96, 4.70)
Conventional alternative	-1.29 [e]	-5.77	3.40
	(-2.33, -1.04)	(-7.10, -4.38)	(2.52, 4.58)

Note: 95% confidence intervals calculated using the Krinsky and Robb (1986) method in parentheses. The CIs are based on 10, 000 replications.
NS: means attribute is not statistically significant.
[a,b,c,d,e] This value is statistically distinct from all other WTP. [f, g] This value is not statistically different from others with the same superscript. The statistical tests on the differences in empirical distribution and is based on the complete combinatorial approach (Poe, Giraud and Loomis 2005).

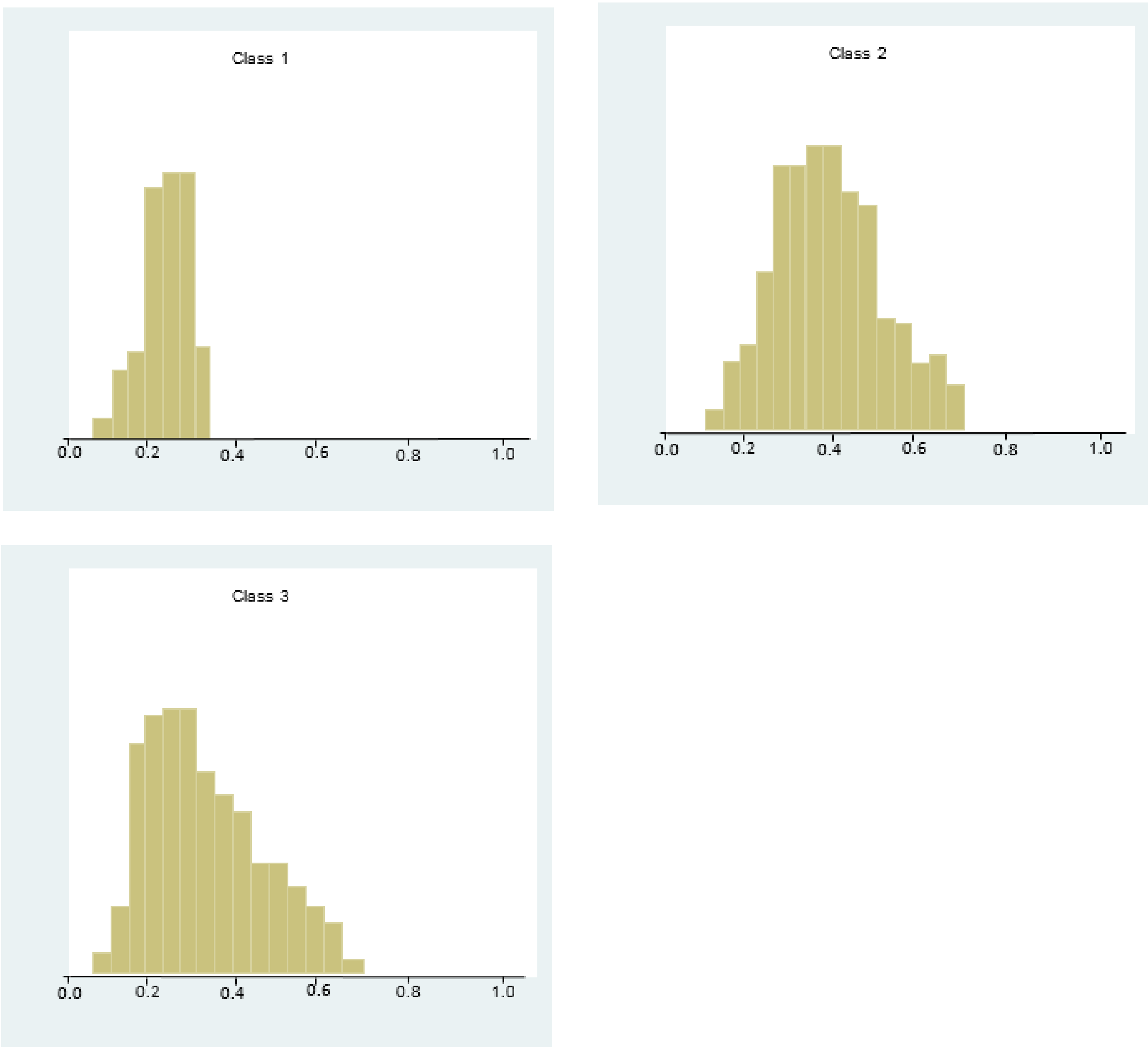

Figure 1: Simulated class allocation probabilities

Advocates Conservatives

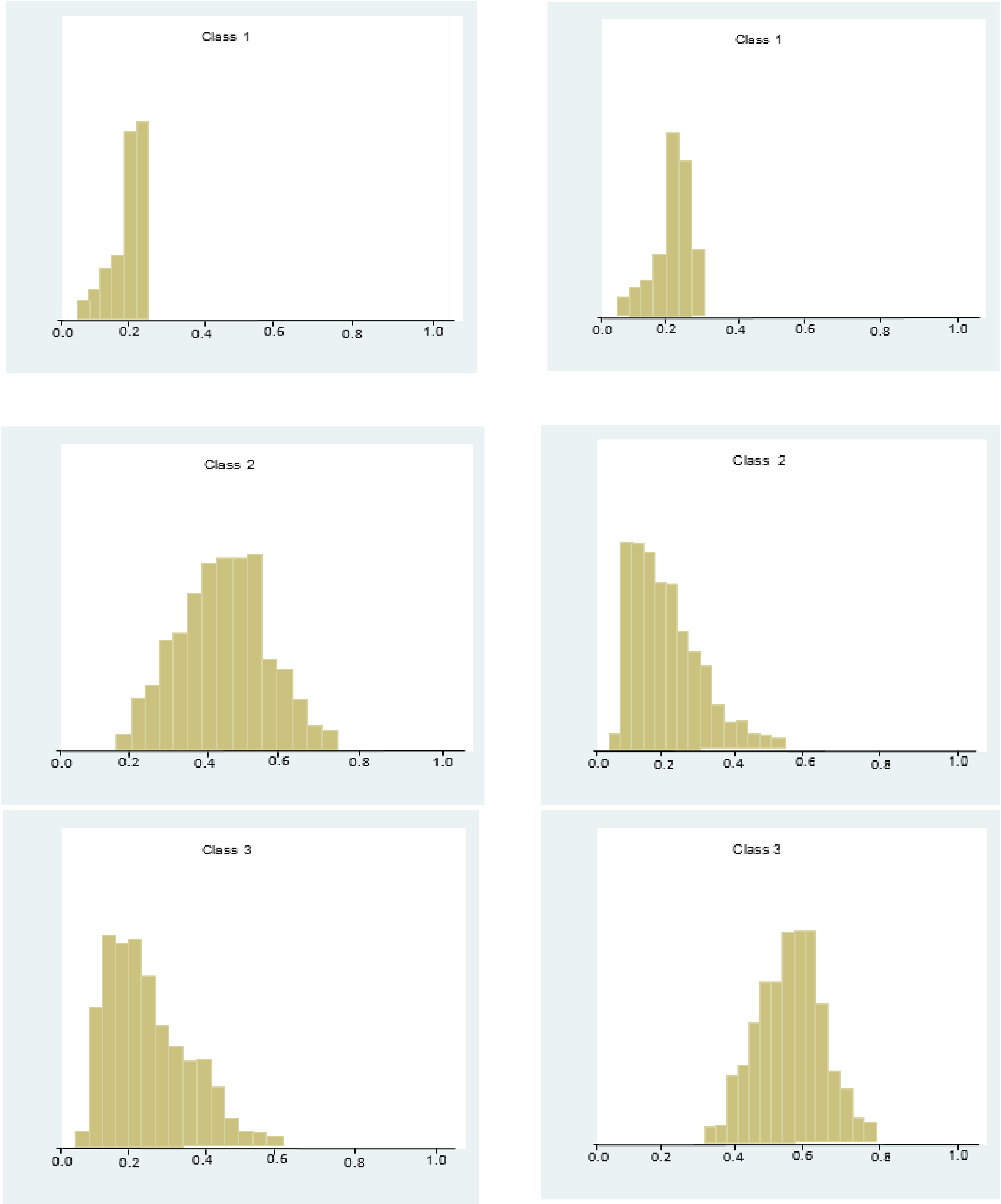

Figure 2: Simulated allocation probabilities for the opposing consumer segments

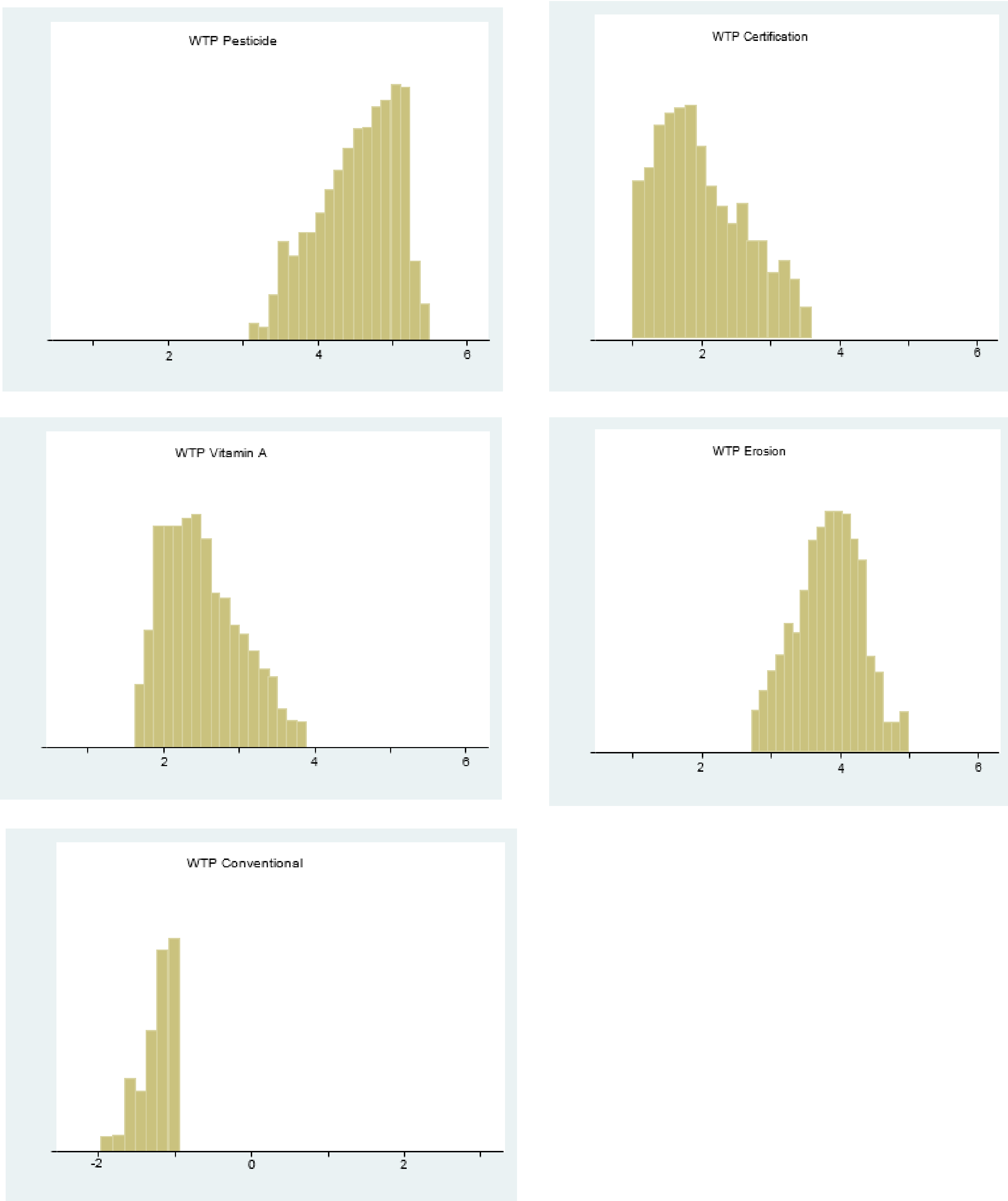

Figure 3: Simulated implied trade-off and monetary valuation

[1] This is based on the assumed relationship between the reduction in environmental pollution associated with organic production practices, which is a public (non-excludable) attribute, and an intrinsic product quality (health), which is a private attribute.

[2] According to Swait (1994), preferences are indirectly affected by attitudes through the latent class to which the consumer belongs, and as such attitudinal data are quite important in explaining choice behavior.

[3] The authors used principal component analysis to identify a limited set of dimensions, and subsequently plugged them as direct measure of respondent's attitudes in choice model.

[4] They point out that these responses are indicators of underlying attitudes rather than a direct measure of attitudes. As such, are likely to suffer from measurement error, which is amplified by the use of categorical formats such as Likert scale. Additionally, these responses may be correlated with other unobserved factors that influence individual's choices, causing correlation between the modeled and random components of utility, potentially leading to endogeneity bias.

[5] Our approach in this study is suited to explaining the sources of heterogeneity (Boxall and Adamowicz 2002) and closely capture consumers' choice processes, by explaining both the answers to attitudinal questions as well as the likelihood of being allocated to a given consumer segment.

[6] Detailed description of the survey design is available in Bello and Abdulai (2016).

[7] However, in estimating the models, we observe that the medium level of the attributes were not statistically significant from zero, thus for the reason of parsimony, the medium and base levels were effectively collapsed to form a single base level (e.g., Collins, Rose and Hess 2012).

[8] Available evidence show that the certification program give consumers quality assurance and guarantee the products' integrity on the market.

[9] The HLC model structure allows for the joint estimation of the choice model and the measurement model.

[10] Our efforts to incorporate an income effect in the final model specification was unsuccessful.

[11] The WTP for organic certification found in this research would be clearly within the range of price premiums identified by other studies. Although evidence from developing countries is limited, the review by Yiridoe, Bonti-Ankomah and Martin (2005) suggests an average WTP premium for organic certification of about 30%. While Coulibaly et al. (2011) on their

study of private households in urban Ghana and Benin, calculate a premium for organic certification of 57–66% for cabbage and 50–56% for tomatoes.