Gaging consumer demand and preference for peeled, packaged, and labeled cooking bananas in Uganda

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ISBN: 978-92-9255-205-3

Citation

Kikulwe EM; Asindu M; Mulumba N; Mbabazi G; Ajambo S. 2021. Gaging consumer demand and preference for peeled, packaged, and labeled cooking bananas in Uganda. Discussion Paper. Bioversity International, Rome, Italy. 21 p.

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April 2021

Acknowledgments

This study was undertaken by Bioversity International (now part of the Alliance of Bioversity International and the International Center for Tropical Agriculture-CIAT), Kampala, Uganda. The research team members express their appreciation to the CGIAR Research Program on Policies, Institutions and Markets (PIM) for funding the research project under the theme 'Understanding upgrading opportunities in the banana value chains in Uganda'. The PIM research program is carried out with support from the CGIAR Trust Fund, including contributors making specific allocations to PIM, as well as through bilateral funding agreements. For details, please visit https://pim.cgiar.org/partners

We greatly acknowledge the contribution of our partners at KIT International, the Netherlands, namely Mr. Cedric Steijn, Dr. Rob Kuijpers, Ms. Esther Smits, and Dr. Froukje Kruijssen for their important contributions to the review process and shaping the write-up of this report. Special thanks go to Dr. Kephas Nowankunda of the National Agricultural Research Laboratories (NARL) for his considerable input and dedicated effort towards the design of the study protocols. We thank all the enumerators who participated in the execution of this work, as well as the consumers in Kampala and Jinja who took part in this study and whose inputs provided the basis for our research results. Thank you all for your support, dedication, and for providing the much-needed information, opinions, and suggestions for improving the banana value chain in Uganda. Lastly, we acknowledge Olga Spellman (the Alliance of Bioversity International and CIAT) for technical review and English editing of this discussion paper.

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Abbreviations and acronyms

ACF	Action Against Hunger [Action Contre la Faim]
AIC	Akaike Information Criterion
ASC	Alternative Specific Constant
BIC	Bayesian Information Criterion
DCE	Discrete Choice Experiment
EU	European Union
FAO	Food and Agriculture Organization of the United Nations
GM	Genetically modified
IID	Independently and identically distributed
IFAD	International Fund for Agricultural Development of the United Nations
KIT	Royal Tropical Institute
LCM	Latent Class Model
LL	Log Likelihood
NARL	National Agricultural Research Laboratories
NARO	National Agricultural Research Organisation
PHL	Post-Harvest Losses
RPM	Random Parameter Model
SUSFOOD	Sustainable Food
UGX	Ugandan Shillings
UNICEF	United Nations International Children's Emergency Fund
USD	United States Dollar
WFP	World Food Programme of the United Nations
WHO	World Health Organization of the United Nations
WTP	Willingness to pay

Abstract

Cooking banana is widely grown and consumed the world over due to its distinct aroma and taste. It also forms the economic lifeline for many countries. However, the fruit is highly perishable owing to its high-water content, disease susceptibility and quick ripening after harvest. This results in significant economic losses across its marketing chain. A breakthrough towards reduction of the bulk of the losses incurred, especially at the retail level, has been achieved through a technological innovation that extends the shelf-life of fresh cooking banana in peeled and packaged form. However, consumer preference and demand for this novel product remains widely unknown. Our study therefore investigated consumer demand and preference for peeled banana products with varied attribute levels in two major banana consuming cities of Uganda—Kampala and Jinja. A Discrete Choice Experiment (DCE) was conducted with 360 banana consumers who were randomly picked using a systematic sampling approach from 8 banana retail markets located within the two sample cities. Principal factor analysis, based on perceptions and attitudes towards peeled banana products, was conducted to segment the respondents into market niches. Then, a latent class model (LCM) was estimated to identify the different segments for peeled banana products and the values they derive from the different products. Lastly willingness to pay (WTP) estimates for the different customer segments for peeled banana products with varied attribute levels was also determined.

The results reveal that two homogenous market segments exist:

SEGMENT 1
PEELED BANANAS
CONSTITUTING **34%**
OF THE SAMPLED CONSUMERS.

SEGMENT 2
UNPEELED BANANAS
CONSTITUTING **66%**
OF THE SAMPLED CONSUMERS.

The most valued attribute level for respondents in segment 1 was excellent taste, for which they offered a premium of up to UGX 773, while soft texture was the least valued at a premium of UGX 445. Those in segment 2, valued most the soft textured peeled banana instead, offering a premium of UGX 164 for it, and packaging and labeling was their least valued at a low premium of UGX 48. Overall, respondents in segment 1 emerged as the potential buyers for the peeled banana products with those in segment 2 preferring the status quo (bananas as currently sold in the market). Our study findings suggest that promoters of the peeled banana products should prioritize pricing to avoid the product becoming uncompetitive, compared to the alternative of unpeeled bananas, if overpriced. Secondly, given the diversity in attribute level preferences for the different segments, it is advisable to offer a product pool featuring the numerous attributes given the existing preference heterogeneity observed. Lastly, promotion campaigns are needed with messages carrying some of the enticing attributes such as excellent taste, soft texture, and packaging, together with the labels, which was a feature preferred by consumers in both segments to expand market potential.

Key words: Peeled banana, shelf-life, choice experiment, WTP, preference heterogeneity.

1. Introduction

Today, one of the main global challenges is ensuring food security for a growing world population, whilst ensuring long-term sustainable development.

ACCORDING TO THE **FOOD AND AGRICULTURE ORGANIZATION OF THE UNITED NATIONS** (FAO, 2011),

FOOD PRODUCTION WILL NEED TO **GROW** BY **70%** TO FEED THE WORLD POPULATION, WHICH IS ESTIMATED TO REACH

9 BILLION BY 2050.

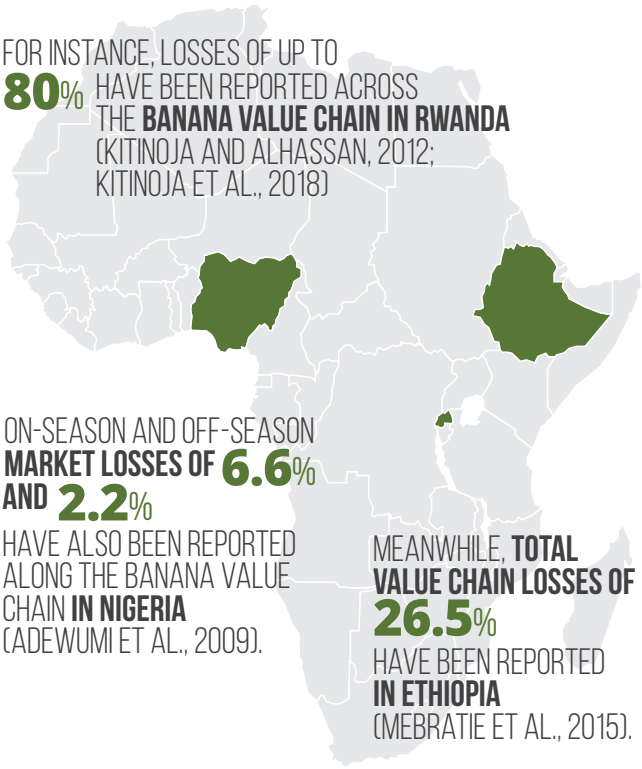
Consequently, there is a need for an integrated and innovative approach to the global effort towards ensuring sustainable food production and consumption (Broekaert et al., 2014). In the meantime, while the number of food insecure populations remains unacceptably high (FAO et al., 2020), each year, and worldwide, massive quantities of food are lost due to spoilage and infestations on the journey to consumers (FAO, 2011).

THOUGH NO ACCURATE ESTIMATES OF THE EXTENT OF FOOD LOSS AND WASTE ARE AVAILABLE, STUDIES INDICATE THAT **FOOD LOSS AND WASTE IS ROUGHLY 30% OF ALL FOOD PRODUCED GLOBALLY** (FAO, 2015), AMOUNTING TO **1.3 BILLION TONS ANNUALLY.**

Food loss and waste affects food supply chains by lowering income for food producers, increasing food costs for consumers, and reducing access to food. Minimizing food loss and waste could therefore lead to substantial food security. Reducing these losses, therefore, is one of the major ways to strengthen food security. As a result, the renewed focus on investment in agriculture that began in 2008 has built increasing interest in effective interventions to reduce post-harvest losses (PHL) (Kiaya, 2014). The investment required to reduce PHL in most food crops is relatively modest and the return on that investment rises rapidly as the price of the commodity increases. Reduction in PHL, therefore, increases the amount of food available for consumption by farmers and poor rural and urban consumers (Kiaya, 2014).

Banana is one of the most widely-grown and consumed fruits in the world. It is a cheap source of carbohydrates and a rich source of potassium, calcium, antioxidants, and other micronutrients (Mohapatra et al., 2010), but the fruit is highly perishable. This is attributed to its high water content and production of large quantities of ethylene that leads to rapid changes in its physical and chemical properties including colour, texture, aroma, chemical composition, respiration rate and senescence. Improper post-harvest management practices during transportation do not spare the banana fruit either; it gets bruised and eventually ripens rapidly, leading to huge postharvest losses.

FOR INSTANCE, LOSSES OF UP TO **80%** HAVE BEEN REPORTED ACROSS THE **BANANA VALUE CHAIN IN RWANDA** (KITINOJA AND ALHASSAN, 2012; KITINOJA ET AL., 2018)



ON-SEASON AND OFF-SEASON **MARKET LOSSES OF 6.6% AND 2.2%** HAVE ALSO BEEN REPORTED ALONG THE BANANA VALUE CHAIN **IN NIGERIA** (ADEWUMI ET AL., 2009).

MEANWHILE, **TOTAL VALUE CHAIN LOSSES OF 26.5%** HAVE BEEN REPORTED **IN ETHIOPIA** (MEBRATIE ET AL., 2015).

In Uganda, Kikulwe et al. (2018) pointed out that PHL affect 14.9% of the volume of cooking bananas produced, translating into a loss of 1.1 million tons per year. This represents significant food losses to consumers of about 21.3 kg per person per year, along with considerable income losses to other value chain actors. Retailers incurred the highest loss along the value chain. At retail level, for instance, physical losses during periods of scarcity are estimated at about 6.2%, while economic losses affect approximately 6.5% of traded banana, reducing its price by about 52%. During surplus periods, physical losses increase to 9.8% and volumes affected by economic losses almost double to 11.9%, resulting in a 60% discounted selling price per damaged bunch (Kikulwe et al., 2018). Physical losses are attributed mainly to ripening and bruising, and while the economic ones are caused by ripening, bruising, and finger plucking in scarcity seasons.

Photo: A woman peeling cooking banana (matooke) (Kephas Nowakunda, NARO).

One key important and sustainable approach to reduce these losses at the retail level is to enhance the shelf life of bananas, which is likely to reduce losses due to ripening and bruising, and to promote sale of bananas in peeled, labeled, and packaged form placed under a cost-effective temperature-controlled technology such as a charcoal cooler. Mohapatra et al. (2010) indicates that peeling delays banana ripening, reduces respiration rate, and controls disease-causing organisms, thus minimizing losses. Sale of bananas in peeled form is also associated with numerous other advantages including use of peels for on-farm production of organic manure, reduction of transport weight, and minimizing waste in urban consumption areas. With most families becoming smaller in size, the latest trends in emerging markets do indicate that peeling and packaging of bananas accompanied by a designated weighing system offers the opportunity to reduce food losses at home that are linked to bulk buys. More so, the labeling aspect in the peeled banana technology is likely to conveniently meet the needs of a growing consumer population that is looking for specific varieties of bananas to purchase for consumption. The outstanding constraint, however, is that while sale of bananas in peeled, labeled, and packaged form, to avoid losses at the retail end of the chain, may sound promising given its anticipated benefits, evidence on consumer demand and preference for such products is scant. This study will therefore add to the literature by deploying the latent class model (LCM) to identify consumer segments that are likely to take-up peeled and packed bananas as well as determine factors that will facilitate or constrain their demand in Uganda.

2. Consumer demand and preference for value-added products

Consumer preferences are diverse, and the motives underlying food selection are typically characterized by the importance that consumers place on the intrinsic and extrinsic attributes of food (Alphonce et al., 2015; Verain et al., 2016). For instance, the experiential eating quality that derives from intrinsic, natural product characteristics such as organoleptic or other biophysical and biochemical characteristics has been shown to have a significant influence on consumer demand and preferences. According to Mowat & Collins (2000), value chain actors need to be conscious of overall consumer preferences, as well as the specific preferences of each consumer segment, both of which need to be addressed to improve value chains.

The intrinsic attributes are the parts of the product that cannot be altered without manipulating the nature of the product itself. These include the product's physical appearance, ingredient composition and organoleptic properties (Jimenez-Guerrero et al., 2012; Alphonce et al., 2015). These intrinsic attributes can be further classified into the attributes sought by consumers prior to purchase known as search attributes, including freshness, color, size, and variety, as well as the attributes experienced during consumption known as experience/sensory attributes such as hardness, taste, aroma, acidity, and ripeness (Poole et al., 2007; Moser et al., 2011; Badar et al., 2015). On the other hand, **extrinsic attributes** are those product characteristics that do not form the physical part of the product (Jimenez-Guerrero et al., 2012; Alphonce et al., 2015), which are referred as safety attributes (such as certifications, labels on organically grown or fair-trade) and marketing attributes (such as price, packaging, among others) (Moser et al., 2011; Adhikari et al., 2012; Badar et al., 2015).

To date, a significant amount of evidence from recent studies exists on consumer preference for several agricultural products. For instance, Bonany et al. (2013, 2014) found that sweet taste and firmness of apples were the most preferred value attributes in European countries. In countries like Argentina and France, the apple consumers preferred intrinsic attributes such as juiciness, sweetness, firm texture, crunchiness, taste, and freshness (Galmarini et al., 2013). Meanwhile in Switzerland, taste, aroma, and freshness were reported as the three most important intrinsic quality attributes of apples (Péneau et al., 2006). Studies have also revealed that extrinsic attributes are becoming more important for consumers. Gunden and Thomas (2012) found that consumers in the USA value taste, hygiene, nutritional value, and affordable price when purchasing fruits and vegetables, while a Danish study of several product categories revealed that consumers greatly value the healthiness and sustainability aspects of food, together with intrinsic attributes (Verain et al., 2016). Furthermore, studies have highlighted that consumer value preferences and consumption patterns are influenced by demographic characteristics. Konopacka et al. (2010) showed that consumers' age and gender have a significant influence on fruit consumption. Aseete et al. (2018) investigated consumer demand heterogeneity and valuation of a processed bean product, 'precooked beans', with substantially reduced cooking time in Uganda. Their results revealed that there are three homogeneous consumer segments with one accounting for 44.3% comprising precooked bean enthusiasts. These bean consumers derived high utility from the processed bean product with improved nutrition quality, reduced cooking time, hence saving on water and fuel. The demand for the processed bean was driven by cost-saving and preference for convenience, which were reflected in WTP a premium to consume it. Heterogeneity in attribute demand was explained by sex and education of the respondents, the volume of beans consumed, location, and sufficiency in own bean supply.

The current study will contribute to the literature by focusing on peeled, packed, and labeled cooking bananas. The paper employs the discrete choice model to understand consumer demand and preference for peeled, labeled, and packed bananas. The outcome of the paper is expected to inform potential promoters of the technology on the likely attributes and other requirements that will boost or deter uptake of such banana products in the Ugandan markets.

3. Model and analytical approach

Theoretical framework for Discrete Choice modeling

Discrete Choice Experiment (DCE) is a stated preference method for valuation of non-market goods. DCE method has a theoretical foundation in Lancastrian consumer theory (Lancaster, 1966), which assumes that choices that consumers make can be modeled based on utility from attributes embodied in the product rather than the product itself. The method relies heavily on the random utility approach (McFadden, 1973) for modeling of choices made to account for possible unobserved heterogeneity. Individual preferences are heterogeneous as they depend on socioeconomic characteristics, individual objectives, or resource endowment (McFadden, 1973). DCE arose from conjoint analysis but differs from this method in that individuals are asked to choose from alternative bundles of attributes instead of ranking them. Unlike contingent valuation method, DCE enables estimation of values of attributes and provides the opportunity to identify marginal values of attributes rather than value of the good as a whole only (Bateman et al., 2002; Hanley et al., 1998). Originally, the DCE method was used in transport economics (Hensher & Truong, 1985) and marketing literature (Louviere & Woodworth, 1983), but it has increasingly been applied in other research areas, including environment (Adamowicz et al., 1998; Colombo et al., 2009), food safety and quality (Ifft et al., 2012), and other related disciplines. There is also growing literature in application of DCE in the valuation of animal and plant genetic resources (Elbakidze et al., 2014; Eric et al., 2008; Kassie et al., 2009; Ouma et al., 2007; Kikulwe et al., 2011; Vestal et al, 2013). A few recent studies like those of Aseete et al. (2018), used the DCE method for assessing consumer demand heterogeneity and valuation of value-added pulse Products, with precooked beans being the main crop under investigation.

When estimating preferences using the DCE approach, conditional logit (McFadden, 1974), random parameter logit (RPL) model (Greene and Hensher, 2003), and the latent class model (LCM) (e.g., Kikulwe et al., 2011; Aseete et al., 2018) are often used to estimate preference with weights attached to attributes. The conditional logit, however, assumes that the taste parameters are homogeneous across respondents and therefore does not take into consideration the heterogeneity of preferences. Both the RPL and LCM incorporate heterogeneity in attributes, the systematic component of utility, but are based on different assumptions about the heterogeneity distribution.

While RPL accounts for taste heterogeneity, the scale is generally normalized to one, assuming that all individuals respond to the choice experiment with identical error variances. It further assumes a continuous distribution of the parameters to introduce heterogeneity. The LCM, on the other hand, assumes a discrete distribution over unobservable endogenous (latent) classes of the respondents (Kamakura & Wedel, 1999; Wedel and Kamakura, 2000). Further assuming that preferences are homogeneous within each class but can differ across classes or segments (Hynes & Hanley, 2005). The approach generally depicts a population as consisting of a finite and identifiable number of segments or groups of individuals. Preferences are relatively homogeneous within segments but differ substantially across segments. The allocation of an individual into a specific segment is probabilistic and depends on the respondent-level characteristics. Furthermore, respondent characteristics indirectly affect the choices through their impact on segment membership (Birol et al., 2011).

The robustness of LCM in modelling heterogeneity, together with its fewer restrictions and being less prone to biases often associated with model assumptions such as linear relationships and normal distributions (Louviere et al., 2000), has encouraged many scholars in recent years to embrace it for the estimation of farmers' and consumers' preferences for various agricultural technologies and foods. For instance, Scarpa et al. (2003) and Ruto et al. (2008) utilized the model for the valuation of livestock attributes. Hu et al. (2004), Kontoleon & Yabe (2006), Kikulwe et al. (2011) and Birol et al. (2007) used it to investigate consumer preferences for genetically modified (GM) food. Birol et al. (2009) used it to examine farmer preferences for agrobiodiversity conservation and GM maize adoption. This study therefore employs LCM for assessing consumer demand and preference for peeled banana products in Uganda.

Following the LCM approach, the utility that consumer i, who belongs to segment s, derives from choosing peeled banana alternative $j \in C$, is denoted by:

$$U_{ij/s} = \beta_s Z_{ij} + \varepsilon_{ij/s} \ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

where Z_{ij} is a vector of attributes associated with the peeled banana alternative j of a choice set C and consumer i. The β_s represent a vector of segment-specific parameter coefficients to be estimated, whereas $\varepsilon_{ij/s}$ 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 (Gumbel) distribution, the probability $P_{ij/s}$ that option j will be chosen by the i^{th} consumer who belongs to segment s is denoted by:

$$P_{ij/s} = \frac{exp(\beta_s Z_{ij})}{\sum_{t=1}^{c} exp(\beta_s Z_{it})} \quad \ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Suppose H^* is a segment membership likelihood function that has been introduced to classify banana consumers into one of the S finite number of latent segments with some probability P_{is}, the membership likelihood function for banana consumer i and segment s is now given by:

$$H^* = \lambda_s X_i + \alpha_{is} \ldots\ldots\ldots\ldots\ldots\ldots (3)$$

where X_i represents the observed characteristics of the consumer such as their socio-demographic characteristics, including monthly income, age, marital status, source of bananas, household size, among others. λ_k(k = 1, 2, ... S) is the segment-specific parameters to be estimated. α_{is} is the error term assumed to be IID and distributed across consumers and segments, following a Gumbel distribution. The likelihood of the i^{th} individual being a member of segment s is now expressed as:

$$P_{is} = \frac{exp(\lambda_s X_i)}{\sum_{k=1}^{s} exp(\lambda_k X_i)} \quad \ldots\ldots\ldots\ldots\ldots\ldots (4)$$

With the previous indication that class membership is not observed, the joint probability that the i^{th} individual belongs to segment s and chooses peeled banana alternative j is thus represented as:

$$P_{ij/s} = (P_{ij/s})^*(P_{is}) = \left\{ \frac{exp(\beta_s Z_{ij})}{\sum_{t=1}^{c} exp(\beta_s Z_{it})} \right\} * \left\{ \frac{exp(\lambda_s X_i)}{\sum_{k=1}^{s} exp(\lambda_k X_i)} \right\} \ldots\ldots\ldots\ldots\ldots\ldots (5)$$

After estimation of attribute coefficients in the LCM, the willingness to pay (WTP) was then computed as a ratio of marginal utility of the attributes and price coefficient. Confidence intervals were then calculated using the delta method (Carson and Czajkowski, 2013).

$$WTP_{attribute\ level} = - \frac{\beta_{attribute\ level}}{\beta_{price}} \quad \ldots\ldots\ldots\ldots\ldots\ldots (6)$$

Choice experiment design

Design of the choice experiment commenced with the identification and definition of the most important attributes and attribute levels for peeled bananas. This was possible through a consultation of the literature (Jimenez-Guerrero et al., 2012; Alphonce et al., 2015), which pointed out the intrinsic attributes people use when selecting fruit (such as freshness, color, size, and variety). Other intrinsic attributes experienced during consumption, including hardness, taste, aroma, acidity, and ripeness were also considered (see e.g., Poole et al., 2007; Moser et al., 2011; Zamzami & Ariyawardana, 2019 and Badar et al., 2015). Extrinsic attributes such as labeling, and certification of products were identified following Jimenez-Guerrero et al. (2012) and Alphonce et al. (2015). To make the attributes align with the context of Ugandan markets, where the study was conducted, we further searched for literature on consumer preference for banana, based on attributes identified for Uganda. Banana attributes, including taste, flavor, price, size, food color, banana flesh color, aroma, and texture were considered following Kikulwe et al. (2011), Marimo et al. (2020), Akankwasa et al. (2013) and Barekye et al. (2013).

After identifying numerous attributes through reviews and setting levels for the different attributes, we consulted experts from the National Banana Research Program of the National Agricultural Research Organisation (NARO). Some of these experts were also among the project implementing partners who have vast experience in conducting sensory and organoleptic evaluations with consumers for new banana cultivars. Through this consultation, we narrowed down our search to five attributes (Flesh color, Texture, Taste, Packaging and labels, and Price,) each with three attribute levels (See table 1).

Table 1. Attributes, their definitions, levels, and coding.

Attribute	Definition	Attribute level (status quo underlined)	Coding style
Flesh color	Flesh color of the banana finger	Pale yellow Medium yellow Bright yellow	Dummy coding
Texture	Texture of the banana finger	Hard Firm Soft	Dummy coding
Taste	Taste of the banana when cooked	Fair taste Good taste Excellent taste	Dummy coding
Package and labels	Labels and packaging used for marketing the peeled banana	Not packaged, not labeled Packaged unlabeled Packaged labelled	Dummy coding
Price	Cost (UGX) per kg of peeled banana product presented	1000 1200 1500	Continuous (actual values)

Source: Authors

The first attribute **(banana flesh color)** captured the color of the green edible cooking banana flesh presented to the customer. The flesh color is always critically observed by customers during purchase and is considered an indicator of micronutrients composition, as well as how appealing the banana would be when it has been fully prepared for consumption. Three levels (ranging from pale yellow to medium yellow to bright/dark yellow) were defined for this attribute, with the pale yellow color indicating the status quo (bananas as currently sold in the market).

Texture, the second attribute, captured the stability of the banana finger. Three levels (including hard, firm, and soft) were defined for this attribute, with the hard type being the status quo and soft type indicated as the most desired, based on published literature (Marimo et al., 2020).

Photo: Peeled banana ready to be packed (Nasser Mulumba, Alliance of Bioversity International and CIAT).

Taste was the third attribute considered in the design because it strongly influences the decision to buy or not to buy; three attribute levels (fair taste, good taste, and excellent taste) were created. Fair taste was the status quo, while the excellent taste was the most desired.

The fourth attribute defined as **package and labels** was included to cater for food safety, certification, and as a way of identifying the variety, and of obtaining more information about the peeled banana product being sold on the market. Three levels were also created for this attribute including 'not packaged, not labelled', which was the status quo; 'packaged unlabeled', and 'packaged labeled', which was the most desired. Lastly, an attribute for **price** was included to allow for the estimation of the implicit prices (or consumer's WTP) of peeled banana attribute levels. The initial price level of Ugandan shillings (UGX) 1000 was the current price (status quo) for a kilogram of unpeeled banana in the market. Two other price levels were subsequently added to the list of price attribute levels, i.e., UGX 1200 and UGX 1500. The assumption for the price levels was based on the theory of demand, which indicates an inverse relationship between price and quantity demanded of a given product. Holding all other factors constant, we therefore expected consumers to opt for a cheaper peeled banana product option.

Using a fractional factorial approach[1], we came up with a total of 27 choice sets using Ngene software, which were blocked into three, with each block constituting nine choice sets. An example of one of the choice cards generated is shown in Figure 1. Blocking improves the quality of choice data without compromising the diversity of choices, minimizes respondent fatigue, and improves the cognitive ability of the respondents (Kuhfeld, 2005). As previously indicated, each choice set had three alternatives (product options) i.e., Options A and B, which both represented peeled banana products with different attribute levels, while option C represented the status quo (bananas as it is currently sold in the market). For each block, two additional choice sets were designed, to be used at the outset of the choice experiment. Carlsson et al. (2012) indicates that normally there is a very high error variance in the first two choice sets compared to the remaining choice sets across the sequences. Often, these two choice sets are found to have the largest share of respondents changing their choices (also referred to as ordering effect). As a result, the two additional choice sets were introduced for the purpose of eliminating such biases that could arise due to ordering effect during the bidding process. Following Carlsson et al. (2012), the results of the two choice sets were not considered for empirical analysis. The option for status quo (option C), 'unpackaged unlabeled unpeeled banana', was maintained to eliminate forced bidding/choice for consumers who neither preferred option A nor option B of the proposed peeled banana products presented on the choice cards. An alternative specific constant (ASC, equaled to 1 if either option A or B was chosen and 0 if option C was chosen) was generated to identify the status quo level from other attribute levels in the model. A negative and significant ASC means that the consumer is in favor of the status quo, while a positive and significant indicates a higher tendency of a consumer to choose either option A or B.

1 A full factorial design would generate a total of 243 choice scenarios. However, given the time constraint and the fact that it is impossible and tiring to subject a respondent to all the 243 choice sets, we opted for a fractional factorial approach.

Data

Study sites and sample characteristics

The study was conducted in two major cities of Uganda—Kampala and Jinja. The two cities were purposely selected because they are the major consumption hub and end market for most of the cooking bananas produced from various banana growing areas in Uganda. Furthermore, these cities have a huge urban population with emerging markets for novel food products. The study was implemented in eight randomly selected banana retail markets (including six in Kampala and two in Jinja) that were identified through an earlier scoping visit to the two cities. Systematic random sampling was then deployed to select the consumers (respondents) to be interviewed. In this approach, enumerators were placed at different banana retailing stalls within the eight markets randomly identified for the study. The first consumer to approach the banana retail stall was not interviewed, but every second customer was requested to participate in the interview. Once they consented, they were ushered away from the stall to a convenient setting for the interview. Upon return to the stall, the enumerator would approach the second consumer for an interview. A total of 360 banana consumers were interviewed, comprising 240 from Kampala markets and 120 from Jinja markets. Out the 360 banana consumers surveyed, one third each were subjected to choice sets in blocks of 1, 2, and 3, respectively.

Since the proposed peeled, packaged and labeled banana products were not yet in the market, each enumerator was tasked with clearly explain the peeled banana product attributes, their attribute levels, and the choice process to each consumer before proceeding with the bidding process. This helped the consumers become acquainted with the attributes and their levels, as well as the bidding process. Enumerators also read out a short cheap talk script, which informed the consumers that even though the choices they were going to make were hypothetical in nature, we expected them to think carefully about their choices, as if they were conducting actual shopping for bananas in the market. Besides that, while making the choices, they were told to bear in mind their budget and overall available income to be spent considering other daily household needs (Birol et al., 2011; Kikulwe et al., 2011). An example of a choice set presented to the consumers is illustrated in Figure 1 below.

Choice Set 19

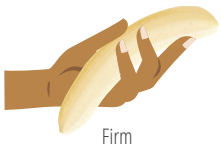
Attribute	Product Options		
	Option A	Option B	Option C
Flesh color	Medium yellow	 Bright yellow	Neither Option A nor Option B, I prefer bananas in the current form I obtain from the market.
Texture	 Soft	 Firm	
Taste	 Good taste	 Excellent taste	
Package and labels			
Price	 shs. 1000 / kg	 shs. 1200 / kg	

Figure 1. Example of a choice set presented to respondents during the choice experiment process. Source: Authors

Photo: Retailers being trained on how to use a charcoal cooler (Ambrose Atuhaire, Alliance of Bioversity International and CIAT).

Photo: Peeled packed banana in charcoal cooler (Ronald Katwaza, NARO).

Photo: Retailers checking the status of stored peeled bananas in a charcoal cooler (Nasser Mulumba, Alliance of Bioversity International and CIAT).

The questionnaire also captured additional information related to some of the attributes that consumers consider when purchasing their regular cooking bananas from the market. These were captured using a five-point Likert scale, ranging from strongly disagree to strongly agree. Each respondent's attitudes and perceptions towards a number of statements concerning peeled bananas were also captured. Lastly, the questionnaire elicited information on the socio-demographic characteristics of each consumer including age, sex, annual income, source of bananas, distance to workplace, and nearest banana markets, among others.

Consumer perceptions and attitude towards peeled, labelled, and packaged banana

During the survey, 22 attitudinal and perceptional statements on peeled banana products were given to the consumers. Their response was captured using a five-point Likert scale from 'strongly disagree (1) to 'Strongly agree (5). Principal factor analysis was conducted on these statements to generate variables to be used for consumer segmentation in the LCM. The valid factors were determined using the Kaiser criterion (Eigen value > 1), with only factors scoring from one and above being retained and crosschecked through a scree plot (Cattell, 1996). Items with factor loadings of less than 0.40 were excluded (Kontoleon 2003; Birol et al., 2007; Kikulwe et al., 2011). To make interpretation of the factors a bit clearer and eliminate overlapping, a promax rotation was applied. Finally, Cronbach's alpha scores were calculated to test for internal-scale reliability of the statements used during the analysis. Table 2 presents the results of the principal factor analysis.

Table 2. Factor loadings for consumer perceptions and attitudes on peeled bananas.

Perception/attitudinal statements	Traditionists	Convenience seekers
I would buy peeled bananas if no brown spots		0.9359
I would buy if same price as unpeeled		0.7296
I would buy if I have no use for peels		0.4965
I can only buy if am present during finger selection	0.6626	
I would buy if hygienic and processed under clean conditions	0.6008	
I would buy if sold at higher price than the unpeeled		0.6434
I would purchase if no maid or chef at home		0.5539
I would buy to avoid waste management costs	0.5244	
I would purchase if am cautious of my nails		0.58
I would buy if my workplace is far from residence	0.5328	
I would buy because of my personal relationship with seller	0.6356	
I would purchase if well graded and labeled	0.6822	
I would purchase if more nutritious than other bananas	0.5765	
I would purchase if tastier than other bananas	0.5381	
I will get food poisoning if I purchase peeled banana	0.4004	
I would buy if I had lots of work to do with no time for peeling	0.8182	
If most people prefer it and its their favorite, I will purchase	0.6267	
I would buy if I am aware of the source	0.7082	
I would buy if approved by a standards body like UNBS	1.0159	
I would buy if processed by a reputable company	0.9994	
I would buy if it requires little fuel to prepare	0.8099	
I would buy if readily available and accessible	0.7146	

Source: Authors

From the data in Table 2, we observe that two variables were generated. The 'convenience seekers' variable, named thus as it reflected higher loadings on statements related to consumer convenience. For example, these consumers indicated that they would buy the peeled bananas if sold at the same price as the unpeeled or even at a premium price. Yet, again, they were mainly concerned about their nails getting dirty during the banana peeling process and would ideally purchase the bananas if they had no maids and chefs at home to prepare meals. The second variable, which we refer to as the 'traditionists', factored highly on statements that reflected that the consumer was more interested in having bananas presented in their current, usual/traditional state. For instance, they looked out for the usual market attributes and followed the existing market protocols while making purchase decisions for bananas.

4. Results and discussions

Estimation of the Latent Class Model

Estimation of the latent class model (LCM) commenced with the determination of the optimal number of segments for the LCM. We relied on a balanced assessment of the log-likelihood function and full information maximum likelihood, which follows four criteria (Hurvich and Tsai, 1989). These four criteria included the Akaike information criterion (AIC), Bayesian information criterion (BIC), log-likelihood (LL) and McFadden pseudo R^2 (ρ^2). Models were estimated in accordance with recommendations from Masyn (2013) and Nylund et al. (2007). Beginning with a 1-class model, models were tested, and absolute and relative fit indices were compared to choose the most parsimonious, conceptually-, and empirically-valid and well-differentiated model. The number of classes increased until the model convergence was no longer reached, which was reached after the two-class solution. Based on this finding, we therefore estimated the model with a maximum of two segments. The results of the two-segment LCM are shown in Table 3. The first panel of the table presents the utility coefficients associated with the peeled banana attribute levels, while the second panel gives the coefficients for segment membership. The membership coefficients for the second segment are normalized to zero, permitting us to identify the remaining coefficients of the model (Boxall and Adamowicz, 2002). Both of these identified segments are labeled based on the significance level of the Alternative Specific Constant (ASC) for each segment. For instance, if the ASC for segment 1 is positive and significant, it implies that they are in favor of the peeled banana products, while if the ASC for segment 2 is negative and significant, it implies that they are in favor of the status quo rather than the peeled bananas.

Table 3. Two segment LCM estimates for peeled banana attribute levels.

Attribute levels	Segment 1 (Prospective buyers)	Segment 2 (Questionable buyers)
Utility function estimates: peeled banana attribute levels		
ASC	4.463***(0.538)	-1.843***(0.129)
Price per kg of peeled banana	-0.002***(0.001)	-0.003***(0.000)
Soft texture	0.810***(0.301)	0.462***(0.074)
Firm texture	0.288(0.320)	0.218***(0.071)
Good taste	0.381(0.378)	0.158***(0.070)
Excellent taste	1.407***(0.324)	0.288***(0.071)
Medium yellow flesh color	0.002(0.292)	0.013(0.072)
Bright yellow flesh color	-0.072(0.313)	0.117*(0.071)
Packaged unlabeled	0.447(0.334)	0.400***(0.074)
Packaged and labeled	0.898***(0.320)	0.136*(0.071)
Segment membership function estimates: consumer characteristics		
Constant	1.368***(0.454)	-
Respondent age (years)	1.245*(0.668)	-
Traditionist	-2.902***(0.356)	-
Banana source (market only)	-1.010***(0.369)	-
Salaried employment (1 = Yes)	0.597*(0.362)	-

Source: Authors' derivations from the 2020 survey data set.
Notes: *, **, and *** indicate the coefficient is significant at 10, 5 and 1% levels, respectively.

As shown in Table 3, the utility coefficients reveal that consumers in segment 1 prefer peeled banana with soft texture coupled with an excellent taste. They also like to have their peeled banana product packaged and well labeled. The coefficient for the ASC for segment 1 is positive and significant, implying that they are the 'prospective buyers' for peeled bananas if available in the market. It is worth noting, however, that the coefficient for price per kg of peeled banana is negative and significant. This is in line with the law of demand that indicates

an inverse relationship between price and quantity demanded of any product. The membership coefficients for segment 1 of the prospective buyers reveal that consumers that are older and have salaried employment are more likely to belong to this segment, whereas those who only source their bananas from the markets and are traditionists (conservative in nature) are less likely to belong to this segment.

The utility coefficients for segment 2 reveal that consumers in this segment prefer peeled bananas that have either soft and firm texture as opposed to hard, with either good or excellent taste and a bright yellowish flesh color. They like their product packaged with or without labels. Like segment 1, the price coefficient for consumers in segment 2 (referred to as 'questionable buyers') is negative and significant implying that they too would opt for cheaper peeled banana product options if available in the market. Since the ASC coefficient is negative and significant, consumers in segment 2 prefer banana as it is currently sold in the markets as opposed to the peeled banana products. The membership coefficients of this segment suggest that younger consumers without salaried employment, the traditionists in nature, and those who only source their bananas from the markets are more likely to belong to this segment.

Consumer characterization based on generated segments

The relative size of each segment was estimated by running post estimation commands with the LCM coefficients, and subsequently generating a series of probabilities that show that a given consumer belongs to a given segment as described by Pacifico and Yoo (2013) and Hole (2013). Consumers were then assigned to the different segments based on the probability scores obtained. Using this procedure, 66% of the sampled population belonged to segment 2, while the smallest share of only 34% belonged to segment 1 (Table 4).

Table 4. Consumer characteristics by segment.

Consumer characteristics	Pooled (N= 360)	Segment 1: Prospective buyers (N= 123)	Segment 2: Questionable buyers (N= 237)	Chi2/T-test
Age (years)	33.97 (9.94)	33.31 (9.67)	35.25 (10.34)	9.18***
Years of schooling	8.39 (3.70)	8.45 (3.85)	8.28 (3.37)	-2.06**
Respondent sex (male)	21.39	22.78	18.70	-4.66***
Household size (persons)	4.22 (2.18)	4.10 (2.10)	4.46 (2.32)	7.69***
Monthly income (UGX)	310903.80 (435771.40)	315773.70 (455275.30)	301520.50 (395384.90)	-1.53
Salaried employment (%)	14.44	12.24	18.70	8.63***
Distance to nearest banana market (km)	2.70 (2.39)	2.62 (2.35)	2.85 (2.45)	4.50***
Banana source (market only)	86.39	90.72	78.05	-17.54***
Throw away banana peels (%)	43.88	50.21	31.71	-17.71***
Sell banana peels (%)	3.33	2.53	4.88	6.12***
Distance from workplace to home (km)	3.07 (3.88)	3.04 (3.83)	3.13 (3.97)	1.01
Respondents with hired persons to prepare meals at home (%)	5.55	7.17	2.44	-9.71***
Kampala-based respondents (%)	66.67	65.82	68.29	2.45**
Traditionists (index)	-1.8E-09 (0.99)	-0.65 (1.00)	0.34 (0.80)	-53.09***
Convenience seekers (index)	-8.0E-09 (0.96)	-0.02 (0.92)	0.01 (0.97)	-1.57

Source: Author-generated results based on 2020 survey data set.
Notes: Figures in parenthesis are standard deviations; Exchange rate at time of survey (1 USD = UGX 3640).

Photo: A woman holding a bunch of Matooke ready for marketing.
Sara Quinn, Scaling Up Nutrition (SUN) Movement in Geneva, Switzerland (formerly with CIP).

The results in Table 4 indicate that the consumers in segment 1, who form 34% of the entire sample, are 2 years younger than their counterparts in segment 2. This is a much expected result as younger people tend to like experimenting and quickly take up new technologies and products. Segment 1 consumers are also more educated than the segment 2 consumers. Segment 1 constitutes a bigger proportion of males compared to segment 2. It is a common practice in Uganda that men like trying out a variety of food products while women tend to be slightly conservative and stick to predefined food products, thus justifying this finding. Consumers in segment 1 belong to households with fewer members and with a relatively smaller proportion of members having salaried employment compared to consumers in segment 2. Larger household sizes for consumers belonging to segment 2 was highly expected and aligns to the findings of Ahmed et al. (2020) who reported that as family sizes increase, interest in products with labelled traits decreases. Results also do reflect that a significantly higher percentage (91%) of the respondents in segment 1 rely solely on market sources for their bananas compared to those in segment 2. More so, consumers in segment 1 throw away banana peels as waste as opposed to those in segment 2 who mostly sell the peels to livestock farmers to earn an income. More of the consumers in segment 1 are also characterized with hiring of persons to prepare for them meals at home compared to those in segment 2 who rarely hired even though they were mostly Kampala based who would be more expected to hiring helpers to prepare meals for their household members. As expected, the prospective buyers' segment had very high negative values for the traditionists index compared to the questionable buyers in segment 2. This implies that traditionists are very unlikely to be among the 34% of the surveyed consumers who are potential buyers of peeled bananas.

Willingness to pay for peeled banana products with various attribute level trade-offs

Table 5 below shows consumer's marginal WTP a premium (positive WTP values) or a discount (negative WTP values) to purchase peeled banana products with various attribute levels. The WTP estimates presented here represent the marginal rate of substitution between prices and attribute levels of the peeled banana product profiles used in the DCE.

Table 5. Marginal WTP for peeled banana attribute levels.

Attribute levels	Segment 1 (Prospective buyers)	Segment 2 (Questionable buyers)
ASC3	2453.568*** (600.53, 4306.62)	-654.802*** (-763.55, -546.06)
Soft	445.392** (15.90, 874.89)	164.084*** (112.73, 215.44)
Firm	158.377 (-207.44, 524.20)	77.331*** (27.90, 126.76)
Good taste	209.427 (-226.30, 645.16)	56.017** (7.15, 104.89)
Excellent taste	773.373** (130.40, 1416.35)	102.244*** (53.06, 151.43)
Medium yellow	0.918 (-314.07, 315.91)	4.762 (-45.40, 54.92)
Bright yellow	-39.355 (-376.95, 298.25)	41.639 (-8.01, 91.29)
Packaged unlabeled	246.010 (-151.86, 643.89)	141.935*** (91.11, 192.76)
Packaged labelled	493.792**(33.91, 953.67)	48.387* (-0.99, 97.77)

Source: Survey data.
Notes: *, **, and *** indicate Coefficient is significant at 10%, 5% and 1% levels, respectively. Figures in parentheses represent the 95 percent confidence intervals.

The results show significant variation in the ranking of peeled banana product attributes and their corresponding impact on consumer utility across the two segments, which underscores the significance of examining the consumers' preference heterogeneity. Overall, results in Table 5 show that there was generally a positive WTP for the peeled banana products in both segments, and consumers in segment 1 (prospective buyers) were willing to pay higher premiums for all the peeled banana products than consumers in segment 2 (questionable buyers). For segment 1, the WTP estimates showed that the implicit price for peeled banana with excellent taste is the highest (UGX773) compared to all other peeled banana attributes. This is followed by the packaging and labeling attribute level for which consumers were willing to pay a premium of up to UGX 494, and the least was the attribute level for soft texture, for which a premium of only UGX 445 was offered.

Unlike consumers in segment 1, whose WTP estimates for peeled banana with soft texture was the lowest, consumers in segment 2 were willing to pay the highest premium of up to UGX 164 for this attribute. This result is in line with previous studies conducted in Uganda indicating that soft matooke cultivars are preferred over others (Akankwasa et al. 2013; 2016; Barekye et al. 2013; Nowakunda et al. 2000). This was followed (in descending order) by the packaged unlabeled attribute, excellent taste, firm texture, good taste, and lastly having a packaged labeled product. The negative and significant coefficient on the ASC3 for segment 2 revealed that even though they were willing to pay a premium for certain attribute levels of the peeled banana product, they were generally more in favor of the status quo product. The willingness of consumers in both segments to pay a premium for packaged and labeled product is in line with the findings of Zamzami and Ariyawardana (2019) who reported that today's consumers increasingly buy with their eyes first. Symmank et al. (2017) further asserts that while consumers tend to favor bananas based on taste, this does not usually translate into positive purchasing intentions because of the initial visual impression. Thus, packaging and labeling could be a huge purchase trigger in the visual dimension of the peeled banana product. Lastly, the peeled banana attribute levels of soft texture, firm texture, good taste, and excellent taste, around which WTP for both segments is centered, are justifiable as a number of scholars (Ssali et al., 2010; Akankwasa et al., 2013; Barekye et al., 2013; Nasirumbi et al., 2018) have previously reported that consumption traits such as good food quality, good taste, soft food, and good flavor are ranked high in Uganda.

5. Conclusions and policy recommendations

This paper investigated consumer demand and preferences for peeled banana products with varied attribute levels in two major cities of Uganda—Kampala and Jinja. The study's purpose was to evaluate the likelihood of consumer uptake of alternative banana products, in peeled and packaged form—whose shelf-life has been extended through novel technological innovations—to counter massive annual economic losses due to the high perishability of the fresh fruit. A discrete choice experiment was designed and conducted among 360 banana consumers who were randomly picked using a systematic sampling approach from eight banana retail markets located within the two cities. Principal factor analysis based on perceptions and attitudes towards peeled banana products was conducted to segment the respondents into market niches. Later, a latent class model (LCM) was estimated to identify the different segments, of which two were chosen, for peeled banana products and the values they derive from the different products. Lastly, willingness to pay estimates for the different consumer segments for peeled banana products with varied attribute levels were also determined.

Study findings revealed that about a third of the studied consumers (referred to as 'prospective buyers') are willing to pay for peeled bananas, while the remaining two thirds (referred to as 'questionable buyers') are still hesitant, even though they are willing to offer premiums for certain attributes of the peeled banana products. Significant heterogeneity exists in consumer valuation and preferences for peeled banana product attribute levels. This heterogeneity is basically based on price, consumers' age, income, source of the bananas, market niche to which the consumer belongs, and participation in a salaried employment. The results further show variation in the ranking of peeled banana product attributes and their corresponding impact on consumer utility across the two segments. Consumers in segment 1 valued highest the peeled banana with excellent taste, for which they offered a premium of up to UGX 773, followed by packaging and labeling valued at UGX 494, while soft texture was the least valued for which they offered a premium of UGX 445. Those in segment 2 valued most the soft-textured peeled banana, offering a premium of UGX 164 for it, while they valued the least for the packaging and labeling, for which they offered a very low premium of UGX 48. These findings suggest that prospective buyers for the peeled banana products, representing about 34 percent of the sampled population, are in segment 1. The availability of these products on the market would benefit mostly the younger and better educated consumers, with smaller household sizes, and with banana purchases frequently made by men rather than women, who have shown to be less inclined to try new products. Consumers in segment 2 preferred the status quo over the novel peeled banana products.

Our findings suggest that there is potential demand for peeled banana products in urban markets. Thus, efforts to promote these products can be fruitful especially if they are reasonably priced to ensure that they are not outcompeted by the existing alternative of unpeeled cooking bananas. Furthermore, given the diversity in attribute level preferences for the different segments, it is advisable to offer a product pool featuring the numerous attributes based on the existing preference heterogeneity, which in turn is likely to increase the proportion of the prospective buyers. It is imperative that packaging is given due consideration, as both segments registered a preference for it. To expand the market potential for the peeled banana products, key messages to promote them should emphasize the most highly-valued attributes such as excellent taste, soft texture, and packaging together with labeling. Lastly, further studies need to be conducted to compare the unit cost of producing peeled banana products with the value consumers are willing to pay for them.

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Bioversity International and the International Center for Tropical Agriculture (CIAT) are part of CGIAR, a global research partnership for a food-secure future.

Bioversity International is the operating name of the International Plant Genetic Resources Institute (IPGRI).

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