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Heterogeneity in consumer preferences for organic and genetically modified food products in Ghana

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ABSTRACT

Consumers are increasingly becoming very concerned about food safety, with many giving preference to organic food products over conventional food products, which make use of agrochemicals with potential implications for health. Furthermore, to make the food choice decisions even more complex, genetically modified (GM) foods have been introduced in an attempt to meet global food demand. Consumers therefore must make decisions regarding organic and GM foods. This paper investigates consumer heterogeneity for organic and GM tomatoes in Ghana using advanced discrete choice modelling techniques. The data for empirical application come from a choice experimental study conducted among 200 consumers in Ghana. Our econometric modelling revealed that the sampled consumers preferred organic tomatoes that are produced locally and certified by the Food and Drugs Authority. However, we find a likelihood that women and older consumers may have preferences for GM tomatoes with environmental and health benefits. Policy implications are drawn from the findings of the study.

Key words: consumers; organic; choice modelling; GM food; heterogeneity

1. Introduction

Increasingly, consumers are becoming very concerned about food safety issues, and such concerns have resulted in changing purchasing behaviour (Montuori *et al*. 2012). In the past few decades, most consumers have moved to the consumption of organic food products, away from conventional food products, because of the agrochemicals used in the production of the latter, which pose potential health implications. Organic food products are obtained from organic agriculture, which has been defined as a holistic production management system that promotes and enhances agroecosystem health, including biodiversity, biological cycles and soil biological activity (Food and Agriculture Organization [FAO] 2010). Such a production system emphasises the use of management practices in preference to the use of off-farm inputs, considering regional conditions that require locally adapted systems (Huber *et al*. 2017).

On the other hand, increasing global food demand in the light of challenges as a result of climate change have resulted in the introduction of genetically modified (GM) foods, which are produced using genetically engineered technologies. Despite the potential gains from GM technology in transforming agricultural productivity and increasing food security (Oparinde *et al*. 2017), its application remains a controversial issue among consumers, especially in developing countries.

Consumers' attitudes to and acceptance of GM foods are mixed. Generally, public debates on GM foods are entangled in the controversy over the risks for human health and the environment, and associated ethical and social concerns. There are two opposing viewpoints in the GM debate. Advocates for the use of GM foods argue for the potential benefits to society through a reduction in hunger, the curing of diseases, the promotion of health and an increased quality of life (Bukenya & Wright 2007). In contrast, challengers argue that it entails unnecessary interference in nature, which could give rise to unknown and potentially disastrous interactions with human genetics and natural ecosystems (Bukenya & Wright 2007).

Over the years, researchers have examined consumer behaviour regarding the acceptance of GM foods, although with conflicting results. While some studies (Ganiere & Chern 2004) report positive consumer attitudes towards GM foods, others (Carlsson *et al*. 2004; Moon & Balasubramanian 2004; Gaskell *et al*. 2010) report a negative attitude. For instance, Boccaletti and Moro (2000) examined Italian consumers' knowledge and attitude towards GM foods and found that although the knowledge level was low, they generally had a positive attitude towards GM foods. In the Ganiere and Chern (2004) study of US consumers' acceptance of GM foods, the authors found that the sampled consumers generally had a positive attitude towards GM products. In contrast, the Gaskell *et al*. (2010) study showed that about 61% of participants in 32 European countries did not support GM foods. The Costa-Font and Gil (2009) study also revealed that more than half of the respondents perceived GM foods to be unethical and that there was no need to encourage such foods on the market. Other studies have revealed similar consumer behaviour towards GM foods (Carlsson *et al*. 2004; Moon *et al*. 2004).

Despite the number of studies conducted on consumer perceptions and attitudes towards GM foods in advanced countries, only a limited number of such studies exist in the developing world, such as in Africa (Bonah *et al*. 2017). Kimenju and De Groote's (2008) study on urban maize consumers' willingness to pay for GM foods in Kenya revealed that about two thirds of consumers would buy GM maize at the same price as conventional maize. The study by Kushwaha *et al*. (2004) on consumer acceptance of GM cowpea in Nigeria showed that 90% of the respondents were aware of genetically modified products, but 60% disapproved of its use. In Ghana, Buah (2011) examined public references to GM foods and found that respondents were willing to accept GM foods. However, the study by Quaye *et al*. (2009) on consumer perceptions of GM foods in Ghana revealed that about half of the respondents were unwilling to accept GM foods.

Given the long tradition of agricultural food production, organic and GM food production systems are relatively new and, above all, directly opposite of developments in the agricultural sector (Emberger-Klein *et al*. 2016). While consumers generally have positive attitudes towards organic food products (Magnusson *et al*. 2001; Yiridoe *et al*. 2005), they have conflicting attitudes where GM foods are concerned. It therefore is important to analyse consumer preferences for organic and GM foods simultaneously, using robust econometric techniques to examine whether there is a likelihood of joint preferences for organic and GM foods.

This paper therefore contributes to the limited literature on the choices of consumers between organic and GM food products in developing countries. It specifically models consumer preferences for organic and GM tomatoes in Ghana simultaneously, using advanced discrete-choice modelling techniques. The simultaneous modelling of consumer preferences for organic and GM tomatoes using discrete-choice modelling techniques is the first of its kind in Ghana. The discrete-choice experiment (DCE) is a stated preference technique that presents respondents with hypothetical scenarios and allows them to make choices between them (Owusu Coffie *et al*. 2016). Initially, the DCE was modelled using a conditional logit model, which is a model that assumes that all consumers have homogeneous preferences. However, recent advances have introduced models that account for heterogeneity in preferences, such as the mixed logit (MIXL) model and the generalised multinomial logit model (GMNL). In addition to preference heterogeneity, the GMNL model also accounts for scale heterogeneity, which relates to respondents' choice inconsistencies. Our paper empirically applies these recent advances in DCE when modelling consumers' choices of organic and genetically modified tomatoes in the context of a developing country.

We considered tomatoes because they are one of the most important vegetables in Ghana and account for about 38% of total expenditure on food for consumption (Ministry of Food and Agriculture [MoFA] 2015). Their production is characterised by small-scale farmers who employ either conventional or organic methods of production. Although most of the tomatoes consumed in Ghana are produced locally, there is considerable cross-border trade between Ghana and neighbouring countries such as Burkina Faso. Using a total sample of 200 respondents, our econometric analyses revealed that the sampled consumers had positive preferences for organic tomatoes as opposed to conventional tomatoes. They also had strong disutility for GM alternatives in contrast to conventional tomatoes. Regarding certification, they preferred tomatoes certified by the Food and Drugs Authority compared to those with no certification, and such tomatoes should be affordable and produced locally.

The rest of the paper is organised as follows. Section 2 presents the methods employed to investigate the problem, including the data used for empirical application. This is followed by section 3, which presents the results of the econometric model estimations. Finally, section 4 presents the conclusions and policy implications of the findings of the study.

2. Materials and methods

This section describes the econometric modelling techniques and the data employed in examining consumer preferences for organic and GM tomatoes in Ghana.

2.1 Empirical framework

The consistency of choice modelling with the Lancaster (1966) theory of consumer choice has resulted in its wide application. The econometric basis of the approach depends on the framework of random utility theory. Until now, the conditional logit model of McFadden (1974) has been the most common method of analysing consumer choice and willingness to pay for products' attributes. Despite its simplicity, recent advances in the literature have proved the inadequacies of the model in accounting for taste variations and preference heterogeneity among individuals. The advancement in the choice-modelling techniques has resulted in a more appropriate group of models, which include the mixed logit (MIXL) or the random parameter model (RPL), and the generalised multinomial logit model (GMNL). The MIXL and GMNL models resolve all the limitations of the standard logit model by allowing taste variation, unrestricted substitution patterns and correlation in the unobserved portion of the utility over time.

The random utility theory (RUT) of Manski (1977) is applied to the Lancaster (1966) theory of choice on the assumption that consumers act rationally to maximise their utility from a given sets of choices. RUT is based on the premise that not all factors affecting the preferences of individuals are observable to the researcher. Thus, utility is specified as the sum of two components: 1) a systemic component, $V(X_{nit}, \beta)$, which is specified as a function of the alternative attributes i and X_{nit}, which includes a price or cost attribute; and 2) a random component, ε_{nit}, representing an unmeasured variation in preferences. The theoretical model could then be extended to capture $t,$ choice occasions and socioeconomic characteristics, S_n. The individuals' total utility is thus given as in (1):

$$U_{int} = V_{nit}(X_{nit}, \beta, S_n) + \varepsilon_{nit} \quad (1)$$

The probability that an individual n selects an alternative i is the probability that the utility of i is greater than the other alternatives provided in (2):

$$P_n(i|C_n) = P\big(\beta' f(X_{ni},\, S_{ni}\,, \beta)\big) + \varepsilon_{ni} > P\left(\beta' f\big(X_{nj},\, S_{nj}\,, \beta\big)\right) + \varepsilon_{nj}$$
$$P_n(i|C_n) = P_n(i|C_n) = P\big(\beta' f(X_{ni},\, S_n\,, \beta)\big) - P\left(\beta' f\big(X_{nj},\, S_n\,, \beta\big)\right) \geq +\varepsilon_{nj} + \varepsilon_{ni}; i, j \in C_n \quad \forall j \neq i \tag{2}$$

The RUT model may be specified in different ways depending on the distribution of the error terms. If the error terms are independently and identically drawn from an extreme value distribution, we get the conditional logit model (McFadden 1974) which has the following closed form:

$$\Pr(i) = \frac{\exp\,(\beta' x_i)}{\sum_{j=1}^{j=3} (\beta' x_j)} \tag{3}$$

The conditional logit model, a form of the standard logit model, exhibits the independence from irrelevant alternatives (IIA) property, which implies a proportional substitution across alternatives. Depending on the choices offered, this property can be appropriate if the error components are not correlated. Otherwise, it is a restrictive assumption that fails to capture correlations among alternatives (Train 2009). MIXL models, on the other hand, are the integral of the standard logit probabilities over a density of probabilities.

Within the mixed logit model, a consumer's utility for consuming organic and GM tomatoes is specified as in equation (4):

$$U_{njt} = \beta_n' x_{njt} + \varepsilon_{njt}, \tag{4}$$

where x_{njt} relates to the observed variables (i.e. attribute characteristics) of the alternative and the consumer, β_n' is the associated coefficient of the variables, and ε_{njt} is the random term, which comprises *i.i.d.* extreme values. The probability of an MIXL is expressed in equation (5) below:

$$P_{ni} = \int L_{ni}\,(\beta) f(\beta) d\beta, \tag{5}$$

where $L_{ni}(\beta_n)$ is the logit probability function conditioned at the β_n; $L_{ni}(\beta_n) = \frac{e^{v_{ni}(\beta_n)}}{\sum_{j=1}^{j} e^{v_{ni}(\beta_n)}}$; $f(\beta)$ is the density function, which can be either continuous or discrete; and $V_{ni}\beta$ is the part of utility that is dependent on β_n, with weights given by the density function. Given a linear utility in β, $V_{ni}\beta = \beta' x_{ni}$, the model becomes as in equation (6):

$$L_{ni}(\beta_n) = \int \frac{e^{\beta_n' x_{nj}}}{\sum_{j=1}^{j=3} e^{\beta_n' x_{nj}}} f(\beta) d\beta \tag{6}$$

Since β_n is unobserved by the researcher, the choice probability is unconditional and therefore can be obtained through the integral of $L_{ni}(\beta_n)$ over all possible values of β_n, as specified in equation (7):

$$P_{ni} = \int \frac{e^{\beta_n' x_{nj}}}{\sum_{j=1}^{j} e^{\beta_n' x_{nj}}} f(\beta) d\beta \tag{7}$$

The model estimation requires that the researcher make assumptions about the $f(\beta)$ coefficients over the population. The distributional assumption of the $f(\beta)$ coefficient can be either normal, triangular, non-stochastic and log-normal among others. For a complete list of the $f(\beta)$ distributions, see Greene and Hensher (2010). In this paper, we assume a normal distribution for all attributes (Train 2009).

The MIXL specified earlier accounts for unconditional heterogeneity only, and not for conditional heterogeneity. To account for conditional heterogeneity, model expansion is required to incorporate the socioeconomic characteristics of the respondents. This process enables the model to pick up both random and conditional heterogeneity and further improves the model fit (Birol *et al*. 2006). Including the respondents' socioeconomic characteristics as S_n results in model (8):

$$P_{ni} = \int \frac{e^{\beta_n' x_{nj} + S_n}}{\sum_{j=1}^{j} e^{\beta_n' x_{nj} + S_n}} f(\beta) d\beta, \tag{8}$$

where all parameters are as defined earlier.

The mixed logit model was applied in this study because it results in the estimation of unbiased estimates of individual preferences and enhances the accuracy of total welfare estimates (Green *et al*. 1997). The model is also very useful for policy design and implementation resulting from accounting for the equity concerns of a group of individuals. Besides, recent applications have revealed an improvement in the overall model fit and welfare estimates.

We further draw an extension of the mixed logit model into a generalised multinomial logit model (GMNL). The GMNL model was developed by Fiebig *et al*. (2010) to account for both scale heterogeneity (choice inconsistency) and preference heterogeneity. In the GMNL model, the utility of individual *n* choosing from alternative *j* on choice occasion *t* is given as

$$U_{njt} = [\sigma_n \beta + \gamma \eta_n + (1 - \gamma)\sigma_n \eta_n] x_{njt} + \varepsilon_{njt}, \tag{9}$$

where γ is a scale parameter between 0 and 1. The effects of scale on the individual idiosyncratic component of taste can be separated into two parts: unscaled idiosyncratic effect ($\gamma\eta_n$) and scaled idiosyncratic effect $(1 - \gamma)$. Several interesting models are formed based on the restrictions on the parameters (see Fiebig *et al*. (2010) for details). Specifically, we have GMNL-I and GMNL-II. The difference between G-MNL-I and G-MNL-II is that, in G-MNL-I, the standard deviation $\gamma\eta_n$ is independent of the scaling, whereas in G-MNL-II, it is proportional to the scale heterogeneity (σ). G-MNL approaches G-MNL-I as γ approaches 1, and it approaches G-MNL-II as γ approaches 0. In this paper, the GMNL-II was adopted in the estimation of both scale and preference heterogeneity.

Heterogeneity in preferences requires an estimation by maximum likelihood (ML). The rationale behind ML is to search for a solution by simulating *n* draws from distributions with given means and standard deviations. Joint simulated distribution integration is used to obtain probabilities. The standard approach to simulation estimation is based on random draws. However, with large samples and complex models, this can be very time consuming. The Halton draw has been proposed as an alternative, with the advantage of speed gains and no degradation in simulation performance (Revelt & Train 1998). The Halton draw was therefore adopted in this paper.

2.2 Data and description of choice experiment

The data employed in this study comes from a consumer survey conducted in the Cape Coast Metropolis to examine consumer preferences for organic and GM foods. The data collection was conducted in November 2018. Targeted consumers were those with some level of knowledge about organic and GM foods (Al-Rabaani & Al-Shuaili 2014). In selecting the sample for the study, we employed a multistage sampling technique. In the first stage, we purposefully selected three suburbs in the Cape Coast Metropolis – the University of Cape Coast (Cape Vars), Amamoma and Akotokyire. Within the suburbs, we selected 80 consumers from Cape Vars, and 60 each from the Amamoma and the Akotokyire suburbs. The selection of the consumers was based on their prior knowledge of organic and GM foods. In total, 200 consumers responded to the survey and the entire sample was used in the data analysis.

The first step in the discrete choice modelling was the selection of attributes and their levels. The selected attributes had to be as close to reality as possible. The attributes selected for the choice experiment (Table 1) were based on the literature review and interaction with a section of respondents from the University of Cape Coast. Following Emberger-Klein *et al*. (2015), the following attributes were selected: production technology, origin, certification and price. Production technology was defined as the method employed in the production of the tomatoes. There were four levels – the conventional production system, the organic production system, GM with health benefits, and GM with environmental benefits.

Table 1: CE attributes and levels

Attributes	Descriptions	Levels
Production technology	Method used in the production of tomatoes	Conventional Organic GM with health benefits GM with environmental benefits
Origin	Origin of the production of the organic and GM tomatoes	Locally produced Imported
Certification	Endorsement of the organic and GM tomatoes by the appropriate authorities	No certification Food and Drugs Authority (FDA) certification
Purchase price (per kg)	Price charged per kg of organic and GM tomatoes	GH₵* 6 GH₵ 12 GH₵ 18

Note: * GH₵ stands for the country's currency, Ghanaian cedi

There were two levels of the origin attribute – locally produced in Ghana or imported from other countries. The certification attribute also had two levels – no certification and certification by the Food and Drugs Authority (FDA). Consistent with the choice experiment literature, a price attribute was included to compute the willingness to pay for the attributes. The price variable, which was defined as the price of tomatoes per kilogram, had three levels – GH₵6, GH₵12 and GH₵18.

Each respondent was presented with three alternatives on each choice card/set. Alternatives 1 and 2 were associated with different levels of the selected attributes, and alternative 3, which was to opt out. Based on the specified attributes and levels, an efficient design was generated in STATA 14. Priors for the efficient design were obtained from a pilot study that was conducted earlier. The respondents responded to 10 choice sets (see Table 2 for a sample choice set).

Table 2: Sample choice set

Attributes	Option A	Option B	Option C
Production technology	Organic	Conventional	Opt out
Origin	Locally produced	Imported	
Certification	Food and Drugs Authority	No certification	
Producer price (kg)	12	6	
I would prefer to buy	☐	☐	☐

2.3 Socioeconomic characteristics of the sample

Table 3 shows the key socioeconomic characteristics of the sample. From the table it can be seen that about 65% of the sampled consumers are women and 35% are men, and this is mostly due to the sample under study. Their ages ranged between 17 years and 38 years, with an average of 21 years, implying a youthful sample. The income variable ranged between 500 Ghana Cedis to 2 500 Ghana Cedis, with a mean of 663 Ghana Cedis annually.

Table 3: Socioeconomic characteristics of the sample

	Mean	**Min**	**Max**
Age	21	17	38
Income	663	500	2 500
	Percentage response		
Gender	Males = 35% Females = 65%	0	1

3. Results and discussion

To examine the preference heterogeneity of consumers for organic and GM foods, variants of mixed logit and generalised multinomial logit (GMNL) models were estimated. Specifically, we estimated five models. Model 1 is the base model, which is the conditional logit model. Model 2 is the MIXL model without socioeconomic characteristics. Model 3 is the generalised multinomial logit model without socioeconomic characteristics. Model 4 is the MIXL model extended to incorporate socioeconomic characteristics, while Model 5 is an extension of the GMNL with interactions of socioeconomic characteristics. The models were estimated in Stata 14 using 10 000 Halton draws. The estimation of the models required that distributions were assumed for the individual taste parameters, as suggested in the literature. Specifically, normal distributions were assumed for all parameters.

3.1 Standard models

Table 4 presents estimates of the conditional logit, mixed logit and generalised multinomial logit models. The conditional model (Model 1) estimates are in column 2, the mixed logit model (Model 2) estimates are reported in columns 3 and 4, while those of the generalised multinomial logit model (Model 3) are presented in columns 5 and 6. With the exception of Model 1, all models allow preference variation in all attributes. However, Model 3 accounts for scale heterogeneity in addition to preference heterogeneity. The results from Model 1 show that all the estimated coefficients were significant, with the exception of GM with health benefits and GM with environmental benefits. The price coefficient was negative and significant in the results of all five models, suggesting that consumers' utility decreases with price increases. The results also show that consumers had higher utility for the organic alternative compared with the conventional method. However, the coefficients on the GM alternatives were not significant.

The results from the MIXL model (Model 2) show that, with the exception of GM with health benefits, all attributes were significant and had the expected signs on the coefficients. The positive sign on the organic alternative shows that consumers prefer tomatoes produced using organic methods as opposed to conventional methods. The negative coefficient on the GM with environmental benefits indicates that consumers' utility was lower for a GM alternative compared with the conventional one. These findings are consistent with the outcome of the study by Emberger-Klein *et al*. (2016). The coefficient on certification was also positive, showing that consumers prefer tomatoes certified by the Food and Drugs Authority as opposed to those with no certification. The coefficient on the origin attribute was also negative, giving an indication that consumers prefer locally produced tomatoes in contrast to imported ones. The price attribute was negative and significant, which suggests that consumers have a high disutility for tomatoes that are very expensive. The opt-out variable, which is a measure of opting out in the choice experiment, was negative and significant, showing that consumers benefit from choosing an alternative rather than opting out (alternative specific constant – ASC). In Model 3, we find that all attributes in addition to GM with health benefits were significant, which could result from the superiority of the model, given that it had the lowest Bayesian Information Criterion statistic (3 003) as opposed to Models 1 and 2. The significance of GM with health benefits under this model shows that preference and scale heterogeneity are relevant in investigating issues of GM foods in Ghana.

Table 4: Parameter estimates of the MIXL and the GMNL models

Taste parameters	Model 1 = CLM	Model 2 = MIXL		Model 3 = GMNL-II ($\gamma = 0$)	
	Mean	**Mean**	**SD**	**Mean**	**SD**
Organic	0.308*** (0.091)	0.527*** (0.141)	-1.015*** (0.163)	1.243*** (0.425)	-1.961*** (0.559)
GMH	-0.104 (0.095)	-0.195 (0.122)	-0.135 (0.450)	-0.475* (0.272)	-1.151 (0.396)
GME	-0.144 (0.099)	-0.261** (0.130)	0.274 (0.365)	-0.623** (0.297)	0.976 (0.446)
Certification	0.878*** (0.057)	1.317*** (0.139)	1.388*** (0.146)	2.957*** (0.712)	2.812*** (0.661)
Origin	-0.307*** (0.057)	-0.468*** (0.089)	0.626*** (0.122)	-1.138*** (0.336)	1.478*** (0.426)
Price	-3.559*** (0.640)	-6.008*** (1.230)	10.943*** (1.484)	-13.580*** (3.973)	24.406*** (6.319)
ASC	-0.705*** (0.117)	-3.083*** (0.477)	4.213*** (0.512)	-7.486*** (1.900)	11.207*** (2.696)
Tau	- -	- -	- -	-1.215*** (0.175)	- -
N	6 000	6 000		6 000	
LL	-1 913.909	-1 451.058		-1 436.482	
BIC	3 888.714	3 023.911		3 003.456	

Note: GMH = GM with health benefits; GME = GM with environmental benefits; LL = Log likelihood; N = Number of observations; *, ** and *** represent the 10%, 5% and 1% levels of significance respectively

Associated with each mean coefficient are standard deviations, indicating the variability that exists in the sample population. The standard deviation of each random parameter coefficient was highly significant, except for GM with health benefits and GM with environmental benefits. The significance of the standard deviation coefficient is an indication of unobserved heterogeneity in the population.

3.2 Sources of heterogeneity

Although the MIXL model accounts for unobserved heterogeneity, it fails to explain the sources of heterogeneity (Boxall & Adamowicz 2002). Following Birol *et al*. (2006), we accounted for the sources of heterogeneity by interacting a few socioeconomic variables (age, gender and income) with the attributes in the MIXL and GMNL model frameworks. The model estimates are reported in Table 5. These results were obtained after extensive testing of various interactions of socioeconomic characteristics and the attributes of the tomatoes. Based on the Bayesian information criterion (BIC), we discuss the GMNL model with estimates of the interactions.

Table 5: MIXL and GMNL model estimates with heterogeneity in the means

Taste parameters	Model 4 = MIXL		Model 5 = GMNL-II	
	Mean	**SD**	**Mean**	**SD**
Organic	-0.419 (1.344)	-1.031*** (0.165)	-7.446 (4.549)	3.222*** (0.623)
GMH	-2.581** (1.168)	-0.178 (0.334)	-18.038*** (3.719)	-0.113 (0.203)
GME	-2.293** (1.198)	-0.175 (0.505)	-15.408*** (4.058)	0.022 (0.294)
Certification	1.338*** (0.142)	1.414*** (0.149)	5.940*** (1.049)	4.965** (0.882)
Origin	-0.469*** (0.090)	0.645*** (1.504)	-2.043*** (0.395)	2.502*** (0.474)
Price	-9.374*** (2.360)	11.033*** (1.504)	-31.601*** (5.935)	47.365*** (9.049)
ASC	-3.064*** (0.472)	4.216*** (0.519)	-3. 785*** (0.567)	4.472*** (0.629)
Heterogeneity in the mean				
Organic*Age	0.049 (0.061)	-	0.380* (0.204)	-
GMH*Age	0.094* (0.053)	-	0.699*** (0.146)	-
GME*Age	0.101* (0.054)	-	0.508*** (0.156)	-
Org*Gender	0.229 (0.294)	-	1.909*** (0.790)	-
GMH*Gender	0.580** (0.257)	-	2.771*** (0.662)	-
GME*Gender	0.773 (0.270)	-	3.060*** (0.946)	-
Price*Income	0.005* (0.003)	-	0.016*** (0.004)	-
Organic*Income	0.000 (0.000)	-	-0.001* (0.001)	-
Tau			2.027*** (0.187)	- -
N	6 000		6 000	
LL	-14 442.705		-1 425.193	
BIC	3 076.79		3 050.475	

Note: GMH = GM with health benefits; GME = GM with environmental benefits; LL = Log likelihood; N = Number of observations; *, ** and *** represent the 10%, 5% and 1% levels of significance respectively

Unlike the model without interactions, we found that the organic attribute was not significant. However, all other attributes were significant, including the ASC. Specifically, we observed that the interaction between organic attributes and age was positive and significant, suggesting that older people prefer organic tomatoes to conventional ones. Because older people might have a lot more health concerns due to health problems that come with old age, it would make them much more selective when it comes to what to eat, and it is therefore not surprising that they would prefer organic tomatoes to those produced by conventional methods. Similarly, interactions between GM with health benefits and GM with environmental benefits with age were positive and significant, indicating that older people would prefer GM alternatives to conventional tomatoes.

3.3 Willingness to pay

Birol *et al*. (2006) state that the DCE method is consistent with both utility maximisation and demand theory. Using an appropriate model and obtaining the right parameters, welfare measures in the form of marginal willingness to pay (WTP) can be determined. WTP is obtained by estimating the marginal rate of substitution between the tomato attributes and the price coefficient. This conventional approach by researchers to estimating willingness to pay has attracted criticisms in the non-market valuation literature (Greene *et al*. 2006; Hensher *et al*. 2006; Scarpa *et al*. 2008). Recent methods have been proposed to estimate WTP values so that the distributions assumed for the attributes would not have an effect on the distributions of the estimated WTP. Such a method involves estimating WTP coefficients directly, which is referred to as the willingness-to-pay space model (see Scarpa *et al*. 2006 for details). The WTP space model estimates are presented in Table 6.

Table 6: Willingness to pay using the WTP space model

	Mean	**SD**
Organic	0.585** (0.204)	-1.222*** (0.270)
GMH	-0.408** (0.199)	-0.250 (0.259)
GME	-0.433** (204)	0.192 (0.271)
Certification	1.921*** (0.357)	1.626*** (0.307)
Origin	-0.689*** (0.173)	-0.836*** (0.201)
Price	fixed	-
ASC	-5.85*** (1.403)	8.226*** (1.950)
Tau	-1.089*** (1.951)	- -
N	6 000	
LL	-1 470.79	
BIC	3 054.694	

Note: GMH = GM with health benefits; GME = GM with environmental benefits; LL = Log likelihood; N = Number of observations; *, ** and *** represent the 10%, 5% and 1% levels of significance respectively

We can observe from the table that consumers are willing to pay 0.59 cedis per kilogram of tomatoes for an organic attribute and 1.9 cedis for Food and Drugs Authority certification. The sampled consumers, however, associated GM with health and environmental benefits with less value. Also, they associated low value with imported tomatoes compared to locally produced tomatoes.

We now examine the WTP distributions by plotting the kernel density. The results are presented in Figures 1 to 3. Figure 1, which shows the WTP distributions for the origin attribute reveal that, although consumers prefer locally produced tomatoes on average, there are some consumers who have a preference for imported tomatoes (about 8%). The organic attribute (Figure 2) also shows a similar trend, where the WTP distribution ranges from positive to negative, suggesting that, while consumers prefer organic tomatoes on average, there are some who have a preference for conventional tomatoes (about 16% of the respondents). These findings are similar to those of Emberger-Klein *et al*. (2016), who found in their study that, although consumers preferred organic products on average, some consumers preferred conventional food products.

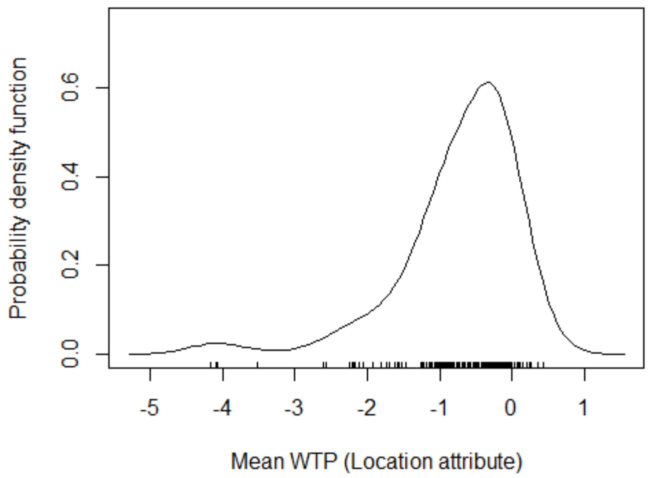

Figure 1: Distribution of origin attribute in relation to WTP

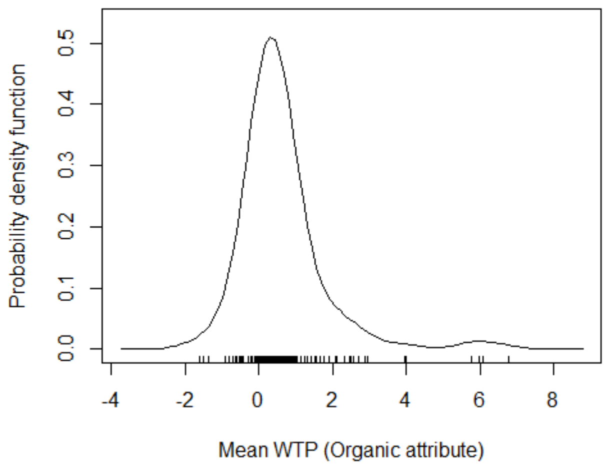

Figure 2: Distribution of organic attribute in relation to WTP

Figure 3, which compares the WTP distributions for organic and GM alternatives, shows wider distributions for tomatoes with organic attributes than GM tomatoes with health benefits and GM tomatoes with environmental benefits. This suggests that almost all respondents had varying utility levels for tomatoes with organic attributes in comparison to tomatoes with GM alternatives, with a closer distribution indicating less variability in the disutility for tomatoes with GM alternatives.

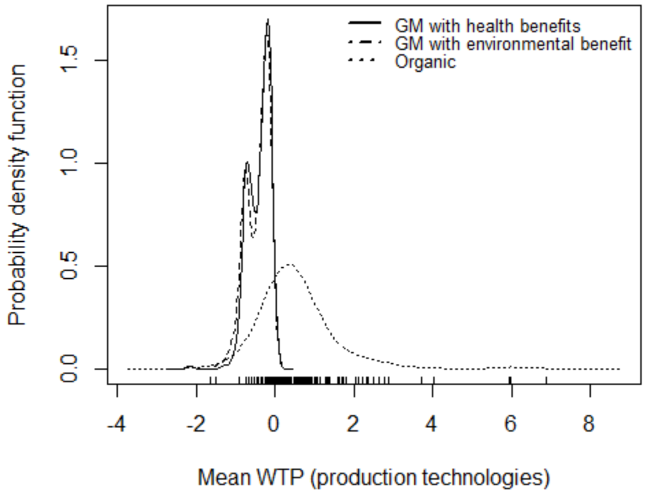

Figure 3: Distribution of WTP for tomatoes with organic attributes and for the GM alternatives

This finding contrasts with that of Emberger-Klein *et al*. (2016), who found that about 39% of their respondents preferred GM alternatives. The findings of the current study therefore contrast with those of previous studies (Buah *et al*. 2011), which reported positive consumer attitudes towards GM foods in Ghana, and tends to support those that have reported negative attitudes towards GM foods (Quaye *et al*. 2009).

4. Conclusion

Given the long tradition of agricultural food production, the GM and organic food production systems are relatively new and, above all, directly in contrast with developments in the agricultural sector. This paper contributes to the limited literature on consumer preferences for organic and genetically modified foods in Ghana using discrete-choice modelling techniques. Specifically, we employed variants of recent advances in the discrete-choice modelling literature, such as the mixed logit model (MIXL) and the generalised multinomial logit model (GMNL). While the MIXL accounts for preference heterogeneity in consumer preferences, the GMNL model accounts for both scale and preference heterogeneity. We used consumer survey data from 200 respondents to examine the preferences of consumers for organic and genetically modified foods.

Our econometric modelling generally revealed that respondents from Cape Vars had strong preferences for organic tomatoes rather than conventional tomatoes. Furthermore, our sampled consumers had less of a preference for GM tomatoes with health and/or environmental benefits. Furthermore, the sampled consumers preferred locally produced tomatoes with certification from the Food and Drugs Authority. However, compared to organic tomatoes, for which about 16% held disutility, almost all respondents did not have any preference for GM tomatoes. This finding is quite revealing, given that Ghana has no policy document on GM foods and the country has not accepted the use of GM foods. Consumers have a major role to play in the success or failure of GM crops, and consumers' disutility for GM foods could be one of the reasons why Ghana has still not adopted the use of GM foods.

To examine whether consumers who have preferences for organic tomatoes also have preferences for GM tomatoes, or vice versa, we interacted the tomato attributes with socioeconomic characteristics such as age, gender and income. The findings revealed that female and older consumers had preferences for both organic and genetically modified foods as opposed to the conventional alternatives. A further study using a latent segmentation model with the inclusion of consumer attitudes would provide detailed and useful information on the categorisation of respondents who have preferences for both organic and GM foods.

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