Modelling Consumers' Preference and Willingness To Pay For Organic Amaranth and Tomato in Ondo State, Nigeria: Evidence From a Choice Experiment

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1.0.INTRODUCTION

In Nigeria, vegetables play an important role serving as essential sources of proteins, vitamins, minerals, and amino acids (Okafor, 1983; Coulibaly, *et al.*, 2011). In Ondo state, in particular, the economic importance of vegetables is reflected in its 10.56% share of the total household expenditure on food items ranking second after Tubers and Plantains (23.93%) (National Bureau of Statistics, 2012). Okunlola and Akinrinnola (2013) found that *Ugwu* (*Telfairia occidentalis*) and African spinach/amaranth (*Amaranthus hybridus*) top the list of the most consumed leafy vegetables grown in Ondo state.

Vegetables generally and tomato in particular being perishable products remain susceptible to location-and cultivar-specific pests and diseases. Thus, as farmers attempt to meet growing demand and are faced with strong pest pressure, they increasingly rely on synthetic pesticides to reduce the risk of harvest and income loss (Lund *et al.*, 2010; Williamson *et al.*, 2008; Bello and Abdulai, 2016b). Many inappropriately use toxic pesticides at pre and post-harvest stages and these threaten the health of the farmer and consumers (Echobichon, 1996; Thakur and Sharma, 2005) as well as cause extensive environmental damage (Rosendahl *et al.*, 2008; Lund *et al.*, 2010). Consequently, these have continued to stimulate demand for organic food (Philip and Dipeolu, 2010; Bello and Abdulai, 2016b).

Despite the global increase in the demand for organically produced food (IFOAM, 2017), they are more expensive to assess for consumers in the developing countries (GAIN, 2014). This is principally due to the fact that production, distribution and marketing of organic products include higher cost elements than conventional food system (Barkley, 2002; GAIN, 2014). Mgbenka *et al*. (2015) reported that generally, many farmers have been discouraged from going into organic production because of the lack of or poorly developed local markets for organic products.

Moreover, policy makers and many vegetable farmers in south-western Nigeria, till now cannot ascertain that potential consumers will be willing to pay (WTP) a premium for organic vegetables. Identification of these WTP estimates for vegetables can significantly contribute to sustainable agricultural development in sub-Saharan Africa (SSA) (Bello and Abdulai, 2016b) and Nigeria in particluar. As such, the knowledge of the behavior of the consumers in the study area has huge policy, marketing and production. Also, this study provided the knowledge needed by farmers to decide on the large scale production of organic vegetables.

Going forward, this study's specific objectives include: (i) modelling consumers' preferences for organic vegetables and (ii) estimation of consumers' willingness to pay for organic vegetables in south-western Nigeria. The discrete choice experiment (DCE) framework based on random utility framework and Lancaster (1966)'s new approach to consumer theory was employed to achieve the objectives.

Focusing on Amaranthus Hybidius and tomatoes which are frequently consumed in large proportions (Okunlola and Akinrinnola, 2013) in the study area, the DCE was employed because first, certified organic vegetables is still non-market good in the study area. Also, because we were interested in specific attributes of vegetables that motivate consumers' preferences and WTP. In addition, the use of the DCE in this study is considered by the researcher to contribute to improvement of scholarly works that focus on consumer preference and willingness to pay in Nigeria.

2.0. METHODOLOGY

2.1.The Study Area

The study was carried out in Akure, Ondo State, Nigeria. The state lies between longitudes $4^0 30^1$ and $6^0 00^1$ East of Greenwich Meridian and latitude $5^0 45^1$ and $8^0 15^1$ North of the Equator. Agriculture is the main occupation of the people. Akure, the capital of Ondo state is a medium-sized urban center. Residential districts in Akure can be grouped into three major zones: High Density Residential Zone (HDRZ), Medium Density Residential Zone (MDRZ) and Low Density Residential Zone (LDRZ) (Adebola *et al.*, 2015; Adeoye, 2016).

Cross-sectional data on socioeconomic information, consumers' awareness and past experiences about organic products, buying preferences and choice experiment were obtained through the use of structured questionnaire. Multi-stage sampling was used to select the sample for the study. At the first stage, there was a random selection of two residential areas from each residential zone. Thereafter, a systematic random sampling was primarily used to draw 65 from LDRZ, 98 from MDRZ and 84 from HDRZ to make a total of 247 household units.

2.2 Choice Experiment

A D-Optimal design with a D-efficiency of 99.9% was developed using the "gen_design" function of the "skpr" R package by Morgan-Wall and Khoury (2018). A practical set of 9 choice sets with two product profiles and a status quo alternative was obtained. A preliminary pilot testing of the questionnaire was done. In the choice experiment, each respondent undertook nine choice tasks. A sample of 1764 observations were analyzed for the amaranth data while a sample of 468 observations were analyzed for the tomato data. The attributes and the corresponding levels included in the choice experiment design for this study are presented in Table 1:

Table 1: Attributes and Attribute levels of Vegetables used in the choice experiment

Variable	Description	Levels*	Reference Level
Price	Price of 1kg vegetable in naira	N50, N100, N150	N50
Chemical reduction (CHR) in %	Level of chemical reduction while growing the vegetable	0, 25, 80, 100	0
Certification	The organic certification scheme used	No certification, National Agency for Food and Drug Administration and Control (NAFDAC), Nigerian Organic Agriculture Network (NOAN)	No certification
Freshness	Describes the extent to which the vegetables appear fresh	Completely fresh (CFR), Partially Fresh (PFR), Not fresh at all	Not fresh at all
Taste	Describes the level of natural tastiness of the vegetables	Naturally tasty, Not naturally tasty	Not naturally tasty

Source: Author's Specification, 2018; *N represents Naira, Nigerian currency

In order to mitigate hypothetical bias in this study, a certainty follow up mitigation strategy was combined with the traditional cheap talk script (Cummings and Taylor, 1999). Use of a certainty follow-up question is among the most popular *ex post* corrections in stated preference valuations (Jerrod and Wuyang, 2018). The certainty follow up approach used in this study is a form of "price confirmation". This is different from the recently advocated *ex ante* "repeated opt out reminder" approach by Mohammed and Søren (2018) in that it allowed the preference responses of the respondents to be separately captured from their willingness to pay (WTP) responses. With the repeated opt out reminder, even though respondents preferred a particular option, because they were advised to opt out if the price was more than their WTP, both the preference and WTP behavior of the respondents were not captured. The similarity, though, is the fact the certainty follow up question was also asked at the choice task level and not at the end of the whole choice sequence. The question was stated like this:

"*Please note that the price of the vegetable you just chose is 100 naira. Are you sure you can afford this price?*"

2.3. Econometric Framework

Generally, discerete choice models estimated in the present study was specified such that the probability that individual *i* chooses organic vegetable j in choice set t and 0 otherwise is given as

$$P(j, X_{it}, \beta_{ir}) = \frac{\exp(x'_{itj}\,\beta_{ir})}{\sum_{j=1}^{J_{it}} exp(x'_{itj}\,\beta_{ir})} \qquad (1)$$

where x'_{itj} is the vector of explanatory variables including the attributes of organic amaranths and tomato and also socioeconomic characteristics of the respondents, β_{ir} is a vector of utility weights.

Focusing on heterogeneity (Huang and Zhao, 2015), the mixed logit model (MIXL) is favored for its flexibility to accommodate different forms of parameterization (McFadden and Train, 2000; Greene and Hensher, 2013). MIXL, being one of the extensions of the Multinomial logit model (MNL) relaxes the independence of irrelevant (IIA) assumption. MIXL allows parameters to vary randomly over individuals by assuming some continuous heterogeneity distribution *a priori* while keeping the MNL assumption that the error term is independently and identically distributed (iid) extreme value type 1. Hence, the individual specific utility weight (β_i) for a given attribute in MIXL will be given as

$$\beta_i = \beta + \Gamma v_i \quad (2)$$

where β is the vector of mean attribute utility weights in the population, Γ is a diagonal matrix which contains σ (the standard deviation of the distribution of the individual taste parameters (β_i)) round the population mean taste parameter (β)) on its diagonal and v is the individual and choice specific unobserved random disturbances with mean 0 and standard deviation 1 (Kassie, *et al.*, 2017).

A scaled multinomial logit (S-MNL) model is a version of mixed logit in which variation in utility weights across respondents is induced by the variance or scale of the error term. In S-MNL, the utility weights are given as

$$\beta_i = \beta\sigma_i \quad (3)$$

where β_i is the vector of utility weights for individual i , β is the vector of mean of the estimated utility weights of the population and σ_i is the scaling factor which differs across individuals but not across choices.

In order to properly account for heterogeneity, Fiebig et al. (2010) and Greene (2012) developed G-MNL model that nests MIXL and S-MNL. In G-MNL, the utility weights are given as

$$\beta_i = \beta\sigma_i + \gamma\Gamma v_i + (1 - \gamma)\sigma_i\Gamma v_i \quad (4)$$

where β_i is the vector of utility weights for individual i , β is the vector of mean of the estimated utility weights of the population, σ_i is the scaling factor which differs across individuals but not across choices. Γ is the lower triangular Cholesky factor of Σ such that ΓΓ′ = Σ. v_i is the individual and choice specific unobserved random disturbances. v_i ~ N(0, 1). γ is scalar distribution parameter that determines how the variance of residual taste heterogeneity, Γv_i, varies with scale. $\gamma \epsilon [0,1]$. The parameter γ also determines how the variance of residual taste heterogeneity varies with scale in a model that includes both (Fiebig *et al*., 2010).

When the scale of the error term is set to constant such that $\sigma_i = \sigma = 1$, then the G-MNL becomes MIXL. The S-MNL is obtained if $\gamma = 0 \; and \; \Gamma = 0$.

By simply combining 2 (MIXL) and 3 (S-MNL), G-MNL-I is formed whereby the utility weight is given as:

$$\beta_i = \beta\sigma_i + \Gamma v_i \quad (5)$$

The other form is called G-MNL-II developed based on MIXL and explicit specification of the scale parameter to yield

$$\beta_i = \sigma_i (\beta + \Gamma v_i) \quad (6)$$

Four specifications of the G-MNL (full G-GMNL, G-MNL-I($\gamma = 1$), G-MNL-II($\gamma = 0$) and G-MNL ($\tau = 1$)) and MIXL models were used in this study for both unobserved and observed heterogeneity estimations. In revealing source and shape of heterogeneities, Greene's specification of the utility weight as expressed below were used:

$$\beta_i = \sigma_i (\beta + \triangle z_i) + (\gamma \Gamma v_i + (1 - \gamma) \sigma_i \Gamma v_i) \quad (7)$$

where β_i is the vector of respondent-specific coefficients , and β is the vector of population-specific coefficients for vegetables' attributes and

$\triangle z_i$ = Observed heterogeneity

Γv_i = unobserved heterogeneity

σ_i = individual specific standard deviation of the idiosyncratic error term

The specifications above is according to Kassie, *et al* (2017).

For the present study, M characteristics of individuals included:Age of household head (Years), Gender of the household head (Dummy, 1 = Male, 0 = Female), Years of formal education of the household head (Years), Household size (Number), Average Household monthly income including transfers (Naira), Awareness of organic vegetable (Dummy, 1 = Aware, 0 = Not Aware), Vegetarian (Dummy, 1 = Yes, 0 = No), If respondent is placed on any special diet (Dummy, 1 = Yes, 0 = No), Incidence of food-related disease (Dummy, 1 = Yes, 0 = No), Own vegetable Farm (Dummy, 1 = Own, 0 = Do not own), Frequency of purchasing vegetable (Dummy, 1 = Frequently, 0 = Not Frequently),

Ethnicity (Dummy, 1 = Yoruba, 0 = Other ethnic group), Contribution of wives' income to total household income for male-headed households (%), and If respondent goes for medical checkup always (Dummy, 1 = Always or Most of the times, 0 = Occassionally or Never). Respondents were categorized as 'Frequently' purchasing vegetable if they purchase it at least once in a week and 'Not Frequently' otherwise.

2.4 Estimating Willingness to pay for Attributes

The welfare measures respresenting the willingness to pay estimates of the respondents were estimated using WTP-space models. In the MNL specification of Eq. (1), the willingness to pay (WTP) for an attribute is traditionally calculated as $wtp_n = -\beta_n^a/\beta_n^p$ where β_n^a is the coefficient of the attribute and β_n^p is the price coefficient (Hess and Train, 2017). This approach can lead to WTP distributions which are heavily skewed (Train and Weeks, 2005; Hess and Train, 2017). However, models in WTP-space reparameterize utility such that the distribution of WTP is estimated directly (Train and Weeks, 2005; Fiebig *et al*., 2010). In models in WTP-space,

$$U_{njt} = -P_{njt} + \beta_n^p wtp'_n x_{njt}^a + \frac{1}{\beta_n^p} \varepsilon_{njt} \quad (8)$$

where P_{njt} is price, x^a_{njt} is a vector of non-price attributes, and wtp'_n is a corresponding vector of the consumer's WTP for the non-price attributes and the standard deviation of the unobserved factors is the inverse of the random price coefficient, which represents scale heterogeneity (Hess and Train, 2017).

The simulated log likelihood function for the sample data is specified as:

$$\log L = \sum_{i=1}^{N} \log\{\frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T_i} \prod_{j=1}^{J_{it}} P(j, X_{it}, B_{ir})^{d_{itj}}\} \quad (9)$$

where $\beta_{ir} = \sigma_{ir}[\beta + \Delta zi] + [\gamma + \sigma_{ir}(1 - \gamma)]\Gamma v_{ir}$, $\sigma_{ir} = \exp[\frac{-\tau^2}{2} + \delta' h_i + \tau w_i]$, v_{ir} and w_{ir} are the R simulated Draws on v_i and w_i, d_{itj} = 1 if individual i makes choice j in choice set t and 0 otherwise.

2.5. Estimation Procedure

All models were estimated using the 'G-MNL' package in R (Sarrias and Daziano, 2017) using simulation based estimation. In each of the four specifications of the G-MNL, 500 Halton Draws was specified given that this number gave model with the best fits based on comparision using the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and the Log-Likelihood (LL). Furthermore, suggestions in Sarrias and Daziano (2017) about starting values were also heeded in estimating all the G-MNL model formulations. Mixed Logit Model (MIXL) was also estimated to explain heterogeneity in mean by allowing the socio-economic characteristics of the respondents to enter the mean of the preference estimates for the attributes. This was preferred to G-MNL model and reported in that it was less sensitive to the scaling of variables which is suspected the later to make to produce "NAs" when employed to estimate observed heterogeneity specifications. In all of the model formulations, all parameters except price were specified as random parameters with normal distribution (Sarrias & Daziano, 2017; Train, 2009; McFadden and Train, 2000). In the G-MNL formulations where γ was not restricted, it should be noted that in order to impose the positive domain of γ, following the approach of Fiebig et al. (2010) γ was estimated indirectly by first estimating γ* and re-parameterizing γ such that γ = exp(γ*)/ (1 + exp(γ*).

Furthermore, correlation among the attributes included in this study's choice experiment was theoretically anticipated. For instance, consumers who have strong positive preference for food safety in terms of chemical reduction may be expected to also favor quality attribute like freshness or certification. Consequently, the four G-MNL model formulations and the MIXL model were estimated allowing for correlation among the coefficients and retrieving the full covariance matrix, Σ. The diagonal elements of Σ recovered unobserved heterogeneity in the mean parameters of the attributes while the off-diagonal elements retrieved correlation among the coefficients of the choice-specific attributes of amaranth and tomato.

3.0. RESULTS AND DISCUSSION

3.1. Socio-Economic Characteristics of the respondents:

The results of major socio-economic characteristics showed that respondents in the amaranth and tomato groups had mean ages of 48 and 44 respectively. Male respondents dominated the survey with 67.9% and

84.3% in the amaranth and tomato groups respectively. Most of the respondents have smaller households with average of 4 members in the amaranths group and 3 in the tomato group. About 17.86% of the households in the study area have children who are 5 five years or below in the amaranths category while 11.53% of the households in the tomato group have children in this age group. Relating to the aged adults, 6.12% and 1.92% of the respective households in the Amaranths and tomato groups have adults aged 60 years or above. Some 28.06% and 5.77% were really fully aware of the organic products in the amaranth and tomato groups. In both commodity groups, less than 10% of the respondents went for medical checkup always.

3.2. Preferences of Consumers for Organic Amaranth and Tomato

The results of the estimation of four specifications of the G-MNL models are presented in Table 2. The full G-MNL is preferred most by the AIC and LL while G-MNL ($\tau = 1$) is preferred most by the BIC. In all of the G-MNL formulations for organic amaranth, price, chemical reduction, taste, freshness and NAFDAC certified attributes were consistently significant at 1% and carried expected signs. Only mean preference for NOAN-certified attribute was not statistically different from zero even at 10% in our best performing G-MNL model specifications.

In relation to the results for tomato presented in Table 3, the full G-MNL reveals price, taste, complete and partial freshness were significant at 5% with the expected signs. Chemical reduction, however, was consistently significant at 1% in all the G-MNL specifications for tomato.

Table 2: Estimates of Mean Preferences for Organic Amaranths

Taste	Full G-MNL Est.	G-MNL-I (γ = 1) Est.	G-MNL-II (γ = 0) Est.	G-MNL (τ = 1) Est.
ASC1	1.9883***(0.283)	0.604(0.603)	1.521**(0.604)	0.426(0.466)
ASC2	2.1840***(0.304)	0.880(0.611)	1.800***(0.609)	0.714(0.455)
Price	-0.0744***(0.008)	-0.033***(0.005)	-0.044***(0.007)	-0.037***(0.005)
CHR	0.133***(0.009)	0.046***(0.006)	0.062***(0.009)	0.069***(0.009)
Taste	5.061***(0.547)	1.862***(0.302)	2.220***(0.379)	2.681***(0.435)
CFR	4.7862***(0.624)	1.881***(0.448)	2.248***(0.550)	2.406***(0.536)
PF	4.3503***(0.761)	2.141***(0.452)	2.712***(0.620)	2.665***(0.523)
NOAN	1.1433(0.936)	0.800**(0.391)	1.172**(0.507)	0.581(0.486)
NAFDAC	7.477***(1.016)	3.031***(0.565	3.883***(0.745)	3.567***(0.620)
Tau	1.892***(0.207)	1.791***(0.330)	1.427***(0.220)	
Gamma*	−6.217(11.948)			1.056***(0.118)
Model Fit Criteria				
AIC	2166.64	2195.470	2174.528	2169.619
BIC	2423.344	2447.179	2426.237	2421.328
LL	−1036.082	−1051.735	−1041.264	−1038.809
N	1758	1758	1758	1758
AIC/N	1.23	1.25	1.24	1.23

*Significance codes: 1% '***'; 5% '**'; 10% '*'*

Source: Field Survey, 2018.

Overall, considering the fitness of the data to all of the estimated models, the attributes included in the choice experiment proved theoretical intuitiveness of our model specifications as well as plausibility of the survey.

Table 3: Estimates of Mean Preferences for Organic Tomato

	Full G-MNL	G-MNL-I (γ = 1)	G-MNL-II (γ = 0)	G-MNL (τ = 1)
	Coeff(S.e)	**Coeff(S.e)**	**Coeff(S.e)**	**Coeff(S.e)**
Price	-0.029** (0.010)	-0.015*** (0.004)	-0.019*** (0.007)	-0.017**(0.006)
CHR	0.056*** (0.017)	0.032*** (0.009)	0.034*** (0.010)	0.050*** (0.012)
Taste	3.513** (1.464)	1.290*** (0.499)	2.197*** (0.594)	2.020** (0.615)
CFR	3.501** (1.324)	1.102** (0.522)	1.938*** (0.653)	1.870** (0.700)
PFR	2.282** (1.149)	0.793* (0.470)	0.618 (0.532)	1.490* (0.633)
NOAN	-4.131*** (1.457)	-1.104* (0.668)	-2.373** (0.945)	-1.364 0.948)
NAFDAC	0.698 (1.034)	1.088* (0.628)	1.617* (0.838)	1.641 (0.879)
ASC1	-2.955*** (0.892)	-2.078*** (0.717)	-1.326** (0.630)	-2.689** (0.891)
ASC2	-2.344*** (0.794)	-2.049*** (0.683)	-1.384** (0.594)	-2.165** (0.741)
tau	1.494*** (0.228)	0.489***(0.170)	1.455*** (0.241)	
Gamma	-0.008 (0.078)			-0.068 (0.137)
Model Fit Criteria				
LL	-313.915	-317.177	-320.119	-316.815
AIC	721.830	726.353	732.237	725.630
BIC	915.896	916.290	922.173	915.567
N	459	459	459	459
AIC/N	1.57	1.58	1.59	1.58

*Significance codes: 1% '***'; 5% '**'; 10% '*'*

Source: Field Survey, 2018.

First about preference for food safety, reduction of chemical residue in amaranth was significantly important to an average consumer in the study area. The estimates for this attribute were positive and statistically significant at 1% in all of the G-MNL specifications both for organic amaranth and tomato. This strong preference for chemical reduction for an average respondent in the study area was anticipated. It underscores the importance of food safety related attributes to consumers' choice of food in the study area. This compares favorably with findings in similar studies (Bello and Abdulai, 2016b; Bello and Abdulai, 2016a; Philip and Dipeolu, 2010).

The preference weight for the only sensory trait of amaranth elicited, that is tastiness, was also significantly positive in all of the G-MNL formulations for both amaranth and tomato groups. These results which also confirm *a priori* expectation underscore the importance of taste in food to the respondents when purchasing amaranth. Related studies (Probst *et al*., 2012; Philip and Dipeolu, 2010) also reported taste to be a significant predictor of choice of food, particularly vegetables.

Consumers' valuation of the two freshness attributes (completely fresh and partially fresh) were positive and highly significant in all the G-MNL formulations for amaranth. Comparatively, only G-MNL-

I shows insignificance even at 10% in preference for partial freshness in tomato. It is at 1% in full G-MNL and G-MNL-II but at 5% in G-MNL-III specifications. Complete freshness is significant at 1% in full G-MNL and G-MNL-II but at 5% in G-MNL-I and G-MNL-III specifications. The results were expected since in sub-Saharan African context, traditional markets are characterized by fresh produce being sold in piles in open air (Alphonce and Alfnes, 2017). Hence, physical attributes including freshness, among other factors, remain one of the major sources of information signaling food quality and other credence attributes to consumers (Alphonce and Alfnes, 2017; Oladejo and Oladiran, 2014; Probst *et al.*, 2012; Chengyan and Cindy, 2009; Bonti-Ankomah and Yiridoe, 2006).

Concerning certification attributes, in the amaranth group, estimates for NAFDAC certification attribute was significant and positive at 1% in all of the G-MNL results. Only G-MNL-I and G-MNL-II show NOAN to be significant and positive at 5%. NAFDAC, the more popular food regulatory body in Nigeria, does not currently certify compliance to standards for organic food production but only prospecting to do (NOAN, 2018). It was therefore included as a prospective option considering its popularity. Model results show that the researcher's anticipation of its acceptability as a certification option for organic vegetables was not illusive. Whereas, NOAN is a Participatory Guarantee System (PGS) of certification (Reganold and Wachter, 2016). Though, it is only currently active in Oyo state, Nigeria, where its head-quarters is located, its acceptability by the consumers as a certification option was also revealed to be positive in the G-MNL model results. Confirming findings in (Bello and Abdulai, 2016b; Bello and Abdulai, 2016a), the results show that the certification attributes contributed positively to consumers' likelihood of choosing organic amaranth and tomato.

In the tomato group, the results were remarkably different. Where significant, coefficients for NOAN certification were consistently negative indicating disutility for this scheme of certification by the tomato consumers. It is negatively significant at 1% in the full G-MNL specification but at 5% in G-MNL-I and G-MNL-III. In contrast, in all but one G-MNL specification, consumers maintained positive preference for NAFDAC certification at both 5% (Full G-MNL and G-MNL-III) and 1% (G-MNL-II) levels of significance. Strong and positive preference for this relatively more popular certification option, NAFDAC, by the tomato consumers may not be unconnected to the fact that very large proportion of tomatoes consumed in the study area come from other regions (mainly northern part) of the country. As such consumers may perceive higher level of market information asymmetry in the case of tomato compared to amaranth which is majorly produced within the study area. This might be the motivation for a certification option that the consumers were more familiar with and perceived to have stricter standards and control (Janssen and Hamm, 2012).

As regards price attribute, the negative preference for price at 1% level of significance in all the G-MNL specifications for both amaranth and tomato was obvious. This is consistent with economic theory and also findings in similar studies (Bello and Abdulai, 2016; Probst *et al.*, 2012; Philip and Dipeolu, 2010). This implies that for an average consumer in our study, the more expensive the vegetables the less likely they will be preferred holding other factors constant.

3.3. Unobserved Heterogeneity in Mean Taste Parameters for Organic Amaranth and Tomato

Tables 4 and 5 present the standard deviations of the taste parameters for amaranth and tomato estimated G-MNL models as well as their standard errors. The variations in mean estimates for all of the attributes were significant at 1% implying strong variation in consumers' valuation of all of the attributes of the vegetables in this study.

Table 4: Heterogeneity in Mean Preference for Amaranth

	FULL G-MNL	G-MNL-I	G-MNL-II	G-MNL ($\tau = 1$)
CHR	0.093*** (0.002)	0.036*** (0.006)	0.044*** (0.007)	0.052*** (0.008)
Taste	3.204*** (0.311)	1.708*** (0.304)	1.99*** (0.4)	2.248*** (0.342)
PFR	2.035*** (0.366)	1.436*** (0.375)	1.439*** (0.386)	1.415*** (0.387)
CFR	2.903*** (0.498)	1.091*** (0.341)	1.559*** (0.439)	1.879*** (0.471)
NOAN	5.189*** (0.596)	1.621*** (0.464)	2.589*** (0.811)	1.382*** (0.419)
NAFDAC	5.84*** (0.476)	2.859*** (0.547)	3.677*** (0.710)	3.361*** (0.641)
Coefficient of Variation				
CHR	0.697	0.790	0.710	0.754
Taste	0.633	0.917	0.897	0.838
PFR	0.425	0.763	0.640	0.588
CFR	0.667	0.509	0.575	0.781
NOAN	4.540	2.026	2.209	2.379
NAFDAC	0.781	0.949	0.947	0.942
Model Fit Criteria				
AIC	2166.640	2195.470	2174.528	2169.619
BIC	2423.344	2447.179	2426.237	2421.328
LL	−1036.082	−1051.735	−1041.264	−1038.809
N	1758	1758	1758	1758
AIC/N	1.23	1.25	1.24	1.23

*Significance codes: 1% '***'; 5% '**'; 10% '*'*

Source: Field Survey, 2018.

In the amaranth data, NOAN certification attribute was revealed to have highest degree of heterogeneity in all the estimated model specifications. This was not unexpected as it was mentioned previously that NOAN was a relatively unknown scheme in the study area.

Table 5: Heterogeneity in Mean Preference for Tomato

	FULL G-MNL Coeff.(S.e)	G-MNL-I Coeff.(S.e)	G-MNL-II Coeff.(S.e)	G-MNL (τ = 1) Coeff.(S.e)
CHR	0.099*** (0.030)	0.027*** (0.009)	0.060*** (0.019)	0.030*** (0.009)
Taste	5.043*** (1.486)	1.993*** (0.655)	2.985*** (0.926)	3.881*** (1.177)
PFR	3.756*** (1214)	1.029 (0.675)	2.854*** (1.017)	1.848*** (0.672)
CFR	2.725*** (0.804)	1.254*** (0.477)	3.362*** (1.051)	1.519** (0.764)
NOAN	8.373*** (2.549)	3.286 (0.917)	3.959*** (1.221)	4.702*** (1.125)
NAFDAC	8.695*** (2.354)	3.026 (0.818)	3.675*** (1.316)	3.811*** (1.088)
Coefficient of Variation				
CHR	1.768	0.844	1.765	0.600
Taste	1.436	1.545	1.359	1.921
PFR	1.646	1.298	4.618	1.240
CFR	0.778	1.138	1.735	0.812
NOAN	-2.027	-2.976	-1.668	-3.447
NAFDAC	12.457	2.781	2.273	2.322
Model Fit Criteria				
LL	-313.915	-317.177	-320.119	-316.815
AIC	721.830	726.353	732.237	725.630
BIC	915.896	916.290	922.173	915.567
N	459	459	459	459
AIC/N	1.57	1.58	1.59	1.58

*Significance codes: 1% '***'; 5% '**'; 10% '*'*

Source: Field Survey, 2018.

Turning to tomato, results in table 5 shows NAFDAC to have the highest degree of variation. However, all consumers tend to converge to homogeneity in their valuation for complete freshness for tomato. This indicates that majority of the consumers regard complete freshness of tomato to signal quality.

3.4. Explaining Heterogeneity in Preference for Organic Vegetables

In explaining heterogeneity, the MIXL model performed best compared to G-MNL formulations in terms of the AIC, BIC and plausibility of estimates. Therefore, discussion of observed heterogeneity is based on MIXL model estimates presented in Tables 6 and 7.

The interaction variables NAFDAC*awareness and chemical reduction*age were found to be positive and significant at 5%. Furthermore, the interaction of chemical reduction*awareness and taste*gender were found to be positive and significant at 10% level of significance. These results show that sensitivity to chemical reduction attribute was higher among older respodents who were previously aware of organic products. Several studies (Nocell and Kennedy, 2012; Philip and Dipeolu, 2010) have similarly associated ageing with increasing consciousness of healthy feeding.

In relation to interaction between chemical reduction and real awareness, the MIXL model results show that 28.06% of the respondents in the amaranth group, who were really aware of organic products were found to value chemical reduction as a positive inducement to choosing organic amaranth. This was expected as increasing level of awareness makes consumers understand the objective risk associated with chemical residue in food (IFOAM, 2017; Bello, 2016).

Table 6: Estimates of Observed Heterogeneity MIXL Model For Organic Amaranth

Taste Parameters	**Coeff.(S.e)**
Price	−0. 016*** (0.002)
CHR	0.021 (0.012)
Taste	1. 068*** (0.297)
CFR	0. 822** (0.291)
PFR	1.340 *** (0.221)
NOAN	0. 028 (0.265)
NAFDAC	1. 347*** (0.382)
Observed Heterogeneity	
CHR*Age	0. 003** (0.002)
CHR*Aware	0. 009* (0.006)
CHR*Checkup Always	−0. 005 (0.006)
CHR*Radio	−0. 003 (0.012)
CHR*Household Size	−0. 003 (0.005)
CHR*Own Farm	0. 006 (0.005)
CHR* % Spouse Income Contribution	0. 015 (0.010)
Taste*Special Diet	0.057 (0.240)
Taste*Vegetarian	−0. 590 (0.458)
Taste*Gender	1. 119* (0.585)
Taste*Ownfarm	−0. 130 (0.261)
NAFDAC*Aware	0. 754** (0.355)
NAFDAC*Radio	0. 030 (0.338)

*Significance codes: 1% '***'; 5% '**'; 10% '*'*

Source: Field Survey, 2018.

An observed heterogeneity MIXL model to explain variation in consumers' preference for organic food attributes in the pooled (amaranth and tomato) data was also estimated. The results are presented in Table 7. Consumers' sensitivities to all the choice-specific attributes but NOAN were significant and carried expected signs. "Chemical reduction*Age" interaction was significant at 5% while "Chemical reduction*Spouse Income contribution" and "NAFDAC*Aware" were significant at 10%. The positive effect of age on preference for chemical reduction revealed that older consumers were positively induced by chemical reduction in vegetables. Also, the effect of spouse income contribution on chemical reduction shows the higher the percentage contribution of spouse' income to the household income, the more likely the household will prefer chemical reduction in food. Where the spouse is the wife, this result is particularly instructive as to the effect of women empowerment on likelihood of healthy feeding for household in the population for this study as confirmed in (Bogue *et al.*, 2005).

Table 7: Estimates of Observed Heterogeneity MIXL Model for Pooled Data

Taste Parameters	Coeff.(S.e)
Price	-0.01705*** (-0.00193)
CHR	0.014417* (0.007649)
Taste	1.106699*** (0.290391)
CFR	0.86953** (0.347032)
PFR	1.274933*** (0.328094)
NOAN	0.070707 (0.34695)
NAFDAC	1.352991*** (0.409086)
Observed Heterogeneity	
CHR*Age	0.003616** (0.001553)
CHR*Aware	0.00853 (0.005518)
CHR*Checkup	-0.00937 (0.010885)
CHR*Radio	-0.00715 (0.005639)
CHR*HHS	-0.00065 (0.005189)
CHR*Ownfarm	0.006508 (0.005258)
CHR*Spouse_Income_Contribution	0.016556* (0.010064)
Taste*Special_Diet	0.046618 (0.240018)
Taste*Vegetarian	-0.61557 (0.480841)
Taste*Gender	0.935829 (0.598774)
Taste*Ownfarm	-0.12132 (0.255181)
NAFDAC*Aware	0.79921* (0.469781)
NAFDAC*Radio	0.028458 (0.433319)
NOAN*Aware	0.111326 (0.423935)
NOAN*Radio	-0.10741 (0.407134)
CFR*Purchase_Frequency	0.010123 (0.079625)
PFR*Purchase_Frequency	0.022044 (0.097057)
AIC/N	1.32

*Significance codes: 1% '***'; 5% '**'; 10% '*'*
Source: Field Survey, 2018.

3.5. WILLINGNESS TO PAY FOR ORGANIC VEGETABLES

Two models were estimated to obtain the welfare measures of the respondents for organic amaranth and tomato. The preference space WTP model was added only for comparison. In order to estimate the WTP in the WTP-space, a random parameter full G-MNL specification was estimated using the procedure described in (Kassie, *et al*., 2017; Fiebig *et al.*, 2010). In the case of tomato, the WTP-space is a fixed parameter S-MNL model (Sarrias and Daziano, 2017). The negative of the price attribute was computed using the 'mlogit.data' function of the 'gmnl' package. Next, the values of price parameter and γ were fixed at 1 and 0 respectively. Also, the estimation was done with a constant in the scale. This constant, after proper transformation represented the price parameter (Sarrias and Daziano, 2017). All WTP estimates are in 'naira (N)', the Nigerian currency.

3.5.1. Willingness to Pay for Attributes of Organic Amaranth

The results of the two models estimated to derive the willingness to pay for the traits of organic amaranth are presented in Tables 8. Comparing both WTP models, computation of total willingness to pay shows that the WTP-space model produced more realistic WTP estimates based on the current market price (200N) for 1kg of organic amaranth in Ibadan, Nigeria.

Respondents were willing to pay 1.31N more to have a 1% decrease in chemical residue compared to status quo amaranth with no reduction in chemical residue. This is followed in value by NAFDAC certification, for which they were willing to pay a premium of 89.98N over amaranth that was not certified organic by NAFDAC. In terms of taste, respondents were willing to 44.03N more for an amaranth that was naturally tasty over one that is not naturally tasty. They were also willing to pay 75.20N more for partial freshness and 42.26 more for complete freshness. The lower estimate of the willingness to pay for complete freshness compared to partial freshness, as it was mentioned earlier, may be due to the perception of respondents that complete freshness of amaranth may signal the effect of chemical fertilizer. The insignificant but positive WTP estimate for NOAN may suggest the fact that NOAN is a relatively unfamiliar certification scheme compared to NAFDAC. Going by WTP estimates, respondents were willing to pay for food safety that is chemical reduction, certification, quality, and sensory trait in that order.

On heterogeneity, significant variations in willingness to pay for chemical reduction, taste, complete freshness and NAFDAC certification at 1% were evident. The insignificance of the variation in WTP for partial freshness shows that respondents did not significantly differ in their valuation of partial freshness as an indicator of organic amaranth.

Table 8: WTP Estimates for Attributes of Organic Amaranth in Preference Space and Willingness to Pay Space

	Preference-Space Model Coeff.(S.e)	**WTP-Space Model Coeff.(S.e)**
CHR	1.78*** (-0.196)	1.31*** (0.25)
Taste	68.02*** (8.615)	44.03*** (6.22)
PFR	58.46*** (11.02)	75.20*** (5.76)
CFR	64.32*** (11.373)	42.26*** (9.18)
NOAN	-15.92 (11.438)	16.74 (23.63)
NAFDAC	100.47*** (8.742)	89.98*** (13.04)
het.(Intercept)		235.32*** (32.07)
Unobserved Heterogeneity		
CHR	1.24499 (0.14473)	1.45*** (0.26)
Taste	38.91135 (4.46051)	61.75*** (7.92)
PFR	11.62119 (4.4924)	96.16 (NA)
CFR	13.50967 (10.37286)	53.72*** (12.24)
NOAN	-1.64966 (4.86266)	55.48 (34.1)
NAFDAC	14.86036 (4.27232)	134.11*** (31.85)
Tau	25.42064	169.05*** (18.14)
Gamma		18.08* (10.05)
LL		-1105.5
AIC		2266.204
N		1758
AIC/N		1.28

*Significance: 1% '***'; 5% '**'; 10% '*'*
Source: Computed from Survey Data, 2018

3.5.2. Willingness to Pay for Attributes of Organic Tomato

Interpretation and discussions of WTP for organic tomato are based on the WTP-space results presented in Table 9. The WTP estimate for chemical reduction is significant at 1% while for taste it is at 10%. Respondents were willing to pay 1.49N more for a 1% reduction in chemical residue in tomato. In relation to tastiness, consumers were willing to pay premium of 41.51N over tomato that was not naturally tasty. The results for tomato again revealed consumers were willing to pay 3.59 times more for food safety, than they would pay for taste. It underscores the significance of food safety and healthy feeding to respondents for this study.

Table 9: WTP Estimates for Attributes of Organic Tomato in Preference Space and WTP-Space

	Preference-Space Model Coeff.(S.e)	**WTP-Space Model Coeff.(S.e)**
CHR	1.94** (0.8254)	1.49*** (0.51)
Taste	121.30** (56.83096)	41.51* (22.63)
PFR	120.90** (51.37933)	37.00 (29.25)
CFR	78.79 (48.13067)	-12.47 (31.17)
NOAN	-142.64** (65.89387)	-124.17*** (47.52)
NAFDAC	24.13 (31.77611)	-37.83 (33.28)
het.(Intercept)		-5.00*** (0.26)
Unobserved Heterogeneity		
CHR	3.41*** (1.286)	
Taste	-141.40*** (60.375)	
PFR	44.89*** (18.708)	
CFR	89.97*** (22.471)	
NOAN	-92.77*** (54.457)	
NAFDAC	100.71*** (45.027)	
Tau		

*Significance codes: 1% '***'; 5% '**'; 10% '*'*

Source: Computed from Survey Data, 2018

4.0. CONCLUSIONS

On the average, preference for food safety, in terms of chemical reduction, in particular dominated the preference and WTP patterns of the respondents. In terms of factors driving this behavior, age, level of awareness of organic farming and frequency of medical checkup, were prominently strong. Although, respondents generally believed that they had their own ways of distinguishing organic vegetables from inorganic ones, they were still willing to pay for a third party form of certification instead of a PGS form. Furthermore, acceptability of organic certification may strongly depend on familiarity of consumers with the certification body as well as the level of awareness of organic products.

Overall, the potentials of organic vegetables market in Ondo State and by extension Nigeria were evident going by the results of this study. Consumers, as anticipated care so much about healthy feeding. Consumers in Ondo state cared also about sensory and quality traits of vegetables.

We recommend designing policies that raise consumers' awareness about healthy feeding, which could be informed of organic concept. In relation to certification, NAFDAC should consider including standardization of organic agricultural production in her curricula. Government should also revive the moribund organic fertilizer plant in the study area (Fasina, 2006) to spark up commercial organic agriculture.

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