RESEARCH

Consumer demand heterogeneity and valuation of value-added pulse products: a case of precooked beans in Uganda

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Abstract

Background: This study investigated consumer demand heterogeneity and valuation of a processed bean product—"precooked beans" with substantially reduced cooking time. Common bean is the most important source of protein for low- and middle-income households in Uganda. Its consumption is, however, constrained by long cooking time, high cooking energy and water requirements. As consumption dynamics change due to a rapid expansion of urban populations, rising incomes and high costs of energy, demand for fast-cooking processed foods is rising. An affordable, on-the-shelf bean product that requires less time, fuel and water to cook is thus inevitable.

Methods: A choice experiment was used to elicit consumer choices and willingness to pay for precooked beans. Data used were collected from 558 households from urban, peri-urban and rural parts of central Uganda and analyzed using a latent class model which is suitable when consumer preferences for product attributes are heterogeneous.

Results: Study results revealed three homogeneous consumer segments with one accounting for 44.3% comprising precooked bean enthusiasts. Consumers derive high utility from a processed bean product with improved nutrition quality, reduced cooking time and hence save water and fuel. The demand for the processed bean is driven by cost saving and preference for convenience, which are reflected in willingness to pay a premium to consume it. Heterogeneity in attribute demand is explained by sex and education of the respondents, volumes of beans consumed, location and sufficiency in own bean supply.

Conclusions: Our findings suggest that exploring avenues for nutritionally enhancing while optimizing processing protocols to make precooked beans affordable will increase consumer demand. These results have implications for market targeting, product design and pricing of precooked beans.

Keywords: Precooked beans, Preference heterogeneity, Choice experiment, Latent class model, Uganda

Background

Common bean (*Phaseolus vulgaris* L.) is a part of agricultural systems and diets of urban and rural populations across Sub-Saharan Africa (SSA). The crop is an important rotation crop and intercrop and adds nitrogen to the soil [1]. It is rich in cholesterol-free dietary proteins, energy, folic acid, fiber and micronutrients (iron and zinc)—thus a strategic remedy for hidden hunger and healthy eating for children and women of reproductive age in households with limited sources of protein [2]. Regular consumption of beans decreases the risk of coronary heart disease, diabetes, colorectal cancer and helps with weight management [3].

In SSA, consumption of bean and its contribution to protein intake is among the highest in the world [4]. Although bean consumption demand has been stable since the 1980s, the crop is consumed as dry grain, which takes longer to cook. Cooking time depends on the crop variety, the cooking method, quantity cooked and length of grain storage. It thus ranges from 120 to 180 min when beans are cooked without presoaking or catalyst and

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Aseete *et al. Agric & Food Secur* (2018) 7:51

Page 2 of 13

58–107 min when they are presoaked in water [5–7]. In Uganda, beans are cooked without presoaking using wood fuel products. This poses potential challenges to bean consumption given increasing fuel costs, rapid urbanization and income growth that are transforming consumer preferences to more convenient and easy-to-prepare foods [8, 9]. While breeders have introduced new bean varieties that cook fast, consumers continue to show a desire for bean varieties that cook even faster [10]. Thus, long cooking time coupled with the changing consumption patterns will drive future demand away from bean consumption.

To reduce the cooking time of dry bean, the National Agriculture Research Organization of Uganda and of Kenya, the International Center for Tropical Agriculture and the private sector are exploring industrial base solutions. The intervention entails processing dry bean grains under high temperature and pressure to produce a transformed value-added bean product referred to as the "precooked bean." Such processing methods improve nutrient availability in beans [11, 12]. Once precooked, one only needs to add water and cook for 10–15 min, nearly a 90% reduction in cooking time. While processed bean products with short cooking time already exist on the Ugandan food market, their market share remains small for several reasons. Most processed beans are not affordable to most consumers. For example, canned beans imported from Rwanda, Egypt and the United Arab Emirates [13] cost about UGX 8100-9250[1] per kilogram over three times higher than the cost (UGX 2000-2700 per kilogram) of unprocessed dry bean grain [14]. Other processed bean products like chilled beans need preservation, through refrigeration, a constraint to many consumers. Inadequate demand for processed bean products has thus been a disincentive for private sector investment into bean processing [13].

Like other processed bean products, the potential demand for the precooked bean is a big question for private investors. Their willingness to pay for its different traits will essentially govern consumers' demand for the precooked bean. It is thus important to understand consumer preferences for different attributes of the precooked bean product, estimate their willingness to pay for each and document factors that will affect demand. This is key given that it involves large investments to develop the product and information is needed to design effective marketing strategies. The best way of assessing the effective demand for the desired traits is to quantify the implicit prices of the desired traits. Hence, this study sought to understand consumer preference for different traits of the precooked bean and to estimate the implicit price of each trait. Based on a latent class model (LCM), the study further sought to find consumer segments that are likely to switch from consuming unprocessed bean grain to precooked beans and determine factors that will facilitate or constrain demand.

The next section of the paper discusses the theoretical framework including the applications of LCM in demand analysis and the framework for using choice experiments. "Methods" section describes the design of the choice experiment, its implementation, the sampling strategy and characteristics of the interviewed households. Model estimates and other results are reported and discussed in "Results and discussion" section while the paper concludes with a summary of the key findings and policy implications.

Analytical framework

Since the precooked bean was not on the market, the study used a choice experiment approach to elicit choices and investigate how consumers will value and trade-off product attributes. A choice experiment is a stated preference method that derives from the Lancaster [15] consumer choice theory to value non-market goods or those goods not on the market. According to Lancaster's consumer theory, choices that consumers make can be modeled based on utility from attributes embodied in the good rather the good itself. The method further draws from the random utility approach [16] for econometric modeling of the choices made to account for possible unobserved heterogeneity. Individual preferences are heterogeneous as they depend on socioeconomic characteristics, individual objectives or resource endowment [16].

Commonly used models to account for heterogeneity in preferences include the random parameter logit (RPL) [17, 18] and the latent class model [19, 20]. Both the RPL and LCM incorporate heterogeneity in attributes, the systematic component of utility, but are based on different assumptions about the heterogeneity distribution. The RPL assumes a continuous distribution of the parameters to introduce heterogeneity while the LCM assumes a discrete distribution over unobservable endogenous (latent) classes of the respondents [21]. The LCM assumes that preferences are homogeneous within each class but can differ across classes also known as segments [22]. The number of segments and membership are simultaneously determined with the analysis of choices. The LCM is robust in modeling heterogeneity because; it has fewer restrictions and is less prone to biases that are often associated with model assumptions such as linear relationships and normal distributions [19]. The case in

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[1] Uganda Shilling (UGX) to US $ rate was 1 USD = UGX 3240.65. https://www.bou.or.ug/bou/rates_statistics/statistics.html.

Aseete *et al. Agric & Food Secur (2018) 7:51*

Page 3 of 13

the LCM is one in which an individual resides in a latent class, s, (not revealed to the analyst) and there is a fixed number of classes, *S*.

Denote *s* a class for individuals with homogeneous preferences. Also, let U_{jit} be the utility individual *i* in class *s* derives from choosing precooked bean alternative *j* in choice situation *t* and Z_{jit} a vector of attributes embodied in the precooked bean product. Thus, individuals maximize utility given by:

$$U_{jit} = \beta_s Z_{jit} + \varepsilon_{jit} \tag{1}$$

where β_s is a vector of segment-specific parameter coefficients to be estimated and ε_{jit} is the random component of utility for each segment. When the error terms are assumed to be independently and identically distributed (IID) according to a Type 1 extreme value distribution, the probability that option *j* is selected by a respondent *i* belonging to segment *s* is given by;

$$P_{ij/s} = \frac{\exp(\beta_s^t Z_{jit})}{\sum_{j=1}^{J} \exp(\beta_s^t Z_{jit})} \tag{2}$$

Denote *H**, the likelihood function that classifies respondents to one segment with probability P_{is}. The membership likelihood is a function of individual characteristics in vector (*X*) as in (Eq. 3). Such individual characteristics could include demographic, social and economic factors, bean production and consumption and perceptions on processed foods. Thus,

$$H^* = \lambda_s X_i + \alpha_{is} \tag{3}$$

where α_{is} is the error term assumed to be IID and distributed across consumers and segments and follows a Gumbel distribution. The likelihood of an individual *i* being a member of a segment *s* is expressed as:

$$P_{is} = \frac{\exp(\lambda_s^t X_i)}{\sum_{s=1}^{s} \exp(\lambda_s^t X_i)} \tag{4}$$

As noted earlier, the class membership is not observed. Thus, the joint probability that individual *i* belongs to segment *s* and chooses precooked bean alternative *j* is given by

$$P_{ij/s} = (P_{ij/s}) * (P_{is})$$
$$= \left(\frac{\exp(\beta_s^t Z_{jit})}{\sum_{j=1}^{J} \exp(\beta_s^t Z_{jit})} \right) * \left(\frac{\exp(\lambda_s^t X_i)}{\sum_{s=1}^{s} \exp(\lambda_s^t X_i)} \right) \tag{5}$$

In the estimation the LCM (Eq. 5), as adopted by Zhu [23], we also model the allocation of a respondent within a segment as conditional on their preferences, which, in turn, depend on their characteristics. Although (Eq. 5) is

estimated by the Maximum Likelihood Method, the LCM does not guarantee that the solution generated will be the maximum likelihood solution. Its maximum often converges on the local as opposed to the global maximum [24]. To minimize this problem, we used the tighter convergence criterion and minimized the number of classes to avoid over-fitting the model [25].

After estimation of attribute coefficients in the LCM, willingness to pay was measured as the ratio of marginal utility of the attributes and price coefficient as in (Eq. 6). The negative of disutility from price (cost) was used as a surrogate for marginal utility of income [26] because we did not have an accurate measure of income in the data.

$$\text{WTP}_{\text{attribute}} = -\frac{\beta_{\text{attribute}}}{\beta_{\text{price}}} \tag{6}$$

Confidence intervals were then calculated using the delta method [27].

Methods

Choice experiment (CE) design

The precooked bean can be described in terms of its attributes and levels they take. The most important attributes and their respective levels considered in the CE were selected through a stepwise process. The first step involved reviewing literature on important bean consumption attributes [28, 29], brainstorming among the research team and consultations with the precooked bean processor. The literature provides important attributes considered by bean consumers such as taste, low flatulence, appeal and less cooking time [10, 30]. However, this literature did not specify how reduced cooking time benefits the users, which we also sought to address in this study. Consultations with the processor revealed that after processing, the cooking time for the precooked bean is about 10–15 min which lowers the fuel and water quantities required for cooking. Shorter cooking time also means that the time spent in the kitchen cooking reduces—increasing convenience for persons who cook the beans. The processor also revealed that attributes like taste, color, and flavor will remain unchanged after processing. The study thus excluded them in the design of the choice experiment. In the second step, consultations with communities in study areas during study design revealed that the average cooking time for unprocessed bean, presoaked overnight, averaged 55 min. This is about 266% longer time for cooking when compared to the time for cooking precooked beans. To capture the demand for these benefits of processing beans, we considered five attributes including *cooking time, nutritional enhancement, fuel, and water saving and price* for the CE design. These attributes, embodied in dry bean grain, are altered during processing to create convenience and savings for consumers.

Aseete *et al. Agric & Food Secur* (2018) 7:51

Page 4 of 13

The study defined cooking time (TIME) as the duration (minutes) it takes to boil beans to a point when they are ready for seasoning. This attribute was coded as: fast cooking (15 min) for precooked bean, intermediate cooking (35 min) for beans soaked and cooked with a fast cooking method and long cooking (55 min) with only soaking and no fast cooking method as the base. The a priori expectation was that consumers will choose short cooking time and thus precooked beans over dry grain. The fuel attribute (FUEL) reflects the cost of fuel a household incurs in cooking beans which depends on the fuel used, and type of bean cooked. It was difficult to quantify saving from precooked beans because information on volumes and fuel cost per cooking of beans was not available. We, however, used relative percentage reduction in cooking time based on a household's context to define this attribute. For consumers who combine soaking of dry beans and fast cooking methods, adoption of precooked bean will reduce their cooking time by up to 50%, while those who only soak beans, reduction will be up to 20%. This attribute was defined to have three levels: low saving (20%) as the base for households that cook unprocessed dry beans with only soaking, moderate saving (50%) for cooking soaked beans with a faster cooking technology and high saving (80%) for the precooked bean. Given that the cost of cooking in urban areas of Uganda is going up [31, 32], the expectation was that consumers will choose the high fuel saving option.

Consumers who pay high costs for water because they buy or get it from long distances will enjoy low water requirement of precooked beans. The attribute water requirement (WATER) captured whether consumers will pay for precooked beans because they are water saving. This attribute was effects coded as: maintaining the status quo (high cooking water requirement = −1) or choosing precooked beans (low cooking water requirement = 1[2].) The attribute nutritional enhancement (NUTRI) captures the nutritional quality of bean varieties selected for processing. Integrating nutrition in agricultural innovations to improve nutrition has gained popularity and in response, bean varieties selected for precooking were those with higher protein and iron levels. The attribute (NUTRI) was added to enable us test whether consumers value nutritional enhancement and will pay for it. This will inform whether product labeling with nutritional information and fortification of the product is necessary. Effects coding was used for the NUTRI attribute as: choosing a nutritionally enhanced bean product (*Yes* = 1) and Otherwise (*No* = −1). Following Chowdhury et al.

[34] and Birol et al. [35] who reported that consumers are willing to pay premium prices to consume biofortified foods, our expectation was that consumers will have high demand for a nutritionally enhanced product.

The study added price per kilogram of beans as an attribute (PRICE) to allow computation of the implicit prices of precooked bean product attributes. Price levels were derived from the average annual prices of beans in study sites [14] and then stepped up by increments of 40% to reflect proposed price changes due to processing as per the processors' perspective. Price was defined at four levels: UGX 2500, 3500, 4500 and 5500 with 2500 serving as the base price. The expectation here was that ceteris peribus, consumers would choose a cheaper product set.
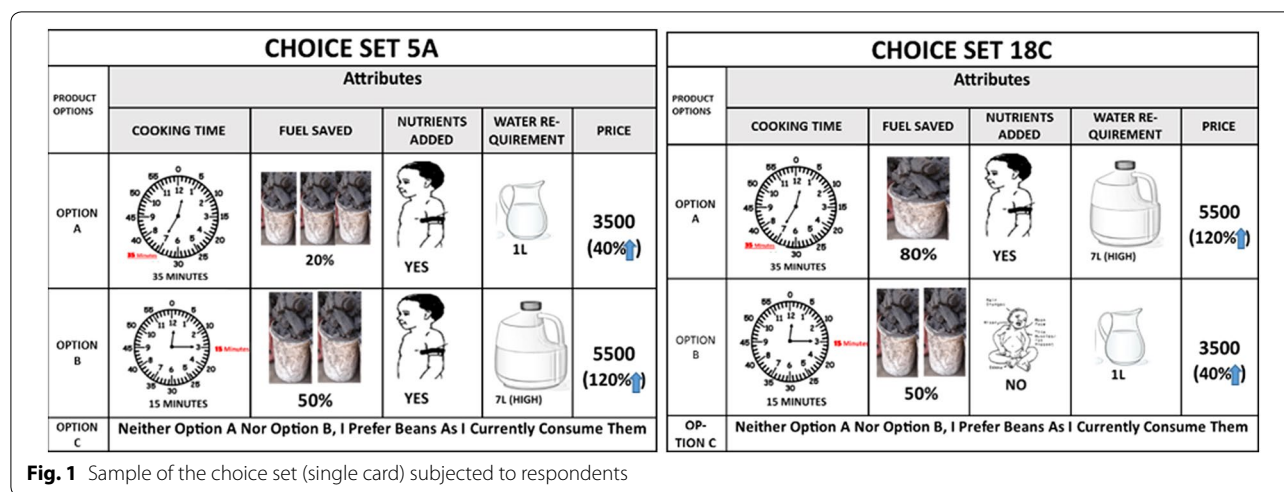
The five attributes and their levels were combined into choice sets using the computer-aided discrete choice design in JMP 12, which generated 21 choice sets of three options each. A profile with a complete list of blocked choice sets used in the choice experiment is supplied as an additional file (see Additional file 1). Options A and B showed an altered product while option C represented the status quo. The option for maintaining the status quo reflects a shopping choice for consumers who may prefer not to consume precooked beans. The alternative specific constant (ASC) was chosen to equal to 1 when the respondents selected options A or B and 0 for the option C [20]. If the ASC is negative and significant, then the propensity of the consumer to choose the status quo is high and vice versa. The choice experiment was broken down into three blocks (A, B and C) of seven choices sets each. Blocking improves the quality of choice data without compromising the diversity of choices, minimizes respondent fatigue and improves the cognitive ability of the respondents [36]. To improve the visual appeal of choice sets, attributes were illustrated using images on cards (Fig. 1).

Study area and survey implementation

The districts of Kampala, Mukono, Wakiso, Buikwe, and Luwero in Central Uganda made up the study sites. These were selected because of their high population density and levels of urbanization, high cost of energy for cooking [37] and the importance of common bean in household diets [38]. Although agriculture employs up to 74% of the households in the study sites, they purchase 54% of the food consumed [39]—depicting a high potential for food trade. They thus make up the most probable market for the precooked bean.

From the selected districts, sub-counties and divisions (for Kampala) formed the second stage of sampling from which the most urbanized/peri-urban sub-county and at least one rural sub-county was selected. A list of villages in the sub-counties/divisions from sub-county and division administrative headquarters then aided the

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[2] Effect coding was chosen for coding nutritional enhancement and water requirement over the dummy coding scheme because effect codding avoids overestimates of WTP and minimizes the effect of boundary value estimates [33].

Aseete *et al. Agric & Food Secur* (2018) 7:51

Page 5 of 13

Fig. 1 Sample of the choice set (single card) subjected to respondents

choice of villages. Because the list of households per village was not available, community leaders provided the estimated number of households used in designing the sampling. Where the number of households in the village divided by the desired village sample size provided the sampling interval. The first household interviewed was selected using a random starting point and all subsequent households assigned using the sampling interval through systematic random sampling. This process led to 558 households (capped due to budget limitations) from which one principle decision maker in a household, either the household head or spouse responded to the full survey. In cases where the household head was absent the spouse was interviewed. Households were randomly assigned to the three choice experiment blocks with each block receiving an equal number of households. Figure 2 shows the distribution and locations of households.

Since the product was not on the market by the time of the study, product profiles and the "cheap talk" also used by Kikulwe et al. [20] served as an introduction, and descriptor of the hypothetical product. The cheap talk was used to explain and simplify choice scenarios to the respondents. It reduces hypothetical biases for information collected with little prior product knowledge [34]. Trained enumerators using computer-assisted personal interviewing techniques uploaded with a structured questionnaire collected survey data. Besides choice data, the study elicited information on household characteristics including demographics, bean production and consumption dynamics, bean preparation methods, perceptions of food processing, market access, incomes, and employment.

Selected sample characteristics

The sample was skewed to urban, but with a sufficient number of observations from the rural setup. Out of 558

households interviewed, slightly more than a half (58.9%) was from urban setup while the remaining was split between rural and peri-urban locations (Table 1). The average household size was 6.30 people with rural households having the largest households. On average, the number of household members above 14 years was 3.02 people, with half being potential workers and the other half dependents. Urban household heads were more likely to be engaged in off-farm employment and earned higher incomes than those from rural areas (Table 1). Most households (98.4%) reported frequent consumption of beans, with an average consumption frequency of 4.2 bean meals/week and a quantity of 0.64 kg/meal/household. Average per capita bean consumption was 22.41 kg/person/year, which is close to 19 kg/person/year reported from previous studies [13]. Bean consumption was significantly higher in rural areas (25.12 kg/person/year) compared to (21.54 kg/person/year) in urban areas.

Urban households consumed 9.7% of beans from own production while those from rural areas consumed up to 74.2% of beans from own production. The proportion is higher for rural household compared to 56.8% in [38] because this study was conducted in July, which comes after harvesting season. Reliance on the market by urban consumers implies that precooked beans stand a high chance of being demanded in these localities. Firewood and charcoal were the most common types of fuel used to cook beans; used by 87.9% of households in the rural and 79.1% of urban households respectively. For the average quantity of dry bean (0.64 kg) consumed by a household (one bean meal), it spent 113.62 min in cooking time (without presoaking) and UGX. 1703 on fuel. Households that adopted time-saving cooking measures (presoaking, using catalysts or cooking fresh beans), cooked for an average of 78.5 min and spend an average of UGX. 1390.

Aseete *et al. Agric & Food Secur (2018) 7:51*

Page 6 of 13

Fig. 2 Location of households sampled for the survey

The study used factor analysis to understand consumer knowledge, attitudes, and perceptions toward processed foods. Using a cutoff factor loading value of 0.4 and eigenvalues above 1, three factors that accounted for 49.7% of the observed variance were identified (Table 2). The first factor was termed "processing benefits" (PB) The first factor was termed "processing benefits" (PB) because it had the highest loading on the questions related to potential enjoys of consuming processed foods. This captures the altruistic interests and awareness of consumers on environmental, employment and other benefits associated with agro-processing. This is consistent with findings by Khachatryan and Zhou [40] and Hu

Aseete *et al. Agric & Food Secur (2018) 7:51*

Page 7 of 13

Table 1 Summary statistics of sampled households. *Source*: Study consumer survey data, 2015

Household characteristic	Pooled (*N* = 558)	Urban (*N* = 329)	Peri-urban (*N* = 115)	Rural (*N* = 114)
Percent				
Occupation of the household head (%)				
Farming (crop and livestock)	21.1	8.2[a]	17.4[a]	61.1[b]
Salaried employment	32.1	34.7[a]	27.0[b]	10.6[c]
Self-employed off-farm	39.8	45.4[a]	41.7[b]	22.1[c]
Casual labor on-farm	0.4	0.0[a]	0.9[b]	0.9[b]
Casual labor off-farm	3.5	3.8[a]	4.3[b]	1.8[c]
Other	7.5	7.9[a]	9.6[b]	4.4[c]
Gender of respondents (% female)	69.2	70.5[a]	65.2[a]	69.3[a]
Perception on the sufficiency of bean consumption levels (% just enough)	78.0	79.9[a]	82.5[a]	67.6[b]
Mean (standard deviation)				
Household head education (av. years)	11.06 (4.24)	12.08[a] (4.12)	11.47[a] (3.88)	7.37[b] (2.80)
Respondent education (years schooled)	9.65 (4.80)	10.77[a] (4.69)	10.01[b] (4.27)	6.06[c] (3.77)
Average household size (no. members)	6.30 (3.26)	6.13[a] (3.58)	6.07[a] (2.43)	7.00[b] (2.94)
Average age of household head (years)	45.38 (13.91)	44.87[a] (14.25)	44.14[a] (13.23)	48.08[b] (13.37)
Average monthly household income (UGX)				
First quartile (25th)	–	200,000[a]	150,000[b]	39,166.7[c]
Median 50th	–	500,000[a]	400,000[b]	112,500[c]
Last quartile (75th)	–	900,000[a]	850,000[b]	250,000[c]

Superscripts a, b and c show significance in the difference between two paired categories. Paired similar superscripts (aa, bb, and cc) mean no significant difference between two categories while paired different superscripts (ab, bc, ac) mean significance difference at *p* < 0.05. Figures in parentheses are standard deviations

Table 2 Factor loading for consumer perceptions on processed foods

Statements used in perception analysis: I would (would not) consume processed foods because of…	Factor loading		
	PB	SI	AS
Employment and incomes benefits for farmers providing raw materials	0.79	–	–
Environmental benefits associated with their consumption	0.75	–	–
Presence of safety and nutrition information on labels	0.41	–	–
Hygiene issues related to food processing	–	0.74	–
Cultural inhibitions on consumption	–	0.58	–
Perceptions of members in the community (if they consume it, I also do)	–	0.55	–
Their availability and accessibility	–	–	0.82
Their safety of the product (presence or absence of additives)	–	–	− 0.48

Likert scale used: 1 = mostly reduces, 2 = have a minimal effect, 3 = DO NOT affect, 4 = slightly increase, 5 = definitely increase

et al. [41] who noted that consumers are often willing to take up new services because of their desire to contribute to society. The second factor termed "social influences" (SI) had a high loading on statements that reflect consumer concerns on societal influence including culture. The third, "availability and safety" (AS) captures social concerns about product availability and safety (Table 2). Three-factor indices created were tested for their suitability in the LCM and only the PB index was used because it fitted the model well.

Results and discussion

Consumer segmentation and preference analysis

Estimation of the LCM to determine the optimal number of segments was based on a balanced assessment of the log-likelihood function and full information maximum likelihood [42]. The four criteria used include: Akaike's information criterion (AIC), Bayesian information criterion (BIC), log-likelihood (LL) and McFadden pseudo R^2 (ρ^2). The AIC and BIC were minimized, and LL and ρ^2 were maximized at three segments (Table 3). Andrews [43] noted that AIC and BIC never under-fit

Aseete *et al. Agric & Food Secur* (2018) 7:51

Page 8 of 13

Table 3 Determination of the optimal number of segments

No. of segments	P	ρ^2	LL	AIC	BIC	p-value**
1	6	0.17	3210.53	6433.1	3235.35	<.001
2	21	0.32	2907.61	5857.2	2994.45	<.001
3	*36*	*0.35*	*2738.23*	*5548.5*	*2887.09*	<.001
4	51	0.30	2963.71	6029.4	3174.59	<.001

Sample size 3906 choices from 558 consumers, number of observations = 11,718. Equations: $\rho^2 = 1 - (LL)/LL$ (*o*); AIC = − 2LL + 3P and BIC = − LL + (P/2) × ln (*N*). The LL is a negative number. ** Log-likelihood ratio test (Prob. chi squared value)

In terms of the Log-likelihood, all models tested (a model with 1, 2, 3 and 4 segment(s)) had thesame *p*-value of 0.000. The values of the LL, AIC, BIC, and ρ2 were then used in modelselection from which the three-segment met the most required criteria

Italic values indicate a model with the best LL and combination of information criteria

the number of segments but may over-fit them leading to larger parameter biases. Since the three-segment model best described the sample, thus the best fitting LCM, consumers were categorized into three homogeneous segments.

A multinomial logit model (MNL), which gives the unconditional probability for the choice of a product attribute, was run as the starting point to check for parameter fit and as a precursor for further iterations. Compared to MNL, the LCM had a higher log-likelihood (− 2738.23 vs − 3210.53) and the adjusted R^2 (0.359 vs 0.174), thus a better specification to describe the data (Table 4).

Looking at the alternative specific constant (ASC), consumers in segment 3 exhibited a positive and significant propensity to switch to consumption of precooked beans since they valued options A and B in the choice experiment over option C (Table 4). Consumers in segment 1 and 2 have a negative and significant ASC, which represents a preference for the status quo (option C) over the processed product. Valuation of product attributes nutrition, fuel saving, and price was significant across all segments with a priori expected signs (Table 4). Although the respective coefficients of these three attributes differ in magnitudes across segments, suggestive of varying weights, they are important to consumers. Consumers would derive utility from nutritious bean products and fuel saving but are sensitive to price changes. The consciousness toward own health and the need to stay healthy could be the motivation to the high value attached to nutritional enhancement of precooked beans [44–46]. The significant valuation of fuel saving as a benefit of precooked beans reflects the growing cost of fuel for cooking [31, 32] associated with increases in population pressure and urban population. Over 90% of Ugandans use energy from biomass

exploitation (firewood and charcoal) which is becoming scarce and expensive [31].

Consumers in segment one, derive higher utility from all attributes especially enhanced quality of nutrition attribute. We therefore term consumers in segment one the "nutrition enhancement lovers" because they derive the highest utility from nutritional enhancement. The probability of belonging to this segment was influenced by self-reliance on the supply of beans for consumption, the quantities consumed, sex of respondent and education. The likelihood of membership in segment one is 53% higher for individuals who have attained primary level of education or above compared to those with no education. However, being male reduced the probability of membership in segment one by 48% while individuals from households that are self-sufficient in supply were 82% likely to cluster in segment one. For one additional kg of bean consumed per week, the probability of being a member of segment one reduced by 0.82 points (Table 4).

Like households in segment one, consumers in segment two ranked nutrition as their most preferred attribute but are less likely to consumed precooked beans (Table 4). This might be because they are very averse to price increases as revealed by the absolute coefficient on price that was second largest within the segment and largest between segments. The probability of membership in segment two was positively influenced by self-sufficiency in bean supply but negatively by quantities of bean consumed and attitude toward indirect benefits of food processing (Table 4). Given their stingy nature, we term members in the group "conservative self-reliant bean consumers."

All the attributes were important for consumers in segment three (Table 4). This segment of consumers derives higher utility from nutrition enhancement, water saving and reduced cooking time attributes. Since members in this segment had a high propensity of choosing precooked beans over the status quo and have a balanced demand for its attributes, we term them "precooked bean enthusiasts." Membership coefficients in segment three are interpreted implicitly in relation to the signs of the estimated statistically significant parameters in segments one and or two [47]. Based on this approach, consumers in segment three rely on beans purchased from the market for home consumption because supply from own production was not sufficient although they consume larger quantities of beans per week.

It is important to note that consumers in urban areas are heterogeneous and belong to all three segments in almost equal proportions contrary to the expectation that urbanites will switch en masse to consumption of processed beans. This shows a diversity of people with different socioeconomic characteristics including among

Aseete *et al. Agric & Food Secur (2018) 7:51*

Page 9 of 13

Table 4 LCM estimates of precooked beans product attributes and segment membership

Attribute	Multinomial logit model	Latent class model		
		Nutrition enhancement lovers	Conservative self-reliant bean consumers	Precooked bean enthusiasts
Utility function estimates: precooked bean attributes				
ASC	− 1.7409*** (0.1363)	− 5.6721*** (0.4747)	− 3.5850*** (1.0841)	0.4933*** (0.1855)
TIME	− 0.0082*** (0.0017)	− 0.0155*** (0.0056)	− 0.0106 (0.0115)	− 0.0075*** (0.0025)
FUEL	0.0051*** (0.0010)	0.0134*** (0.0042)	0.0188** (0.0093)	0.0048*** (0.0015)
NUTRI	1.6555*** (0.0513)	4.1696*** (0.2125)	1.6852*** (0.3883)	0.6213*** (0.0810)
WATER	0.1553*** (0.0473)	0.2159 (0.1527)	− 0.4683 (0.4934)	0.3425*** (0.0677)
PRICE	− 0.0061*** (0.0006)	− 0.0073*** (0.0019)	− 0.0344*** (0.0077)	− 0.0077*** (0.0008)
Segment membership function estimates: consumer characteristics				
Constants		− 0.1316 (0.2692)	− 1.2409*** (0.4307)	–
Age of the respondent (Ln years)		− 0.0001 (0.0009)	− 0.0011 (0.0013)	–
Sex of the respondent (1 = male, 0 = female)		− 0.4845** (0.2370)	− 0.3201 (0.4631)	–
Education of the respondent (1 > primary level, 0 ≤ primary level)		0.5313** (0.2359)	0.1253 (0.4137)	–
Bean supply sufficiency (1 = self-sufficient, 0 = not self-sufficient)		0.8200*** (0.2446)	0.5915** (0.2447)	–
Processing benefits (PB) index		0.1307 (0.1090)	− 0.5639** (0.2438)	–
Consumer location (1 = urban, 0 = otherwise)		0.3316 (0.2452)	0.0825 (0.4171)	–
Quantity of beans consumed per week (kg)		− 0.8211*** (0.2445)	− 0.5944** (0.2445)	–
Household types (1 = dual household, 0 = otherwise)		0.0116 (0.2285)	− 0.7860* (0.4069)	–

Model simulation: MNL LL = − 3210.53, AIC = 6433.1, BIC = 3235.35, R^2 Adj = 0.1742, *LCM*: LL = − 2738.23, AIC = 5548.5, BIC = 2887.09, R^2 Adj = 0.3589, observations (choices) = 3906, sample size = 558

Dependent variable is the Choice option selected by the respondent

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$

others; variations in wealth status, incomes, time and cooking constraints, and perceptions.

Profiles of consumers based on segment membership

To profile consumers in each segment, we first calculate the probability of a consumer belonging to a segment using estimated LCM coefficients (inserted in Eq. 5). Then, each household was assigned to the segment where it exhibited the highest probability of membership. Following this procedure, membership placement showed that 44.3% of the sample belonged to the segment of precooked bean enthusiasts while 47.7 and 8.1% are nutrition enhancement lovers and conservative—self-reliant bean consumers, respectively (Table 5).

Precooked bean enthusiasts have small households of 6.1 people, on average, with bean consumption of 0.54 kg/week, the second highest household level quantities among the sample households. Thus, per member cost of preparing beans could be high in this segment which probably drives their decision to consume the proposed product. They reported the highest expense (UGX 1686.73) for preparing a meal of beans (Table 5). Their choice could, thus, be reflecting cost-saving behavior since they are already buying the beans they consume. Moreover, the average distance to the nearest bean market and water sources was furthest in this segment. The consumers in the segment have the lowest supply of bean from their own production and

Aseete *et al. Agric & Food Secur* (2018) 7:51

Page 10 of 13

Table 5 Profiles of consumers in different segment. *Source*: Study consumer survey data, 2015

Consumer characteristic	Nutrition enhancement lovers	Conservative-self-reliant bean consumers	Precooked bean enthusiasts
Segment size (%) $n = 558$	47.67	8.06	44.27
Mean (SD)			
Household head average age (years)	44.86[b] (13.61)	50.32[a] (16.02)	44.98[b] (13.72)
Household head education (av. years of schooling)	10.81[a] (5.04)	8.77[c] (5.35)	9.79[b] (4.93)
Average household size (number)	6.24[b] (3.02)	6.33[a] (2.96)	6.07[b] (2.78)
Average quantity of beans consumed in a household (kg/week)	2.73[c] (2.57)	3.67[a] (3.36)	3.26[b] (3.32)
Average distance to the market (km)	0.53[b] (0.84)	0.51[b] (0.74)	0.64[a] (1.32)
Average distance to the nearest water source (km)	0.34[b] (0.82)	0.21[b] (0.39)	0.42[a] (1.42)
Average price of beans (UGX/kg)	2425.53[a] (303.19)	2368.87[c] (175.46)	2421.23[b] (366.49)
Average cost of fuel for preparing beans (UGX/0.64 kg/meal)*	1577.00[b] (780.90)	1445.45[c] (760.17)	1686.73[a] (906.85)
Percent			
Self-sufficiency in bean supply (% yes)	29.1[b]	33.3[a]	19.1[c]
Household residence			
Urban	62.0[a]	53.3[b]	56.7[b]
Peri-urban	17.7[a]	15.6[a]	24.7[b]
Rural	20.3[a]	31.1[b]	18.6[c]
Source of beans			
Own production	29.0[b]	43.4[a]	19.5[c]
The market	62.5[b]	54.2[a]	70.7[a]
Both market and own	8.5[b]	2.4[c]	9.8[a]
Household type by decision makers (% yes)			
Dual (male and female present)	80.2[a]	62.3[c]	76.6[b]
Female-headed with no adult male	18.0[b]	37.7[a]	17.8[b]
Male-headed with no adult female	1.8[b]	0.0[a]	5.3[a]
Key cooking fuel used (% yes)			
Firewood	35.7[c]	53.5[a]	39.8[b]
Charcoal	62.4[a]	44.2[c]	58.5[b]
Other sources	2.0	2.3	1.6
Household major income source			
Salary	44.2[a]	35.7[c]	41.8[b]
Agricultural activities	24.6[a]	16.7[b]	21.1[c]
Service provision	25.4[b]	23.8[b]	29.7[a]
Remittances and allowances	5.8[c]	23.8[a]	7.3[b]

Superscripts a, b and c indicate whether there is a significant difference between two paired categories. Paired similar superscripts (aa, bb, and cc) mean no significant difference and paired superscripts (ab, bc, ac) mean significance difference at $p < 0.05$

*The cost of preparing beans is based on the average quantity (0.64 kg) prepared by a household per meal

largely depend on the market to satisfy their bean consumption demand. Approximately 57% of its members were in the urban and earn their income from a variety of sources including agriculture. This is a sign that potential consumers of precooked beans are spread in terms of location and have variable socioeconomic characteristics—which will require integrated marketing strategies to reach them with precooked bean

Aseete *et al. Agric & Food Secur* (2018) 7:51

Page 11 of 13

Table 6 Marginal WTP for precooked bean attributes

Attributes	WTP estimates (95% confidence intervals)		
	Nutrition enhancement lovers	Conservative—self-reliant bean consumers	Precooked bean enthusiasts
Cooking time	− 2.123*** (− 2.293, − 1.833)	−	− 0.974*** (− 1.176, − 0.725)
Fuel	1.856*** (1.000, 3.259)	0.547** (0.226, 1.052)	0.623*** (0.388, 0.913)
Nutri	571.178*** (430.119, 811.5)	48.988*** (30.805, 77.659)	80.688*** (63.565, 101.783)
Water	−	−	44.481*** (32.329, 59.449)
Segment average	142.723*** (107.207, 203.232)	12.384*** (7.758, 19.678)	31.205*** (23.776, 40.355)

The numbers represent the percentage change in price per kilogram of precooked beans

Base price was UGX 2500

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$

products. Households in this segment were headed by individuals in their mid-40s, with 10 years of education and the majority were men.

Members in the segment of "nutrition enhancement lovers" are the most educated with a significant proportion (44.2%) depending on salaried jobs as their major source of income. Households in this segment mostly use charcoal for cooking and consume significantly small quantities of beans (2.73 kg/week) compared to members in other segments (Table 5). This group is less likely to consume precooked beans probably because they depend on their own production, which is just enough (80.5%) for their needs. This group resides in rural areas with small trading centers and part-time in farming combined with other everyday jobs to earn a living. Conservative-self-reliant bean consumers enjoy relatively lower market prices spent on beans and fuels. Table 5 shows that members in this segment faced the lowest bean prices on the market and spend UGX 1445.45 on fuel for preparing beans. About 33% of members in this segment belong to households that reported self-sufficiency in bean supply while 54.2% supplemented their own production with beans from the market. The segment has the largest rural population and least educated members. Given that members of this group produce their own beans dominated by rural households, they have a lot to lose if they are to sell and buy back beans.

Willingness to pay for precooked beans with attribute trade-off

Table 6 shows Consumer's marginal willingness to pay (WTP) a premium (positive WTP values) or a discount (negative WTP values) to consume precooked beans. There was a positive WTP for the precooked bean. All

consumers attached high importance to nutritional enhancement, fuel and time-saving attributes. Their WTP for these attributes varied by consumer segment, with nutrition enhancement lovers willing to pay the highest premiums for precooked beans. Since precooked bean enthusiasts make up the potential market for precooked beans, their willingness to pay can serve as a reference for making pricing decisions for the product.

Precooked bean enthusiasts are willing to pay an average increase of 31.21% in bean prices to consume precooked beans and the highest acceptable price was an increase of 40.36% over the prevailing market price. Consumer willingness to pay premiums for value addition and innovative food products has been reported by Ofuoku and Akusu [48] and Geethalakshmi et al. [49]. It is, however, important to note that consumers may under or overstate their intentions making it unclear if the same willingness to pay will be replicated when they face real product demand [50].

Conclusions

Study findings revealed significant heterogeneity in consumer valuation and preference of precooked bean attributes. Consumer heterogeneity is mostly explained by income abilities and to some extent by sufficiency in bean supply, sex and education of the respondent. Product demand will thus depend on the individual consumer's context meaning the precooked beans should be marketed as a product with diverse benefits and for targeted consumer needs. Such benefits include; contribution to environmental conservation through reduced fuel use, monetary saving from less fuel used, employment opportunities created, and incomes earned by suppliers of the raw materials who are mostly smallholder women.

Aseete *et al. Agric & Food Secur (2018) 7:51*

Page 12 of 13

Consumers in different segments are willing to pay for precooked beans especially for attributes of enhanced nutrition, fuel and time saving. While increased prices for the product reduces such willingness. These attributes will drive demand for the product and should inform product pricing decisions and mechanisms for communicating paybacks from higher prices charged. Mechanisms such as innovative labeling, branding and product differentiation in the market will be key in marketing since precooked bean attributes like nutrition, benefits from using less fuel and timesaving are invisible and are rarely rewarded by product markets. Consumer enthusiasm for nutritional quality through enhancement is a unique selling point. Marketing strategies should thus make nutritional content explicit and part of promotional campaigns to boost demand for the precooked beans.

Findings of the study are indicative of positive opinions that consumers have on value addition of beans and the demand for the product once on the market. While this is evident, the choice experiment used in the study is a none-market method, but the best available to elicit potential demand for precooked beans. Willingness to pay and valuation estimates thus remain hypothetical, so the results reported in this study are not conclusive. A follow-up study with the real precooked bean product on the market may be necessary.

Additional file

Additional file 1. List of blocked choice sets used in the choice experiment.

Abbreviations
ASC: alternative specific constant; CE: choice experiment; LCM: latent class model; RPL: random parameter logit; SSA: Sub-Saharan Africa; WTP: willingness to pay.

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Aseete *et al. Agric & Food Secur* (2018) 7:51

Page 13 of 13

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