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# Evaluating preference variation in discrete choice experiments using farmers' choice decisions for sweet potato varietal traits in Kenya

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***Abstract***
*The goal of this study was to contribute to our better understanding of the role of farmers' preference variation for sweet potato varietal traits in Kenya through the estimation of several behavioural models, namely, the multinomial logit (MNL), mixed logit (MXL), scaled multinomial logit (S-MNL), generalized multinomial logit (G-MNL), generalized mixed logit (G-MXL) models. Data for the study was obtained by evaluating the decision-making behavior of farmer's towards six sweet potato variety traits in a discrete choice experiment (DCE) involving 400 randomly selected farmers from Western Kenya. The six traits evaluated include: yield level, tolerance to pests and diseases, sweetness of the flesh, colour of the flesh, maturity period and price change. Survey results show found significant preference variationin the choice decisions of the farmers on sweet potato traits such as yield level, sweetness of the flesh, colour of the flesh, maturity period and price change. In addition, of all the five choice models estimated in the study, the G-MNL model performed better in modelling choice decisions and in accounting for both taste and scale variation of the sweet potato farmers based on the log likelihood information and the Akaike information criteria.*
***Key words**: Preference variation, discrete choice experiment, sweet potato variety.*

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## I. Introduction

Conventionally, the Conditional Logit (CL) models have all a long been used by researchers to analyze discrete choice data (e.g. Bennett and Blamey 2001; Scarpa et al. 2007). Even though the CL model provides a computationally convenient choice model, it is known to be restrictive in its parameter estimation (Kataria, 2009). Besides the restrictive Independence of Irrelevant Alternatives (IIA) property, CL models have limited ability to capture individuals' preference variation. While socio-economic variables can be included in the specification of the utility function, this approach has tended to rely on the observable differences between respondents. Recent modelling approaches such as the mixed logit (MXL) and latent class (LC) models relax the IIA assumption and account for the unobserved individual heterogeneity in the systematic component of utility (Hensher and Greene 2003). A number of authors (e.g. Louviere et al. 2002; Louviere and Eagle 2006; Boeri et al. 2011) have identified the additional importance of accounting for the differences in variance between individuals, which requires models that can represent unobserved individual heterogeneity in the random errorcomponent of utility.The are two models that are not yet widely published but can account for scale heterogeneity, that is: the scaled multinomial logit (S-MNL), generalizedmultinomial logit (G-MNL) and the generalized mixed logit (G-MXL) model.

Notwithstanding the huge number of research evidence regarding heterogeneity in the systematic andrandom components of utility, there are surprisingly few studies that have compared the differentapproaches to modelling unobserved individual heterogeneity. Keane and Wasi (2009) compare the performance of LC, MXL, G-MNL and G-MXL models using ten empirical choicedata sets for marketed consumer goods. The authors find that G-MXL and G-MNL model specifications outperform the MIXL and LC models. Greene and Hensher (2010) estimate MXL, G-MNL and G-MXL models for a study of transport choices. They find that accounting for scale heterogeneity in the G-MNL model is of limited interest in the presence of unobserved preference heterogeneity that is accounted for in the MXL and G-MXL models.

In the context of valuing environmental goods, Scarpa et al. (2011) investigate the effects of increasing the number of choice alternatives and preference elicitation method (best-worst questions) on the scale parameter for a study of Alpine pastures in Europe. They compare models of scale heterogeneity to models that account for preference heterogeneity and models that includeboth. They find significant effects of the number of alternatives in the choice context on scale. However, once taste heterogeneity is addressed in a MXL specification, the scale effect is no longer significant for choice tasks with five alternatives. Best-worst ranking is associated with lower variance than a single most preferredchoice format. In a study on preference for tap water attributes, Scarpa et al. (2012) conclude that a G-MXL model fits their data best, but find issues related to WTP estimation using the model. Christie and Gibbons (2011) also compare models of scale and preference heterogeneity for environmental goods. Similar to Scarpa et al. (2011), they find that preference heterogeneity is more important than scale heterogeneity in their case studies, with MXL and G-MXL models outperforming CL and G-MNL models. The authors argue that G-MXL models have the potential to improve the rigour of valuation studies for unfamiliar grounds in environmental goods and services. They however call for additional research work so as to shed more light on how these models compare.As such, this paper follows up on the identified need for additional studies that compare approaches to modelling individual heterogeneity (Keane and Wasi, 2009; Greene and Hensher 2010).

The paper describes various model developments in discrete choice analysis that account for unobserved individual heterogeneity in preferences and/or scale in section 2. The choice experiment used for the study is presented in Section 3 of the paper. In Section 4, the results of CL, MXL, S-MNL, G-MNL and G-MXL model specifications and willingness to pay estimates are presented and the final section concludes.

## II. Choice models - CL, MXL, S-MNL, G-MNL, G-MXL

*2.1Multinomial logit model (MNL)*

The development of the multinomial logit (MNL) model by McFadden (1974) provided a statistical framework for modeling how varying policy attributes contribute to the probability of choice. The model has been widely used in applied economics owing to its computational simplicity and closed-form model specification. It assumes that choices are consistent with the independence of irrelevant alternatives (IIA) property such that for any individual, the ratio of choice probabilities of any two alternatives is unaffected by the utilities of any other alternatives (e.g. Louviere *et al*., 2010). The MNL model is based on an indirect utility function where the indirect utility derived by respondent $i$ from alternative $j$ in choice set $C$ is:

$$U_{ij} = V_{ij}\ \{Z_{ij}, S_i\} + \varepsilon_{ij} \qquad (1)$$

where $V_{ij}$ is the observable deterministic component and $\varepsilon_{ij}$ is the unobserved stochastic component. $V_{ij}$ is a function of both the attributes of the alternative options and the status quo in choice set ($Z_{ij}$) and the characteristics of the respondent ($S_i$). Respondent $i$ chooses alternative $j$ if $U_{ij} > U_{ik}$ for all $j \neq k$ in $C$. As such, the probability of choosing alternative $j$ by respondent $i$ is:

$$Prob_i(j|C) = \{V_{ij} + \varepsilon_{ij} > V_{ik} + \varepsilon_{ik}\} = \{V_{ij} - V_{ik} > \varepsilon_{ik} - \varepsilon_{ij}\} \qquad (2)$$

The estimation of Equation (2) requires that assumptions about the distributions of the error terms be made. For the MNL model, the errors are assumed to be independently and identically distributed ($iid$) with a Type 1 extreme value distribution (McFadden, 1974). This suggests that the probability of choosing alternative $j$ by respondent $i$ is:

$$Prob_i(j|C) = exp\{\mu V_{ij}\}/\textstyle\sum_{k\in C_i} exp\{\mu V_{ik}\} \qquad (3)$$

where $\mu$ is a scale parameter that is inversely proportional to the variance of the error term. This parameter is not separately identified and thus, it is generally assumed to be equal to one, which implies constant error variance (e.g. Ben-Akiva and Lerman, 1985). As such, the log-likelihood function takes the form:

$$ln\ LL = \textstyle\sum_{i=1}^{N}\sum_{j=1}^{3}\{Y_{ij} * ln[Prob_i(j|C)]\} \qquad (4)$$

where the value of $Y_{ij}$ is one if the $i^{th}$ respondent chooses alternative $j$ and zero otherwise. Equation (4) is estimated through a maximum likelihood procedure (e.g. Hensher *et al*., 2015). Given the important restrictions in the MNL model because of the rigidity of its error structure, other formulations have been developed with more flexible error term distributions such as the mixed logit (MXL), scaled-multinomial logit (S-MNL), generalized-multinomial logit (G-MNL) and the generalized-mixed logit (GMXL) models.

***2.2. The mixed logit model (MXL)***

Nowadays, the MXL model has largely replaced the MNL model in analyzing discrete choice data. The model was developed to account for the intuitive fact that respondents as decision-makers in a survey differ from each other. Thus, it is able to account, among others, for random taste variation and correlation in unobserved preference factors of individuals (e.g. Hensher *et al*., 2015). Therefore, the utility respondent $i$ receives from a choice alternative $j$ is algebraically formulated as before as follows:

$$U_{ij} = \beta_i^{'} x_{ij} + \varepsilon_{ij} \quad (5)$$

where the deterministic component is a linear function of the policy attributes in vector $x_{ij}$ and the vector $\beta$ of utility weights for each attribute, but $\beta_i$ is now partitioned into a mean part ($\bar{\beta}$) and individual $i^{th}$ deviation ($\eta_i$), thus giving equation (6):

$$U_{ij} = \beta_i^{'} x_{ij} + \varepsilon_{ij} = (\bar{\beta}^{'} + \eta_i^{'}) x_{ij} + \varepsilon_{ij} \quad (6)$$

Following Train (2009), the probability of choosing alternative $j$ by respondent $i$ expressed by a vector of policy attributes $x$ is obtained by integrating the distribution density over the range of parameter values, thus:

$$Prob(j|x_i, b, w) = \int exp\left(\bar{\beta}_i^{'} x_{ij}\right) / \sum_{j \in k} exp\left(\bar{\beta}_{i_{ij}}^{'}\right), \ \Omega(\bar{\beta}|b, w) d\beta \quad (7)$$

The utility function of each respondent has some random taste parameters $\bar{\beta}_i^{'}$ with values that depend on the values of the parameters $b$ and $w$ of an underlying distribution $\Omega(\bar{\beta}|b, w)$, where w is the information or variance-covariance matrix. As Hensher and Green (2003) note, the choice of distribution strongly affects the properties of the model. As such, random taste parameters $\bar{\beta}_i$ induce correlation across choices made by the same respondent, but maintain the advantageous logit probability. In effect, $\varepsilon_{ij}$ is $iid$ Gumbel and therefore the choice probability remains logit conditional on the parameter draw. The MXL formula is thus a weighted average of the MNL probability calculated at different values of $\beta$. The weight is the probability density ($\Omega$) of $\beta$ over respondents with mean $b$ and variance-covariance matrix $w$. Since Equation (8) does not have a closed form solution, it is estimated by simulated maximum likelihood methods (e.g. McFadden and Train, 2000). In view of the fact that the MXL formulation still maintains the MNL model assumption that the idiosyncratic error term is $iid$, it is unable to account for scale heterogeneity. To account for the potential effect of scale heterogeneity, the S-MNL model has been developed which relaxes the $iid$ assumption (e.g. Fiebig *et al*., 2010).

### *2.3. The scaled multinomial logit (S-MNL)*

The MXL model only accounts for the unobserved taste heterogeneity in the deterministic component of utility. Typically, the scale factor $\mu$, which is inversely related with the error variance $\sigma_\varepsilon^2$, is normalized to one to allow estimation of the model. Past studies (e.g. Louviere and Eagle, 2006) suggests that such a constant scale of the error distribution may not be appropriate in explaining individual choice behaviour. Thus, Fiebig *et al*. (2009) developed alternative modelling methods that could accommodate the variance across respondents in the random component of utility, namely the S-MNL and G-MNL model. In the S-MNL model, the error variance $\sigma_\varepsilon^2$ is allowed to be heterogeneous in the population so that the utility $U_{ij}$ that respondent $i$ derives from alternative $j$ can be written as follows:

$$U_{ij} = (\beta \sigma_i)^{'} x_{ij} + \varepsilon_{ij} \quad (8)$$

where β denotes a vector of average population attribute parameters, $\sigma_i$ refers to the individual's specific standard deviation of the idiosyncratic error term that captures scale heterogeneity, $x_{ij}$ denotes a vector of the observed explanatory variables, and $\varepsilon_{ij}$ is as before the stochastic error that is $iid$ over the alternatives and individuals (Fiebig *et al*., 2009). The individuals' scaling factor has to be restricted to be positive and this is attained through the use of an exponential transformation (e.g. Fiebig *et al*., 2009; Greene and Hensher 2010), that is:

$$\sigma_i = exp(\bar{\sigma} + \tau w_i) \quad (9)$$

where $\bar{\sigma}$ denotes the mean parameter related to the error variance, $\tau$ is the coefficient associated with the unobserved scale heterogeneity, and $w_i$ refers to the unobserved individual heterogeneity related to the scale that is standard normally distributed. Since $\bar{\sigma}$ is unidentified separately from $\tau$, $\sigma_i$ is normalized as $\bar{\sigma} = \tau^2/2$. Thus, larger parameter values for $\tau$ show a greater degree of scale heterogeneity (Fiebig *et al.*, 2009). The S-MNL model is estimated through a simulated maximum likelihood procedure.

***2.4. The generalized multinomial logit model (G-MNL)***

The need to account for both taste and scale heterogeneity in one and the same model led to the development of the G-MNL model (e.g. Keane *et al.*, 2006; Fiebig *et al.*, 2010; Greene and Hensher , 2010). The G-MNL model nests both the MXL and S-MNL model. First operationalized by Fiebig *et al.* (2010) and subsequently by Greene and Hensher (2010), the marginal utility for alternative *j* for the G-MNL model is represented as follows:

$$U_{ij} = \sigma_i \bar{\beta}_j + \gamma\theta_{ij} + (1-\gamma)\sigma_i\theta_{ij} \quad (10)$$

where $\gamma$ takes any value between 0 and 1 and where:

$$\sigma_i = e^{\bar{\sigma}+\tau v_i} \quad (11)$$

In Equation (11), $\bar{\sigma}$ denotes the mean parameter of scale variance, $\tau$ is as before a parameter of unobserved scale heterogeneity, and $v_i$ is a standard normal distribution representing the unobserved scale heterogeneity. Ignoring $\sigma_i$ and in the extreme case where $\gamma$ takes the value 0, Equation (11) collapses to:

$$U_{ij} = \sigma_i(\bar{\beta}_j + \theta_{ij}) \quad (12)$$

suggesting that scale impacts equally upon both the mean and standard deviation parameters. Fiebig *et al.* (2010) refer to this model as G-MNL II. If on the other extreme $\gamma$ equals 1, Equation (11) is equal to:

$$U_{ij} = \sigma_i \bar{\beta}_j + \theta_{ij} \quad (13)$$

suggesting that the scale factor impacts only upon the mean attribute parameters. Fiebig *et al.* (2010) refer to this model as G-MNL I. Values of $\gamma$ between 0 and 1 suggest that scale impacts both the mean and standard deviation parameters, but to different extents. Returning to $\sigma_i$, if $\sigma_i = 1$ and all $\theta_{ij} = 0$, then the model collapses to the standard MNL model. If $\sigma_i$ is estimated to take the value 1, then the marginal utilities obtained from the model would collapse to the MXL model. Similarly, if all $\theta_{ij}$ simultaneously equal 0, then the model collapses to the scaled version of the MNL model, namely the S-MNL model (Fiebig *et al.*, 2010), such that the marginal utilities obtained from the model would algebraically be given as:

$$U_{ij} = \sigma_i \bar{\beta}_j$$
(14)

***2.5. The generalized mixed logit model (G-MXL)***

Finally, a more flexible G-MXL modelling approach accommodating individual taste as well as individual scale heterogeneity was proposed by Fiebig *et al.* (2009). The G-MXL model specification accounts for the unobserved heterogeneity both in the deterministic and in the random components of the individual utility function. In this model utility, $U_{ij}$, is defined by:

$$U_{ij} = \{\sigma_i\beta + \gamma\eta_i + (1-\gamma)\sigma_i\eta_i\}' x_{ij} + \varepsilon_{ij} \quad (15)$$

where $\sigma_i$ denotes the respondent's specific standard deviation of the idiosyncratic error term that captures the scale variance, $\eta_i$ is the respondent's specific deviation from the mean, capturing individual teste heterogeneity, and $\gamma$ is a weighting parameter between 0 and 1 that captures how the variance of the individual respondent's taste varies with scale. While estimating the G-MXL model, several normalizations are required. $\sigma_i$ is again normalized as $\bar{\sigma} = -\tau^2/2$ to enable identification of $\bar{\sigma}$ so that $E[\sigma_i] = 1$. In addition, to ensure that $\tau \geq 0$, the model is fit in terms of $\lambda$, where $\tau = \exp(\lambda)$ and $\lambda$ is unrestricted (e.g. Hensher *et al.*, 2011). τ is the parameter that captures scale variance. If approaches 0, then the G-MXL model approaches the MNL model (Fiebig *et al.*, 2009).

## III. Experimental design

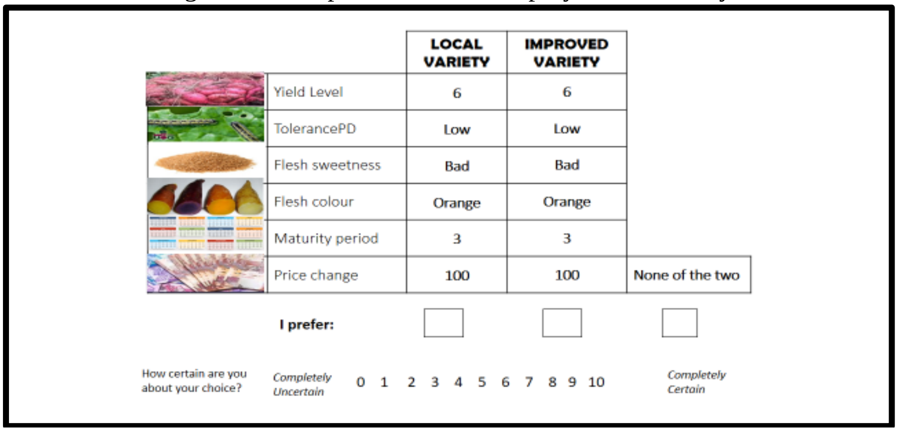
In DCEs, respondents are presented with alternative descriptions of policy interventions, differentiated by different combinations of attribute levels. Respondents are then asked to choose their preferred alternative. For each choice made, the alternative selected is assumed to yield a higher level of satisfaction than that rejected. This enables the probability of an alternative being chosen to be modelled in terms of the attribute levels used to describe the policy intervention.In this paper, respondents were presented a series of variety traits that include: yield level, tolerance to pests and diseases, sweetness of the flesh, colour of the flesh, maturity period and price. Respondents were asked to choose their most preferred varietal alternative. Based on expert interviews in an open-ended pre-test ($N = 50$), different levels for the selected varietal traits were selected as shown in Table 1.

**Table 1: Descriptions and levels of the chosen attributes**

| Attribute | Description | Levels | Coding |
|---|---|---|---|
| Yield | The amount of sweet potato out per hectare | Level 1: 6 tons/hactre<br>Level 2: 10 tons/hactre<br>Level 3: 14 tons/hactre | Actual values |
| Tolerance | Forbearance to common crop pests and diseases | Level 1: High<br>Level 2: Medium<br>Level 3: Low | Effect coding |
| Sweetness | Taste of the sweet potato flesh. | Level 1: Good<br>Level 2: Average<br>Level 3: Bad | Effect coding |
| Colour | Colour appearance of the sweet potato flesh. | Level 1: Orange<br>Level 2: Yellow<br>Level 3: White | Effect coding |
| Maturity | Period sweet potato takes to mature. | Level 1: Upto 3 months<br>Level 2: Upto 5 months<br>Level 3: Upto 7 months | Actual values |
| Price | Change in price per unit of output. | Level 1: 100<br>Level 2: 200<br>Level 3: 300 | Actual values |

There were also different alternative varietal scenarios created by combining these six variables based on their different attribute levels. Because respondents cannot be shown all different choice options, the number of possible combinations was reduced to 10 choice sets of 10 choice tasks each based on an orthogonal fractional factorial design generated in the statistical software Ngene, enabling the estimation of main effects and two-way interactions. Each respondent was randomly shown one of these 10 choice sets of 10 choice cards. Each choice card shows two hypothetical choice alternatives describing a future policy scenario along with the option to choose none of the two. Inclusion of this latter 'status quo' alternative is instrumental to be able to estimate welfare measures that are consistent with demand theory (Bateman et al., 2003). It was emphasized that respondents would not have to pay anything extra if they choose the opt-out. An example of a choice card is presented in Figure 1.

Figure 1: Example choice card employed in the study




The design of the choice experiment mainly comprised three sections. The first section was intended to measure respondents' general knowledge on sweet potato varietal traits so as to familiarize them with the attributes of interest that were being evaluated. The second section contained questions for DCE analysis that were designed to elicit respondents' WTP for sweet potato varietal traits by estimating trade-offs between price and the other attributes. In this case, common photographs of the attributes were also inserted in the DCE cards to enhance respondents' understanding regarding the attributes. The final part elicited socio-demographic information of the respondents such as age, gender, education and income. The choice experiment instrument was first pre-tested and subsequently implemented between October – December 2019 through 400 in-person interviews in Western Kenya. The response rate was 100%, which is not unusual for this kind of stated preference research in a developing country (Whittington, 1998). A predetermined random sampling plan was used to obtain respondents for the survey. Trained local enumerators were also used for the interviews to ensure choice scenarios were presented to respondents in a more informative way. The enumerators had instructions to limit all explanations to facts so as to minimize the introduction of any interviewer bias. Moreover, respondents were given adequate time to understand and answer each question so as to enhance the validity of responses obtained. The results are presented in the following section.

## IV. Results and discussions

### 4.1 Descriptive results

Descriptive results of the socio-demographic and farm characteristics of the survey sample are presented in Table 2. As shown, the mean age of the respondents was 45 years with men accounting for the largest share (78%) of the respondents. Most respondents (93%) had primary and post-primary level of education with only 11% and 14% of the respondents having had access to farm credit and agricultural extension services, respectively. On average, the distance to a reliable input/output market centre was about 3kms with membership to farm organizations having a share of 16% of the interviewed farmers. Land holdings were, on average, 0.37 acres with household heads having a farming experience of about The study also found that 62% of the respondents were growing improved sweet potatoes varieties with 36% of the respondents saying they grew sweet potatoes more than once in a year. Moreover, the study also found that 95% of the interviewed farmers produced sweet potatoes for commercial purposes. As to the source of the sweet potato vines, the study found that 35% of the farmers sourced vines from their own farms. On average, sweet potato production was about 1.91 tonnes that fetched an average income of about KES 11,702.

**Table 2:** Socio-demographic and farm characteristics of the survey sample

| Variable | Mean/proportion | Std error | Min | Max |
|---|---|---|---|---|
| Age (years) | 45 | 13.31 | 20 | 85 |
| Gender (1=male) | 0.78 | 0.41 | 0 | 1 |
| Education (1=educated) | 0.93 | 0.25 | 0 | 1 |
| Access to farm credit (1=access) | 0.11 | 0.31 | 0 | 1 |
| Access to agricultural extension (1=access) | 0.14 | 0.35 | 0 | 1 |
| Membership to farm organizations (1=member) | 0.16 | 0.37 | 0 | 1 |
| Sweet potato variety grown (1=improved) | 0.62 | 0.48 | 0 | 1 |
| Frequency of growing sweet potatoes (1=more than once) | 0.36 | 0.48 | 0 | 1 |
| Sweet potato use (1=commercial purposes) | 0.95 | 0.22 | 0 | 1 |
| Source of sweet potato vines (1=own farm) | 0.35 | 0.77 | 0 | 1 |
| Quantity of sweet potato harvest (tonnes) | 1.91 | 15.23 | 0 | 300 |
| Sweet potato income (KES) | 11,702 | 2,114 | 0 | 180,000 |
| Distance to reliable input/output market (Kms) | 3.07 | 0.71 | 0.1 | 7 |

Table 3. shows farmers perceptions about the severity of challenges faced in sweet potato production. As shown in the table, 81% of the farmers felt that lack of extension services a major problem facing sweet potato farming in the study area. This was followed by unavailability of farm credit (76%), yield variability (67%), input quality (58%), input availability (54%) and price variability (50%). However, low incidences of flooding (18%) and droughts (22%), exploitation by middlemen (22%) and theft of produce were some of the least challenges they faced by farmers in sweet potato production.

**Table 3:** Severity of challenges faced in sweet potato farming among the survey respondents

| **Variable** | **Proportion** | **Std error** | **Min** | **Max** |
|---|---|---|---|---|
| Labour scarcity | 0.31 | 0.46 | 0 | 1 |
| Yield variability | 0.67 | 0.47 | 0 | 1 |
| Frequent droughts | 0.22 | 0.41 | 0 | 1 |
| Frequent floods | 0.18 | 0.38 | 0 | 1 |
| Extension services | 0.81 | 0.39 | 0 | 1 |
| Input quality | 0.58 | 0.49 | 0 | 1 |
| Input availability | 0.54 | 0.50 | 0 | 1 |
| Credit availability | 0.76 | 0.43 | 0 | 1 |
| Market for produce | 0.30 | 0.46 | 0 | 1 |
| Price variability | 0.50 | 0.50 | 0 | 1 |
| Road network | 0.30 | 0.46 | 0 | 1 |
| Theft of produce | 0.29 | 0.45 | 0 | 1 |
| Middlemen | 0.22 | 0.41 | 0 | 1 |

As for the importance of different sources of information for sweet potato farming, the results are shown in Table 5. The study found that friends (91%) were the important source of information, followed by relatives (87%), and radio (68%). However, farmers association (31%), television (30%), input dealers (30%), extension agents (27%) and newspapers (23%) were the least important sources of information in sweet potato production.

**Table 4: Importance sources of information used in sweet potato farming in the study area**

| Variable | Proportion | Std error | Min | Max |
|---|---|---|---|---|
| Friends | 0.91 | 0.29 | 0 | 1 |
| Relatives | 0.87 | 0.34 | 0 | 1 |
| Newspaper | 0.23 | 0.42 | 0 | 1 |
| Radio | 0.68 | 0.47 | 0 | 1 |
| Television | 0.30 | 0.46 | 0 | 1 |
| Input dealer | 0.30 | 0.46 | 0 | 1 |
| Farmer association | 0.31 | 0.46 | 0 | 1 |
| Extension agent | 0.27 | 0.44 | 0 | 1 |

### 4.2 Econometric results

As mentioned earlier, five utility models, namely, MNL, MXL, S-MNL, G-MNL and the G-MXL were estimated to assess preference variation in the choice data. Since the MNL modeldoes not implicitly accounting for either taste and/or scale variationin the discrete choice decisions, researchers have in the past used interaction terms in order to capture taste variation. As for the MXL model, taste variation is captured directly in the systematic component of utility and accounted for by specifying the choice attributes as random parameters. In the S-MNL model, scale variation is implicitly accounted for in the random component of utility. For G-MNL and the G-MXL models, both taste and scale variation is accounted for in both the systematic and the random components of the utility models.

In thisstudy, estimations of the five behavioural models (MNL, MXL, S-MNL, G-MNL and G-MXL) were conducted with choice attributes as therandom parameters in order to assess the significance of taste and scale variation in the choices made by sweet potato farmers in western Kenya. The utility functions were specified as linear functions of the choice attributes with an alternative specific constant (ASC), also included in the utility functions to represent the difference in utility between respondents' choice of the provided choice alternatives (local variety or improved variety) and the status quo option when all attributes are equal. The ASCwas included in the model as dummy variable with the provided choice alternatives being coded as one and the status quo option as zero (Tarfesa and Brouwer, 2012). In addition, following Greene et al. (2006), the random price parameter was assumed to follow a constrained triangular distribution to ensure a negative sign on the price parameter while a normal distribution was defined for the other random parameters. Table 6 presents the estimation results.

To begin with, choice shares across the three alternatives (i.e. for local variety, improved variety and the status quo option) were analyzed and as shown in Table 5, there was a positive attitude among respondents towardsimproved sweet potato variety since the alternative was chosen in 62% of the cases compared to the local variety option that was chosen in 34% of the cases. Majority of those who chose none of the two (3.6%) explained that they did not mind any of the sweet potato varieties.

Table 5: Choice shares across the alternatives in the discrete choice experiment

| Description | Proportion | Standard Error | 95% Confidence Interval | |
|---|---|---|---|---|
| Local variety | 0.340 | 0.007 | 0.326 | 0.355 |
| Improved variety | 0.624 | 0.008 | 0.609 | 0.639 |
| Status quo | 0.036 | 0.003 | 0.030 | 0.041 |

As shown, the coefficient sign of the ASCparameter The ASC parameter is positive, which implies that respondents, on average, prefer the cultivation of either of the two sweet potato varieties as opposed to the status quo option of no cultivation at all. The coefficients for yield level, tolerance to pests and diseases,sweetness of the sweet potato flesh and maturity period of the sweet potato crop are alsopositive and significant and follow theoretical expectations. This study outcome implies that a positive change in the level of any of the attributes would lead to higher utility for the farmers. As for the colour of the flesh and price, they are both negative and insignificant meaning that positive changes in the level of any of these two attributes would yield lower utility for the farmers. Significant standard deviations of the random parameters in the MXL, G-MNL and G-MXL models, namely: yield level, sweetness of the flesh, colour of the flesh, maturity period and price change, provide evidence to the fact that there was significant preference variation (e.g. Christie and Gibbons, 2011; Fiebig et al., 2010) in the choice decisions of the farmers regarding the afore said sweet potato varietal attributes in the study area.

Basing on the five model formulations (i.e. the MNL, MXL, S-MNL, G-MNL and G-MXL) and with reference to the attributes only model specifications, the results in Table 6 show that accounting for taste variation in the MXL model improved the log likelihood (LL) informationby 14.52 points or 0.52% based on the standard MNL values. Similarly, accounting for scale variation in the S-MNL model improved the LL information by 6.73 points or 0.24% based on the standard MNL values. However, the MXL model outperformed the S-MNL model based on the LL information by 7.79 points or 0.28%, which represents the amount of taste variation in the choice data not accounted for by the S-MNL model. It also means that scale variation, accounted for in the S-MNL model was less important than taste variation (e.g. Scarpa et al., 2011) in the current choice data. The G-MNL model, which nests both MXL and the S-MNL models and hence, accounts for both taste and scale variation in the choice data, improved the LL by 17.66 points or 0.637% over the MNL model.

Table 6: Regression results of the estimated utility functions for sweet potato varietal traits in the study area

| **Characteristics** | **MNL** | | **MXL** | | **S-MNL** | | **G-MNL** | | **G-MXL** | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Mean estimate of random attribute parameters** | **Coefficient** | **Std error** | **Coefficient** | **Std error** | **Coefficient** | **Std error** | **Coefficient** | **Std error** | **Coefficient** | **Std error** |
| ASC (1 = none status quo) | 2.806*** | 0.167 | 3.338*** | 0.190 | 4.358*** | 0.469 | 4.263*** | 0.283 | 4.706*** | 0.477 |
| Yield level (1 = high) | 0.041*** | 0.007 | 0.038*** | 0.009 | 0.044*** | 0.007 | 0.042* | 0.008 | 0.044*** | 0.009 |
| Tolerance to pests and diseases (1 = high) | 0.079*** | 0.027 | 0.076** | 0.029 | 0.073*** | 0.024 | 0.084** | 0.029 | 0.068** | 0.032 |
| Sweetness of flesh (1 = good) | 0.106*** | 0.029 | 0.097* | 0.030 | 0.116*** | 0.025 | 0.104*** | 0.029 | 0.108*** | 0.032 |
| Colour of flesh (1 = appealing) | 0.038 | 0.028 | 0.020* | 0.030 | 0.046* | 0.023 | 0.028* | 0.029 | 0.032 | 0.035 |
| Maturity period (1 = longer) | -0.052*** | 0.014 | -0.057** | 0.014 | -0.035*** | 0.012 | -0.053** | 0.014 | -0.052*** | 0.015 |
| Price change (1 = high) | -0.0003 | 0.0003 | -0.0007 | 0.000 | -0.001* | 0.0003 | -0.0002* | 0.0003 | -0.0003 | 0.0003 |
| **Standard deviation of random parameters** | | | | | | | | | | |
| ASC | | | 0.139* | 0.279 | | | 4.632*** | 0.532 | 5.015*** | 0.704 |
| Yield level | | | 0.051** | 0.130 | | | 0.069** | 0.011 | 0.076*** | 0.012 |
| Tolerance to pests and diseases | | | 0.115* | 0.011 | | | 0.162*** | 0.042 | 0.055* | 0.051 |
| Sweetness of flesh | | | 0.037*** | 0.038 | | | 0.088* | 0.047 | 0.095* | 0.052 |
| Colour of flesh | | | 0.126* | 0.046 | | | 0.010*** | 0.042 | 0.003* | 0.061 |
| Maturity period | | | 0.138** | 0.036 | | | 0.011** | 0.024 | 0.051*** | 0.019 |
| Price change | | | 0.042* | 0.016 | | | 0.001* | 0.001 | 0.0007* | 0.001 |
| **Model summary statistics** | | | | | | | | | | |
| Log-likelihood. | -3246.79 | | -3208.73 | | -3197.44 | | -3136.86 | | -3126.51 | |
| LR chi-square | 101.15 | | 2371.44 | | 2394.02 | | 2515.18 | | 2535.88 | |
| Prob > chi square | 0.0000 | | 0.0000 | | 0.0000 | | 0.0000 | | 0.0000 | |
| McFadden Pseudo $R^2$ | 0.0432 | | 0.2698 | | 0.2724 | | 0.2862 | | 0.2885 | |
| Scale (tau) parameter $\boldsymbol{\tau}$ | - | | - | | 0.8247*** | | 0.069*** | | 0.381*** | |
| Weighting (gamma) parameter $\boldsymbol{\gamma}$ | - | | - | | fixed | | fixed | | 0.982*** | |
| Akaike Information Criteria (AIC) | 6507.60 | | 6445.50 | | 6410.90 | | 6303.70 | | 6285.00 | |
| Number of observations | 4000 | | 4000 | | 4000 | | 4000 | | 4000 | |
| Parameters | 7 | | 14 | | 8 | | 15 | | 16 | |

Explanatory notes: ASC alternative-specific constant, which is a dummy for the respondent choosing to grow sweet potatoes as opposed to not growing; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

The G-MXL model specification, which also accounts for both taste and scale variation, had a smaller LL improvement over the MNL model of 7.59 points or 0.365%. The implication here is that the G-MNL model accounted for both taste and scale variation better than the G-MXL model basing on the higher LL information for G-MNL model compared to that of the G-MXL formulation.

Furthermore, the statistically insignificant scale parameter, $\tau$, in the S-MNL, G-MNL and G-MXL models means that scale variation was of lesser significance in the choice data as opposed to taste variation. This means that it was unlikely that the choice behaviour of the farmersin this experimental design may have been characterized by significant choice uncertainties. It also means that this choice study may have also presented a less challenging choice situation to the farmers since according to Fiebig et al. (2010) and Christie and Gibbons (2011), aninsignificant scale factor is usually, but not always, a case of less difficult choice contexts presented to respondents, which in turn minimizes chances for choice uncertainty. The weighting parameter, $\gamma$, was also found closer to zero meaning that the variance of the random taste variation increased with scale.

The AIC values also reveal a similar results pattern as those provided for by the LL information. The AIC value for the MXL model improved over the MNL value by 13.0 points or 0.23% meaning that indeed accounting for taste variation in our choice data was important. As well, accounting for scale variation in the S-MNL model enhanced the LL information by 9.40 points or 0.17% based on the standard MNL values. However, comparing AIC values for MXL and S-MNL show that the MXL model outperformed the S-MNL model by 3.60 points or 0.06%, which implies that scale variation in our choice data was of less significance compared to taste variation. The AIC values for G-MNL and G-MXL models, which account for both taste and scale variation show improvement over the MXL model, which only accounts for the taste variation, by 4.30 points or 0.08% and 2.1 points or 0.04%, respectively. This means that choice models that account for both taste and scale variation perform better as opposed to those either capturing taste (e.g. MXL model) or scale variation (e.g. S-MNL model) (Fiebig et al., 2010; Ndambiri et al., 2016; Scarpa et al., 2011). As in Ndambiri et al. (2016), the G-MNL model was found to capture both taste and scale variation better than the G-MXL model based on both LL information and AIC values.

## V. Conclusions

The purpose of this paper was to assess famers' preference variation in their choice decisions for sweet potato varietal traits in western Kenya by evaluating how five behavioural choice models account for either taste and/or scale variation in the choices made by individuals. Firstly, all the five models (MNL, MXL, S-MNL, G-MNL and G-MXL) with random parameterswere estimated in order to assess their significance in accounting for either taste and/or scale variation. In this case, farmerswere presented with attributes on sweet potato yield level, tolerance to pests and diseases, sweetness of the flesh, colour of the flesh, maturity period and price change. Both log likelihood information and theAkaike information criteria (AIC) were used to evaluate the way the five behavioural models accounted for taste and scale variation. First and foremost, the survey results indicate that farmers were deriving lower utility from both local and improved sweet potato varietal alternatives and the most probable reason for this is that the productivity of the sweet potato land holdings may not be as optimal as would have been expected for either of the varieties. Moreover, farmers seemed to derive lower utility from growing local varietiesas opposed to growing improved varieties.The study results have also shown that any positive changes in sweet potato crop traits such as yield level, tolerance to pests and diseases,sweetness of the sweet potato flesh and maturity period of the sweet potato crop would lead to higher utility for the farmers. However, positive changes in the traits such as colour of the flesh and price was likely to lower utility from sweet potato production by the farmers. The study also found significantpreference variationin the choice decisions of the farmers on sweet potato traits such as yield level, sweetness of the flesh, colour of the flesh, maturity period and price change. In addition, taste variation in this study was more important than scale variation meaning that it was not likely that the choice behaviour of the farmersin this experimental design was characterized by significant levels of choice uncertainties. In other words, it is likely that this choice study presented less challenging choice tasks to the farmers since, aninsignificant scale factor is usually, but not always, a case of less difficult choice contexts presented to respondents, which in turn minimizes chances for uncertainties in the choice decisions made by the farmers. Of all the five choice models, the G-MNL model performed better in modelling choice decisions of the sweet potato farmers as opposed to all the other models based on the LL information and AIC criteria. However, more studies are required to shed more light on the impact of accounting for preference variation on different choice model formulations. Therefore, future choice studies should endeavour to provide more comparative empirical studies about various modelling approaches to preference variation especially with choice data on valuation of differentagriculturaltechnologies especially from the developing world so as to contribute to building more consensus on the preferred approach to modelling preference variation.

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