THE INTERNATIONAL JOURNAL OF BUSINESS & MANAGEMENT

Consumers' Preferences and Willingness-to-Pay for Cowpea Varieties using Three Econometrics Estimation Methods

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Abstract:
Several estimation methods have been used to determine market share and consumer willingness to pay for various attributes of a given product. Our objective in this paper was to determine consumers' preferences and willingness to pay for cowpea attributes and varieties across estimation methods. Results indicate market share and willingness to pay prediction under both classical and Bayesian approaches were quite similar.

***Keywords**: Consumers' Preferences, Willingness-to-Pay, Cowpea Varieties, Estimation Methods*

1. Introduction

The primary goal of marketing is its ability to define patterns on consumer choice. Most of the time, marketplace is the appropriate environment where consumers' preferences are revealed either thorough selecting among alternatives or ratings. The choice among alternatives and ratings are the yardstick used to measure consumers' preferences in the marketplace. Grouping responses across individuals had helped to achieve stability in choice model while hierarchical Bayesian recently provided stable individual models from choice alone.

In the Bayesian approach, the distribution of parameters across population and information about individual choices are combined to form the posterior or conditional estimates, while in the classical setting maximum likelihood of the population distribution and individual choices are combined in mixed parameter choice models (Revelt and Train, 1999).They further stated that the two approaches are numerically related and their estimates converge asymptotically, but the interpretation of their results and the difficulty of maximizing the likelihood function in classical procedure are the main differences.

Train (2009) stated that combining stated preference (SP) and revealed preference (RP) in SP-off- RP questions have been a new method in choice modeling and they provide more information about the respondents than the standard stated preference. This technique further though creating endogeneity, helps to improve the realism of stated preference thereby increasing estimation precision. A series of Monte Carlo analysis were used and results indicated that the variance of the processing error for both the SP-off-RP and SP are identical and they also have the similar level of efficiency in estimation.

The mixed logit, a useful technique, is widely used to study discrete choice since it avoids the Independence of Irrelevant Alternatives (IIA) problem exhibited by the standard logit. In addition, it allows coefficients to vary over a population as well as the introduction of unobserved heterogeneity into preferences. In this paper, the author studies the sensitivity of one set of policy conclusions by analyzing the feasibility of private bus transit provision in urban corridors using mixed logit model. Results indicated that similar conclusion is reached for the conditions allowing the private transit, but unlike fare, route structures and peak highways different significant under the two models (Viton et al 2004).

McFadden and Train (2000) have demonstrated that mixed logit model can approximate any random utility model and it is highly flexible. Unlike multinomial logit, the mixed logit can handle randon taste variation; allow any kind of substitution pattern and correlation of unobserved factors. Stated preference data from survey have been increasingly used by economists to estimate consumers' preferences. Data were analyzed using ordered econometric models and mixed logit. Results revealed that the average willingness to pay (WTP) to save automobile travel time is low with less variability among motorists (Calfee et al, 2001). In addition, Daly et al (2011) studied willingness to pay in random coefficient model and behavior of their moments. The WTP of an attribute is defined as the ratio of individual coefficients as price, cost or income coefficient being entered in the denominator. The distribution of these coefficients is important their range determine whether the WTP may be finite or not. Results showed that

simulation using popular distribution such normal, truncated normal, uniform and triangular in random coefficient models would result in infinite moment of the WTP.
F. J Mishili et al (2007) conducted a study to determine consumers' preference for quality characteristics along the cowpea value chain in Nigeria, Ghana and Mali using hedonic price estimation. The results of their study showed that cowpea consumers in Nigeria, Ghana, and Mali were willing to pay a premium for large cowpea grain. In addition, they found that consumers discount grain with storage damage. Finally, they concluded that price impact on others attributes varied from one place to another. However, consumers' willingness to pay for color, taste, cooking length, and genetically modified varieties have not been thoroughly investigated in their study. Such information would guide plant breeders to develop improved cowpea varieties to meet the demand of both consumers and producers.
The main objective of this research is to determine the consumers' willingness to pay and predict the market share of four varieties of beans using multinomial logit (MNL), mixed logit (ML), and Hierarchical baye (HB).This research is important because it helps plant breeders to develop new varieties cowpea having desirable attributes thereby guiding producers to meet the needs of consumers.

2. Theory

Consumers are assumed to maximize utility by choosing goods and services given budget constraint. Lancaster **(**1996) and McFadden (1973) stated that the demand of a given product is mostly determined by the product attributes. Thus, characteristics such as the grain size, its price, protein content, carbohydrate content, dry matter content, genetically modified varieties and areas where the crop has been originally grown were considered as the most important attributes, consumers frequently value in the marketplace when it comes to purchase bean.
Finally, white and brown bean with large size, high protein content, high carbohydrate content, low dry matter, and grown cowpea in the North were the most preferred varieties. The demand of a product is always determined by product attributes and its price, implicitly demand=f(product characteristics, price).

3. Procedures

This section describes the behavioral model specification for both mixed logit and hierarchical Baye and elucidates their estimation methods.
The behavioral model is specified as follows:
We assume that each respondent faces a choice among J alternatives in each of T choice scenario. Respondent n is assumed to choose the alternative in choice situation t with the highest utility. The alternative utility i as faced by respondent n in situation t can be modeled as follows:

$$U_{nit} = \beta_n' V_{nit} + e_{nit} \qquad (1)$$

Where V_{nit} is a vector of independent variables that have been observed by the researcher while β_n' *and* e_{nit} are terms unobserved by the researcher and they are considered random. The coefficient vector, β_n, is assumed to be distributed normally across the population, independent of e and X , with mean vector b and covariance matrix Φ. The error terme$_{nit}$, is normally distributed iid extreme value.
The likelihood function under classical assumption is formed following the method of Train (2001). The parameters b and Φ representing the true mean and the covariance of the $\beta_n's$, are considered fixed. Thus, the likelihood function can be expressed as:

$$L(b,\Phi) = \coprod_n L_n(b,\Phi) \qquad (2)$$

Where L_n is the probability of respondent n's sequence of choices given b and Φ. This probability is an integral over β_n of a product of logits because e_{nit} is iid extreme value. This integral can be approximated by Simulation using draws of β_n from a normal distribution of mean b and covariance Φ. Therefore, for any given b and Φ, the density of conditional on respondent n's sequence of choice can be written as follows:

$$G_n(\beta_n / b,\Phi) = \frac{L_n(\beta_n)N(\beta_n / b,\Phi)}{L_n(b,\Phi)} \qquad (3)$$

Where $N(\beta_n / b,\Phi)$ is the normal population density with mean b and covariance Φ, and $L_n(\beta_n)$ is the probability of the respondent's sequence of conditional choices on β_n.The expectation of this density would be approximated via simulation by taking draws of from $N(\beta_n / b,\Phi)$, weighting each draw by the ration, and averaging the results. Similarly, under the Bayesian framework, b and Φ are considered as stochastic from the researcher's viewpoint. The researcher has a prior distribution on b and Φ denoted by $P(b,\Phi)$ and combines this prior with the likelihood function of the data to get a posterior distribution. The joint posterior for b and β_n for all n is proportional to $L_n(\beta_n)N(\beta_n/b,\Phi)p(b,\Phi)$
Gibbs sampling is used to draw from this joint distribution. The Gibbs sampling followed a sequence of conditional draws where each parameter is drawn conditional on a draw from the other parameters. Thus, for each draw of b and Φ, the conditional posterior for density of β_n is

$$G_n(\beta_n / b,\Phi) = \frac{L_n(\beta_n)N(\beta_n / b,\Phi)}{L_n(b,\Phi)} \qquad (4)$$

which is the same as the conditional density for β_n used in the classical setting.

4. Data

Choice experiment (CE) approach developed by Louvriere (et al, 2000) has been followed to measure consumers' relative preferences for several bean varieties. Respondents made a series of repeated choices between different products defined by several attributes. For our case, seven attributes, namely color of grain, size, protein content, and dry matter content, GMO, origin and price, carbohydrate content, were used to describe bean varieties. The combination of these attributes were used to create different choice scenarios in which respondents are requested to make repeated choices between two or more alternatives that differ in terms of the seven attributes. Thus, CE has given room for each alternative to be varied across different choice sets. Terms such as large and small grain as well as high and low were clearly explained to respondents in such a way that they had intuitive meaning.

Attributes	**Attribute Levels**			
	Level 1	**Level 2**		
Price	$ 0.7	$0.6		
Size	Large	Small		
Protein Content	High	Low		
Carbohydrate	High	Low		
Dry matter content	High	Low		
GMO	Yes	No		
Origin Color of the grain[a]	North	South		
Varieties	White	Red	Black	Brown

Table 1: Attributes with their respective level

[a]This attribute was treated as a fixed alternative in each choice setting

From the above table1, the full factorial design was computed as follows $Level^{attributes}$: $4*2^7$ which is equal to 512 profiles or full factorial design as mentioned earlier, time and cost constraints will not permit to use all the full factorial. Therefore, fractional factorial designs computed as follows 2^{7-2} equals to 32 profiles were used. These 32 profiles have one block that is orthogonal and one that is not .The orthogonal block, comprising of 16 questions, is a representative sample because it accounts around 80-90 % of the main effect. Nevertheless, it is very important to use blocking technique where 32 profiles were divided in 2 blocks having each 16 questions and these questions were randomly administered to different group of consumers. This would help to achieve a balanced design. Table 2 is an example

- Which option would prefer to purchase choose; white, Bean, Red Bean; Black Bean Brown Bean or None?

Features	**White Bean**	**Red Bean**	**Black Beans**	**Brown Bean**	**None**
Price/Kg	$0.6	$0.6	$0.7	$0.6	Neither option is preferred
Size	Small	Large	Large	Small	
Protein content	Low	Low	Low	High	
Carbohydrate content	Low	High	High	Low	
Dry matter content	High	High	Low	High	
Genetically modified varieties	Yes	No	No	Yes	
Origin	North	North	South	South	
I would choose……					

Table 2: shown above is a sample of a CE question that was presented to respondents to make decision.

5. Results

Multinomial logit, mixed logit and hierarchical baye are the three estimation methods used to compare WTP and market share for the four cowpea varieties. This section summarizes the estimates coefficients, WTP and market share.

Variables	Multinomial logit	Mixed logit	Hierarchical Baye
Intercept	-3.0842** (0.1402)	-3.0842** (0.1404)	-3.0931** (0.1375)
Price	-1.2599 (0.6699)	-1.2601 (0.6700)	-1.2710 (0.6636)
Grain size	0.0414 (0.1005)	0.0414 (0.1005)	0.0402 (0.1015)
Protein content	0.4640** (0.0899)	0.4641** (0.0899)	0.4661** (0.0908)
Origin	0.1005 (0.0722)	0.1005 (0.0722)	0.1008 (0.0709)
Carbohydrate content	0.0095 (0.0940)	0.0095 (0.0950)	0.0104 (0.0942)
Dry matter content	-0.1013 (0.0806)	-0.1013 (0.0806)	-0.1002 (0.0825)
GMO	-0.12340 (0.0716)	-0.1234 (0.0716)	-0.1242 (0.0709)
White bean	3.0699** (0.4633)	3.0701** (0.4634)	3.0821** (0.4577)
Red bean	1.9520** (0.4709)	1.9522** (0.4710)	1.9618** (0.4704)
Black bean	0.9500* (0.4743)	0.9502* (0.4744)	0.9537* (0.4716)
Brown bean	3.2788** (0.4743)	3.2789** (0.4651)	3.2938** (0.4597)

Table 3: Multinomial logit, mixed logit, and Hierarchical baye estimates for four cowpea varieties

Table 3 reports the coefficient estimates of the three estimation methods. Results indicate that price coefficients were all negative, but statistically insignificant in all models, implying that options with higher prices were less likely to be chosen as compared with lower prices. These results were not surprising at all and this suggested that demands in both categories were downward sloping demand curve. Results indicated that protein content is statistically significant across estimation methods; this means that consumers value protein content. Also, the coefficient of white, red, brown and black beans across estimation methods are all statistically significant and this implying that average consumers preferred these varieties as compared to "none". It is also worth noting that coefficient estimates between estimation methods are very similar. This is consistent to the findings of Joel and Train (2001), stating that results from classical and Bayesian methods were equivalent.

Characteristics	Multinomial logit	Mixed logit	Hierarchical Baye
Size large versus small	0.0329[a] [-0.11033,0.1830][b]	0.0329 [-0.1238, 0.1898]	0.0316 [-0.1246, 0.1817]
Protein High versus low	0.3684 [0.2389, 0.5151]	0.3683 [0.2307, 0.5076]	0.3667 [0.2286, 0.4940]
North versus south	0.0798 [-0.03199, 0.1900]	0.0798 [-0.0383, 0.2008]	0.0793 [-0.0298, 0.1773]
Carbohydrates high versus low	0.0075 [-0.1358, 0.1568]	0.0075 [-0.1409, 0.1611]	0.0082 [-0.1332, 0.1579]
Dry Matter high versus low	-0.0804 [-0.2021, 0.0409]	-0.0804 [-0.2109, 0.0523]	-0.0082 [-0.2127, 0.0430]
GMO yes versus No	-0.0979 [-0.2149, 0.0187]	-0.0979 [-0.2103, 0.0196]	-0.0977 [-0.2070, 0.01320]
White Beans	2.4366 [1.8111, 3.1778]	2.4363 [1.7620, 3.2252]	2.4249 [1.6705, 3.0434]
Red Beans	1.5494 [0.8853, 2.2635]	1.5492 [0.8656, 2.3249]	1.5435 [0.8218, 2.2728]
Black Beans	0.7541 [1.9846, 3.3125]	0.7541 [1.9530, 3.4097]	0.7504 [1.8872, 3.2680]
Brown Beans	2.6024 [0.0734, 1.4576]	2.6021 [0.0401, 1.5437]	2.5915 [0.0134, 1.4814]

Characteristics	Multinomial logit	Mixed logit	Hierarchical Baye
White versus Red Beans	0.8872 [0.7401, 1.0674]	0.8871 [0.7361, 1.0556]	0.8814 [0.2154, 1.8502]
White versus Black Beans	0.1658 [1.5117, 1.9340]	2.4363 [1.4798, 1.9101]	1.1666 [0.5542, 2.6383]
White versus Brown Beans	-1.6825 [-0.3187, -0.0267]	-0.1657 [-0.2967,-0.0411]	-1.6746 [-1.1730, -0.8597]
Red versus Black Beans	1.0531 [0.5825, 1.0459]	1.0528 [0.5826, 1.0235]	1.0480 [0.2592, 1.8627]
Red versus Brown Beans	-0.7953 [-1.2470, -0.9145]	-0.7952 [-1.2206, -0.9127]	-0.7932 [-2.0202, -0.0450]
Black versus Brown Beans	-1.8484 [-2.1192, -1.6864]	-1.8480 [-1.6693, -2.0839]	-1.8411 [-2.8490, -0.7852]

Table 4: Willingness to pay for Cowpea A Attributes and Varieties Across Estimation Methods
[a]WTP values were computed from the coefficients from the models in table 3, and the values were measured in Dollar per Kilogram (1 USD = 150 Naira)
[b]Numbers in parentheses are 95% confidence interval generated using Krinsky-Robb bootstrapping method.

Table 4 presents WTP estimates and their confidence intervals. Results suggest that holding others factors constant consumers are willing to pay more for white beans than red and black, willing to pay more for brown beans than white, red and black, and finally willing to pay more for red beans than black beans. Table 4 shows that marginal WTP for high level protein versus low level grain is high in all estimation methods. This implies that regardless of estimation methods used, the conclusion is similar.

Variables	Multinomial logit	Mixed logit	Hierarchical Baye
White bean	37.32%[a] [33.61%,40.94%][b]	37.32% [33.95%,40.85%]	37.30% [15.48%,64.12%]
Red bean	12.20% [10.37%,14.23%]	12.20% [10.39%,14.23%]	12.17% [4.40%,30.02%]
Black bean	4.48% [3.52%,5.64%]	4.49% [3.55%,5.64%]	4.44% [1.44%,11.95%]
Brown bean	46.00% [28.88%,47.35%]	45.99% [42.53%,49.62%]	46.09% [25.69%,99.83%]

Table 5: Predicted Market Share for cowpea varieties and Across Estimation Methods
[a]Market share values calculated from coefficients shown in table 3,
[b]Numbers in brackets are 95% confidence interval generated using Krinsky-Robb bootstrapping method

Table 5 reports market shares of white, red, brown and black beans and their correspondingly confident intervals. Results showed that regardless of estimation methods followed, brown bean has the highest market share followed by white and red beans respectively. Black bean has the lowest market share. The confidence intervals revealed that market share for each variety is statistically significant.

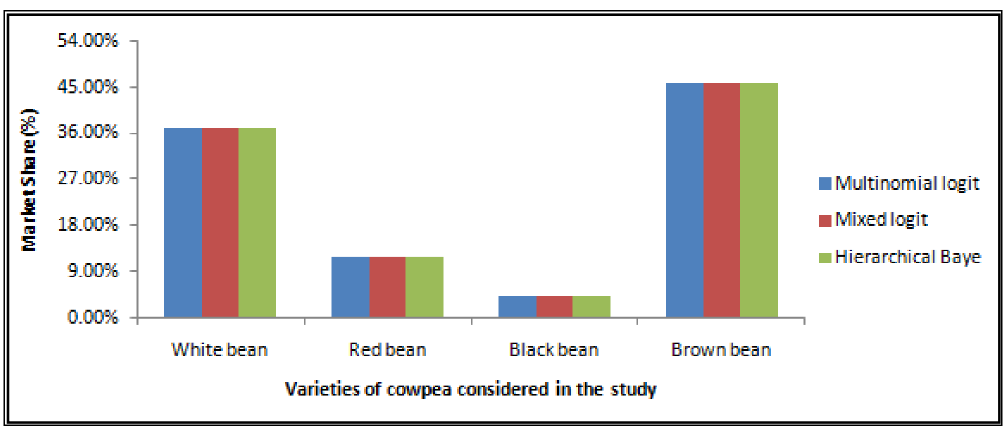

Figure 1: Market share prediction of cowpea varieties using three estimation methods

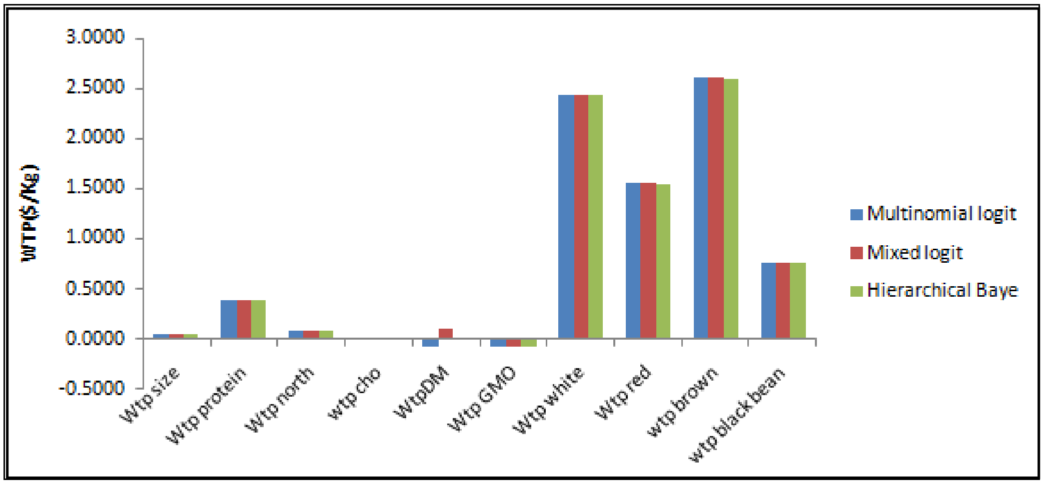

Figure 2: WTP for Size , Protein,Origin, CHO, DM, GMO, white, Red, Brown and Black beans across three estimation methods

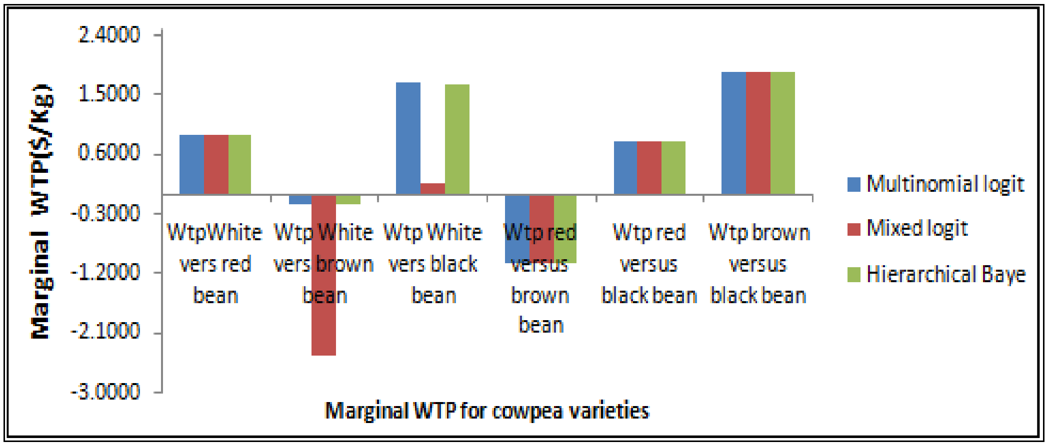

Figure 3: Marginal WTP for the four cowpea varieties across the three estimation methods

For easy interpretation of the results figure1 through figure 3 were used. Figure 1 presents market share for each cowpea variety across estimation methods. Figure 2 shows the WTP for the most important attributes we have considered in this study. Finally, figure 3 presents marginal WTP for the four cowpea varieties and across the three estimation methods.

Results shown in figure 1 show that regardless of estimation method chosen, the market share for brown is the highest followed by white and red bean. The black bean has the lowest market share in the study area. Results also showed that the market share of each variety across estimation methods was identical. This implies that classical and Bayesian techniques would generate the identical results. This is well supported by the asymptotic theorem stating that maximum likelihood and Bayesian method converge to the same estimate as sample size increases.

Results in figure 2 demonstrates that protein content is the most desirable attribute followed by the region of cultivation and size of the grain. Figure 2 also shows that the most undesirable attributes are genetically modified beans followed by dry matter content. This implies that consumers are willingness to pay a premium for cowpea varieties having large size with high protein content and cultivated in Northern Nigeria while consumers discount beans that were genetically modified as well as high dry matter content. Similarly, consumers WTP for brown and white beans were found to be the highest and then followed by red and black beans.

Figure 3 presents marginal WTP for the four cowpea varieties. Results revealed that white beans are more preferred than red and black beans, brown bean more preferred than white, red, and black beans, and the red bean is more preferred than the black bean. This is consistent across estimation methods.

6. Summary and Conclusion

Consumers' preferences and WTP for four bean varieties were investigated across three estimation methods namely multinomial logit, mixed logit and hierarchical baye. Data were collected through conjoint experiment and randomly administered to studies at Kaduna and Sokoto states. Estimates from each estimation were used to compute WTP and market share.

Results indicated that consumers preferred more brown bean relative to white, red and black, the white more preferred than red and black and finally red beans more preferred than black beans. Also, regardless of estimation method, brown bean has the highest market share followed by the white and red beans, while black bean was ranked the lowest in term of market share.

Results also revealed that protein content is the most desired attributes consumers wanted to pay premium followed by large size of grain while genetically modified as well as high dry matter content bean were discounted by the consumers. Market share estimates showed that regardless of estimation method, brown bean followed by white have the highest market share, while black bean has the lowest market.

In summary, the main implication of this research is that classical and Bayesian estimation techniques would lead similar results. This study would also help plant breeders to develop cowpea varieties having attributes such as large size, high protein content thereby guiding producers to take advantage of this identified niche market.

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