Effect of Information on Consumers' Trade-Off Between Subjective Food Safety Cues and Certification: Insights from a Choice Experiment

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Abstract

Suppliers often use certification labels to communicate food safety in food markets, where consumers cannot directly observe or learn about food safety after consumption. However, food markets in many developing countries rarely feature such labels. Consequently, consumers rely on inaccurate intrinsic food attributes to infer food safety, risking exposure to foodborne illnesses. This study investigates consumer behavioral responses to information about the health risks of aflatoxin contamination and the relative predictive strengths of intrinsic food safety cues and food safety certification. Through a theoretical model that accounts for the effect of information on cue utilization for a credence attribute and a discrete choice experiment (DCE) among maize consumers in Nigeria, we disentangled consumers' use of cues for food safety and other food quality dimensions by accounting for heterogeneity with Error-Component Mixed Logit Model. We find that consumers use cues more accurately when informed about the objective predictive strengths of cue attributes and the importance of the inferred credence attribute. In addition, our results show that correctly estimating information treatment effects can depend on accounting for differences in consumers' cue utilization. We discuss implications of our findings for understanding consumer behavior in relation to food safety policies in emerging food markets.

1. Introduction

Food safety is a unique dimension of food quality that consumers cannot directly observe when making food choices. In well-developed food markets, food suppliers use food safety claims in the form of certification labels to communicate food safety to consumers. It is often not the case in domestic food markets of many developing countries where there is a lack of adequate food safety regulations and credible market signals of food quality (Hoffmann et al., 2019). For instance, staple foods in many Sub-Saharan Africa (SSA) domestic food markets seldom carry food safety certification labels (Abate et al., 2021). This is despite growing consumers' concern for food safety (Ortega & Tschirley, 2017; Unnevehr, 2022) and the market potential of food safety certification (FSC) labels (Akinwehinmi et al., 2021; Prieto et al., 2021; Bello & Abdulai, 2018; Groote et al., 2016; Birol et al., 2015). Consequently, consumers often rely on food's intrinsic attributes to infer food safety. Due to the lack of objective knowledge of the association between intrinsic attributes and food safety (Lagerkvist et al., 2013), the tendency to rely on intrinsic food attributes to infer safety is prone to erroneous judgment, leaving consumers exposed to food safety risks (Hoffmann et al., 2021; Akinwehinmi et al., 2022).

Evidence has shown that food consumers do not always make correct inferences when they use cues to make inferences (Thøgersen & Nohlen, 2022; Wilson & Lusk, 2020). Moreover, how consumers make inferences using cues can influence the validity of welfare estimates and policy conclusions from food studies (Gao & Schroeder, 2009; Tonsor, 2011; Caputo et al., 2017). Although studies suggest that consumers use cues to infer credence attributes subjectively (Kardes et al., 2004; Tonsor, 2011) and that correct information can facilitate a more objective use of cues in consumer inferences (Hoffmann et al., 2021), there is a limited investigation into the factors which determine if and to what extent consumers use cues to make objectively correct inferences about credence attributes. We also need to know if and what kind of information can improve consumers' use of cue attributes to make correct inferences about credence attributes in their choices. This study investigates *the information effect of (i) importance of a credence attribute and (ii) relative predictive strengths of cue attributes on consumers' cue utilization and preference for safer food.* Through a theoretical model and analysis of discrete choice experiment (DCE) data, we demonstrate that consumers will only use cue attributes correctly in their food choices if they are informed about the objective association between potential cue attributes and the credence attribute of interest.

Our model emphasizes the crucial role of consumers' understanding in using food attributes to accurately infer a specific credence attribute. This understanding is built on two factors: the significance they attach to the credence attribute and their comprehension of how reliably they can use observable attributes to make inferences about the credence attribute. It is important to note that consumers can place value on a cue food attribute for various reasons, and merely observing this valuation does not guarantee it is for the right reason (Banovi'c, et al., 2012). However, when consumers know that the cue attribute strongly predicts a credence attribute they value, they are more likely to use the cue attribute to infer the credence attribute. This knowledge acquisition can occur when they receive information about the objective meaning of observable attributes and the importance of inferring the credence attribute correctly. We have tested and found support for these predictions through a DCE involving maize consumers in Nigeria.

We introduce a novel perspective to the literature, making three contributions. Our first contribution is to the literature focusing on the role of product knowledge or familiarity in consumers' use of cues in food choices. This literature (Bredahl, 2003; Chocarro, et al., 2009; Grebitus, et al., 2011; Banovi'c, et al., 2012) generally focuses on product knowledge which consumers acquire through product-related experience. However, in a context where consumers may never be able to learn the association between observable attributes and a credence quality attribute, experience-based product knowledge becomes insignificant. An example of such credence food quality attribute is aflatoxin contamination in food which often has delayed health effects and may never be observed by consumers for a long time. In such context, a feasible source of product knowledge to consumers is by receiving expert information about the objective association between either intrinsic or extrinsic observable food attributes and the credence attribute (Steenkamp, 1990). In contrast to what previous studies have focused on, our theoretical model accounts for the unique role of exogenous information as a source of product knowledge in consumers' use of both intrinsic and extrinsic cues for a credence attribute in food choices. Our concept can easily be applied to similar contexts of inferring credence attributes such as production or process attributes.

Our second contribution is to the literature that examines the effect of consumers' cue utilization on WTP estimates for cue attributes. Previous studies in this literature mainly focused on how the number of cue attributes presented to the consumers affects their WTP estimates for the cue attributes (Gao & Schroeder, 2009; Tonsor, 2011; Caputo et al., 2017). Findings from these studies show that when the number of potential cue attributes is increased or reduced, how a consumer uses the attributes changes, resulting in significant changes in WTP estimates of the attributes. In contrast to these studies, we focus on how separately accounting for food safety can affect the WTP estimate of a quality attribute. Food quality attributes often comprise multiple food quality dimensions (e.g., taste, safety, convenience). This raises the question of what precisely consumers value in studies that do not attempt to disentangle these quality dimensions in their analysis. Our contribution in this regard is also through our theoretical model and estimation strategy, where we disentangled consumers' preference for food safety and other food quality dimensions.

Our third contribution is to provide experimental evidence on how information about the objective meaning of attributes and the health risks of food contamination could influence how consumers use attributes as cues to make safer food choices in an unregulated food market. The empirical investigation is about consumers choice of aflatoxin-free maize in Nigeria, one of the countries with prevalence of alarmingly high levels of aflatoxin contamination in food (Liverpool-Tasie et al., 2019; Kamika et al., 2016; Udomkun et al., 2018; Bediako et al., 2019; Sserumaga et al., 2021). When not properly managed, maize is highly susceptible to Aflatoxin contamination (AC), a toxic food contamination that consumers cannot directly observe in food. Dietary exposure to aflatoxin explains a large proportion of liver cancer cases in SSA, South-East Asia and China (Liu & Wu, 2010), and evidence shows that maternal exposure to aflatoxin may lead to increased susceptibility of the fetus to disease (Hernández-Vargas, et al., 2015) and growth faltering in later years of growth (Turner, et al., 2007). Scientific testing remains the only reliable means of detecting the absence/presence of AC because AC, like other food contaminations, is difficult to observe directly. Although there is a risk of misjudging AC using intrinsic food attributes, consumers incorrectly use them to assess AC in food (Hoffmann, et al., 2021). Our third contribution is significant to the food policy conversation regarding how consumer education as a market mechanism can mitigate public health burdens due to consumer exposure to high food safety risks in the context of weak food safety control.

We implemented a DCE among maize consumers, randomized into two experimental groups. Maize alternatives in the DCE were described using intrinsic food and extrinsic attributes, focusing on certification attributes. Treated consumers received information about the health risks of AC and the relative accuracy of color, kernel integrity, and safety certification as cues. In contrast, consumers in the control group were not given this information. Our results show how properly accounting for consumer inferences in choice models can help researchers avoid making wrong conclusions about how consumers value attributes. In addition, our results show that correctly estimating information treatment effects can depend on accounting for differences in consumers' cue utilization.

The other parts of this paper are organized in the following order: the literature review in Section 2, the theoretical model in Section 3, the research design in Section 4, and the results and discussion in Section 5. In Section 6, we make concluding remarks and state policy implications.

2. Literature Review

Food safety is a dimension of food quality that must be treated uniquely for our understanding of consumer inference about product quality. Grunert (2005) 's well-cited review presents the complex relationship between food quality and food safety as consumers perceive it. The author demonstrates that food quality is a multi-dimensional characteristic of food, which can contain a mix of observable, experience, and credence attributes. While consumers can assess observable attributes can be observed at the point of purchase, they can only confirm the presence or absence of experience attributes after purchase. Consumers cannot confirm the presence or absence of credence attributes even after experiencing the product. Food quality and particularly safety may be an experience or credence attribute for all food classes depending on how soon consumers can confirm the health effects of consuming food after purchase. Therefore, consumers commonly use observable attributes to judge experience and credence of food quality dimensions.

Previous studies (Rao & Monroe, 1988; Bredahl, 2003; Chocarro et al., 2009; Grebitus et al., 2011; Banovi'c et al., 2012) establish the significant role of product knowledge or familiarity in consumers' use of cues to judge quality and consequently in product choice probability. In the literature, how authors define knowledge, the type of cues they consider necessary for consumers' evaluation of product quality, and their conclusion about the role that knowledge plays in cue utilization depend on the product category and the quality dimension for the product they considered. For instance, Rao & Monroe (1988) evaluated the effect of prior familiarity on the degree to which extrinsic cues (price and brand) and intrinsic cues (tweed and wool) are used to assess the quality of women's blazers. The authors operationalized knowledge (familiarity) as a single construct captured as the degree to which consumers have learned the association between quality on the one hand and price, brand, tweed, and wool on the other hand. In the study, the authors confirm there was already an observable association between quality and the cues, though the strength of the association differs from one cue to another. In a study about the effect of product knowledge on cue utilization for choosing Canned Asparagus, a food product, Chocarro et al. (2009) instead focused only on extrinsic cues (price, brand, and origin), judging that, in their case, the use of intrinsic cues was not relevant since the product was branded and canned. The authors separately included what they term as familiarity and knowledge and justified their approach based on the factor analysis results of multiple knowledge items they collected.

Generally, the literature classifies knowledge into objective knowledge (what consumers truly know) and subjective knowledge (what they think they know) about the association between the cues and product quality. Although there are inconsistencies in how the studies measure knowledge, the general conclusion points to the positive significant role of product knowledge in choosing products of higher quality. Also, the studies mainly focus on the role that knowledge gained from product-related experience plays in inferring experience quality attributes. The exception is Banovi'c et al. (2012), who modeled cue utilization for credence quality attributes (i.e., health and nutrition) and experience quality attributes. However, in their empirical application, they reported consumers' judgment of credence attributes, i.e., health and nutrition, upon consumption of a beefsteak. They described this variable as "Experienced Credence Quality." Because consumers will not be able to confirm the presence of a credence attribute even after consumption, their argumentation seems illogical.

Aflatoxin contamination in food, a credence food quality (safety) attribute, is a prime example of the need for expert information in consumer cue utilization. Consumers may unknowingly be at risk of liver cancer due to aflatoxin contamination, a risk that they may not be able to associate with their food choices. Therefore, product knowledge developed through product-related experience will likely play an insignificant role in accumulating cues for this dimension of food safety risk. Alternatively, providing expert information to consumers will be crucial in determining their ability to correctly judge which cues to use to infer this food safety risk. Although several studies have investigated the effect of information on consumers' evaluation of food safety and, consequently, on product choice, there is a limited investigation into the role that such information plays in cue utilization, especially for a credence attribute. Our focus on a credence food safety attribute, aflatoxin contamination, allows us to derive a cue-utilization model for a credence attribute in food choices and empirically test the model with experimental data.

3. Theoretical Framework

In this section, we present a theoretical model of factors that determine how consumers use attributes to make inferences about a specific credence attribute of interest. Specifically, we consider a model of food choice that disentagles consumers’ utilities for a credence food safety attribute and other food quality dimensions.

Consider that the utility of consumer *j* for food choice *i* which consists of safety and other quality attributes is given as

$$U_{ij} = \theta_j^q x_i^q + \theta_j^s x_i^s + \ldots \tag{1}$$

x_i^q: level of food quality; x_i^s: level of food safety; θ_j^q: utility for food quality and θ_j^s: utility for food safety. Typically x_i^q and x_i^s are either experience or credence attributes. Here, we assume x_i^q is a vector of experience and credence attrbutes but x_i^s is strictly a credence attribute. Consequently, the consumer will use certain search attributes as cues for x_i^q and x_i^s at the point of purchase. Assume that a cue denoted as c_i^{sq} can be used as a cue both for x_i^q and x_i^s, while another cue denoted as c_i^s can only be used as cue for food safety. To illustrate, consider the example of maize we use in this study, c_i^{sq} could be discoloration, kernel damage which can be used as cues for safety and taste while c_i^s could be food safety certificate which we expect the consumer to use as a cue only for food safety. Cox (1967) demonstrates that the consumer will use the cues according to her predictive & confidence value (PCV) for each cue. In this instance, the predictive value measures the extent to which consumer believe that a cue can be used to infer an unobservable attribute while confidence value refers to the extent to which the consumer is confident in her own ability to use the cue to infer. Therefore, equation (1) becomes

$$\begin{aligned} U_{ij} &= \theta_j^q w_j^q c_i^{sq} + \theta_j^s \left(w_j^{s1} c_i^{sq} + w_j^{s2} c_i^s \right) \\ &= \theta_j^q w_j^q c_i^{sq} + \theta_j^s w_j^{s1} c_i^{sq} + \theta_j^s w_j^{s2} c_i^s \end{aligned} \tag{2}$$

where $w_j^q =$ PCV in using c_i^{sq} to infer x_i^q;

w_j^{s1}= PCV in using c_i^{sq} to infer x_i^s and

w_j^{s2} = PCV in using c_i^s to infer x_i^s.

Further, Steenkamp (1990) identified an important determinant of cue utilization in the context where there is quality risk. The author termed the variable "*perceived quality risk*" and described it as the degree of risk perceived in a quality attribute. Here we term it "*perceived safety risk*" denoted with δ^s. Accounting for δ^s makes equation (2) to become

$$U_{ij} = \theta_j^q w_j^q c_i^{sq} + \theta_j^s w_j^{s1} \delta^s c_i^{sq} + \theta_j^s w_j^{s2} \delta^s c_i^s \quad (3)$$

$$= \beta_{j1} c_i^{sq} + \beta_{j2} c_i^{sq} + \beta_{j3} c_i^s$$

where $\beta_{j1} = \theta_j^q w_j^q$; $\beta_{j2} = \theta_j^s w_j^{s1} \delta^s$ and $\beta_{j3} = \theta_j^s w_j^{s2} \delta^s$

Consider that we inform the consumer that c_i^s is relatively more predictive of x_i^s than c_i^{sq} contrary to her initial believe and also communicate objective food safety risk which is higher than her initial perceived food safety risk, then we can test series of hypotheses from our model:

1. H_1: Information may increase or decrease β_{j2} depending on the relative effects of information on δ^s and w_j^{s1}, although, information is expected to increase δ^s but decrease w_j^{s1}.
2. H_2 : Information is expected to increase β_{j3} by increasing both w_j^{s2} and δ^s
3. H_3 : Ultimately, information is expected to increase β_{j3}/β_{j2}

4. Research Design and Sampling

4.1. Experimental Design

We implemented an information experiment in which we aim to test the effect of informing consumers about the objective relative accuracy of cues on how they use these cues in their choices of maize. In this context, the attributes which the consumer can observe in choosing maize include discoloration – whether and to what extent the maize is discolored; kernel integrity – whether and to what extent the maize kernels are self-broken; and food safety certification implemented by different certification authorities. In this instance, color attribute is expected to be used as a cue for safety (Hoffmann, et al., 2021) as well as other unobserved quality dimensions such as taste (Spence, 2015). While Hoffman et al., 2021 observes that consumers weakly associate kernel integrity with safety, we do not know if consumers associate this attribute with other unobservable maize attributes. However, being an intrinsic maize attribute, we expect that consumers also associate kernel integrity with other unobserved quality dimensions. However, the food safety ceritification label is likely to be used only as cue for food safety and nothing else.

In order to test our hypotheses, we implemented a hypothetically designed choice experiment within which respondents were assigned to one control and one treatment group. Consumers in the treatment group watched a video which described the meaning of aflatoxin, health risks of alfatoxin, susceptibility of Maize to AC, prevalence of Maize contaminated with AC in the markets in the study area, and the fact that AC in Maize can only be reliably detected through scientific testing which is signalled through certification, even though some observable attributes like discoloration and kernel damage may point to its presence in Maize. Thus, we expect the information provided to increase consumers' confidence in the use of certification cue. However, we do not know apriori whether it will reduce their confidence in the use of colour. The control group did not receive this information. The information given to the treatment group was communicated through a videographic.

4.2. Choice Experiment Design

The design of our choice experiment starts with selection of a suitable product with relevant attributes for our study.

4.2.1. Product Selection

On the average, consumers in SSA derive about 30% of their calorie intake from Maize (IITA, 2023). In our study area, Maize is usually consumed either in the fresh form (either as boiled or roasted) or in other processed forms (pounded or grounded) (Adeyemo, 1984). The typical maize purchase and consumption pathways for consumers in this region is represented in Figure 1 in the appendix. In relation to acquisition sources, maize consumer can obtain Maize by either purchasing (from the traders in the market or directly from farmers) or through own production. Later source is typical of rural consumer households. Most urban consumers get their Maize mainly through purchases either in fresh, dried, or processed forms to be consumed immediately or in the future.

We focus on Maize because of its high susceptibility to AC and that for which dangerous levels of AC have been reported in Nigeria (Ayeni, et al., 2020; Liverpool-Tasie, et al., 2019; Kamika, et al., 2016). Ayeni, et al., (2020) observed that more than 50% of the Maize sold in the markets in our study area contain AC levels above regulatory limit. As such, consumers in these markets were exposed to high risks of regularly consuming aflatoxin-contaminated Maize. Moreover, a relatively large proportion of consumers and traders in this region are neither aware of this source of risk nor their daily exposure to it (Sanou, et al., 2021;Ojuri, et al., 2019).

Maize safety can begin to deteriorate pre-harvest through unobservable contamination with AC. Research has shown that this deterioration deepens along the value chain, especially where good drying and storage practices are absent. Contamination of AC at certain stages can manifest in the form of discoloration and self-broken kernels. It is not clear to what extent consumers associate these manifested quality changes with food safety except for the evidence given by Hoffmann, et al. (2021). Therefore, in the absence of other forms of judging food safety, consumer rely on changes in these attributes of Maize.

4.2.2. Attributes Selection

The full description of the maize attributes used to design our choice experiment are presented in Table 1. The attributes selected for this study, therefore, inlcude include color and kernel integrity, form of Maize, certification, and price. Other secondary attributes that are relevant to our study include packaging and maize type. Currently, maize products in the markets in the study area are not sold in packaged form. Furthermore, though packaging is not directly related to our attributes of interest in this study, we included it because it is an attribute that may facilitate the use of certification labels. We are aware that this attribute itself may be used as a cue for quality by certain consumers, yet we do not directly focus on this effect in our analysis. The inclusion of the maize type is because it can be an important attribute determining choice of Maize in the study area (Sanou, et al., 2021). Moreover, it is unfeasible to show the picture of Maize without showing the type(color) of the Maize. And not including this as part of the design might bias the estimates for other attributes as one may not know whether choices are conditional on the color of the Maize shown. Although anecdotal evidence shows that the majority of the consumers in the study area prefer yellow to white Maize, nonetheless, we included the two types of Maize in our design for the reasons above.

Table 1: Choice Experiment Attributes and Levels

Attribute	Description	Levels	Base Level
Colour Integrity	Proportion of maize kernels that is discolored in percentage	0%, 5%, 10%, or Above 10%.	Above 10%
Kernel Integrity	Proportion of dried maize kernels that is damaged (self-broken)	0%, 5%, 10%, or Above 10%.	Above 10%
Certification Authority	The organization that certified that the Maize is free of aflatoxin contamination.	Federal Government of Nigeria (FGN), State Government (SG), Local Government (LG) or Private Organization.	No Certification
Maize Form	Whether the Maize is in a dried or fresh form.	Fresh, Dried	Dried
Maize Colour	Whether the Maize is yellow or white Maize	Yellow or White	White
Packaging	Whether the Maize is packaged and labelled or not	Packaged, Not packaged	
Price	Price of 1 KG of Maize in Nigerian Naira (NGN)	N550, N650, N750, N850	N550

To identify the appropriate levels for each of the attribute, we rely on both literature and our understanding of the study context. For colour[1] and kernel integrity, we selected the levels based on Hoffmann et al. (2021). The levels represent different proportions of maize kernels that are either discolored or self-damaged[2]. As mentioned earlier, these different levels of quality changes can point to AC. The levels selected for the certification attribute is based on our hypothesis that consumers's preference for certification can depend on the certifying authority. Although, there is is currently no maize sold in the market that certified, in our context, the four certification levels in Table 1 represent potential certification authorities.

4.2.3. Design of the DCE

To generate maize alternatives for the choice experiment, we follow state of the art practice to make a fractional Bayesian D-Efficient design in the Ngene software. A fractional design is required here because it is impossible to make use of the full profile resulting from all the combinations of the selected attributes. Thus, it is the practice to take a fraction of the full profile design. One way to do this is to aim at a fractional D-efficient design. D-efficient designs aim to produce data which generate parameters with minimal standard errors.

As a requirement for this design, we started with a D-Optimal design for a pilot study specifying zeros as priors. Thereafter, we used the priors generated from the data from the pilot study to make the final design with a D-Error of 0.86. In total, we generated 18 profiles of Maize which were blocked into two versions. This makes it possible for each respondent to attend to only 9 choice tasks to minimize the cognitive burden associated with long choice tasks. Finally, each consumer

[1] Please note that color integrity as an attribute is different from maize color, which is another attribute, as explained above. Color integrity refers to whether the original color (either white or yellow) is not changing as a result of deterioration in quality. Maize color, on the other hand, refers to whether the Maize is white or yellow.

[2] Self-broken kernels only apply to dried Maize in our DCE design, but discoloration applies to both fresh and dried Maize.

faced two hypothetical maize alternatives with a no-buy option (see Appendix for a sample choice task). To mitigate hypothetical bias (HB) as much as possible, the enumerators read a cheap talk script to each consumer. The DCE instruction and the HB mitigation script can be found in the Appendix.

4.3. Model Specification and Estimation

We estimated three econometric models i.e. Basic Model, Cue Models 1 and 2 presented in the 'Results' section. All the models are random parameter logit models specified in WTP-space with error-component. The error component accounts for correlation of individual effects across choice tasks (Hess, et al., 2008). The benchmark model i.e Basic Model is different from the Cue Models in that later include shifters which capture association between cue attributes and food safety as defined in the theoretical model. Further, in Cue Model 1 we allowed cue shifters to only depend on the attribute's PCV while for Cue Model 2 we additionally account for the *"perceived safety risk"*[3].

We assume that the utility of consumer n for maize alternative j in choice situation t follows the random utility model (RUM) (McFadden, 1986) and for the three models can be specified as:

1. Basic Model:

$$\begin{aligned} V_{int} + \varepsilon_{int} = {} & \beta_{n\,color} color_{it} + \beta_{n\,kernel} kernel_{it} \\ & + \beta_{n\,fg} FG_{it} + \beta_{n\,sg} SG_{it} + \beta_{n\,lg} LG_{it} + \beta_{n\,priv} Private_{it} \\ & + \beta_{n\,yellow} Yellow_{it} + \beta_{n\,fresh} Fresh_{it} + \beta_{n\,packaged} Packaged_{it} \\ & - \exp(\alpha_n) Price_{it} + \varepsilon_{int} \end{aligned} \quad (10)$$

[3] Refer to our theoretical model previously defined.

2. Cue Model 1

$$V_{int} + \varepsilon_{int} = ((\theta_{color})cue\_color + \beta_{n\ color})color_{it}$$
$$+ ((\theta_{kernel})cue\_kernel + \beta_{n\ kernel})kernel_{it}$$
$$+(\theta_{fg}(credibility\_gap * fg_{reliable}) + \beta_{n\ fg})FG_{it}$$
$$+ (\theta_{sg}(credibility\_gap * sg_{reliable}) + \beta_{n\ sg})SG_{it}$$
$$+(\theta_{lg}(credibility\_gap * lg_{reliable}) + \beta_{n\ lg})LG_{it}$$
$$+(\theta_{priv}(credibility\_gap * private_{reliable}) + \beta_{n\ priv})Private_{it}$$
$$+\beta_{n\ yellow}Yellow_{it} + \beta_{n\ fresh}Fresh_{\ it} + \beta_{n\ packaged}Packaged_{it}$$
$$-\exp(\alpha_n)Price_{it} + \varepsilon_{int} \quad (11)$$

3. Cue Model 2

$$V_{int} + \varepsilon_{int} = ((\theta_{color})cue\_color * safety\_risk + \beta_{n\ color})color_{it}$$
$$+ ((\theta_{kernel})cue\_kernel * safety\_risk + \beta_{n\ kernel})kernel_{it}$$
$$+(\theta_{fg}(credibility\_gap * fg_{reliable} * safety\_risk) + \beta_{n\ fg})FG_{it}$$
$$+ (\theta_{sg}(credibility\_gap * sg_{reliable} * safety\_risk) + \beta_{n\ sg})SG_{it}$$
$$+(\theta_{lg}(credibility\_gap * lg_{reliable} * safety\_risk) + \beta_{n\ lg})LG_{it}$$
$$+(\theta_{priv}(credibility\_gap * private_{reliable} * safety\_important)$$
$$+ \beta_{n\ priv})Private_{it}$$
$$+\beta_{n\ yellow}Yellow_{it} + \beta_{n\ fresh}Fresh_{\ it} + \beta_{n\ packaged}Packaged_{it}$$
$$-\exp(\alpha_n)Price_{it} + \varepsilon_{int} \quad (12)$$

where V_{int} is the observable deterministic part while ε_{int} is the unobservable stochastic part of the utility. ε_{int} follows Type 1 Generalized Extreme Value (GEV) distribution giving rise to a logit model (McFadden, 1986). All β_n follow continuous distribution over individuals in our sample. In this study, it is reasonable to allow the β_n to follow normal distribution since positive and negative preferences are possible for the associated attributes. We allow α_n , to follow a negative log-normal distribution to ensure consistency with consumer's negative disutility for price. Based on these assumptions and with reference to Train (2003), the probability that consumer n chooses Maize j in situation t can be specified as a mixed logit model:

$$P_{jt} = \int \left(\frac{exp\ (V_{nj})}{exp\ (V_{nk})} \right) f(\vartheta)\, d\vartheta \qquad (13)$$

where $f(\vartheta)$ is a density function and $d\vartheta$ contains the θ, β_n and $-\alpha_p$ in equation (10).

To estimate the parameters of P_{jt}, the log-likelihood function to be maximized takes the form:

$$L = \sum_t^T \sum_j^J y_{jt} \ln P_{jt} \qquad (14)$$

Where y_{jt} = 1 if Maize j is chosen in situation t and 0 otherwise, T is the number of the choice situations (9 in our case) and J is the number of alternatives (3 in our case) in choice situation t. L in Equation (14) can only be estimated using simulation by drawing parameters from $f(\vartheta)$ over a series of iterations and then averaged to give P_{jt} such that the simulated log-likelihood is given as:

$$SLL = \frac{1}{R} \sum_r^R L^r \qquad (15)$$

Where R is the number of draws for the simulation. In our case R is 500 sobol draws (Hess, et al., 2006).

All estimations were done on pooled data. Following standard practice, we started our estimation with a conditional logit specification. Subsequently, we estimated a Mixed logit model without correlated parameters and thereafter, a mixed logit model with correlated paramaters. Both mixed logit models were specified with an error component, which accounts for correlations among observations from the same individuals. Using the log-likelihood (LL), Bayesian information criterion (BIC) and the Akaike Information criterion (AIC) to compare the models, we found the mixed logit models with error component and correlated parameters best fit to our dataset. All estimations were done using Apollo software in R (Hess & Palma, 2019). More details about the specification and output of the model we finally selected will be available as part of the supplementary materials.

4.3.1. Measurement of Key Variables

It is helpful to explain how the key variables in our models were measured. We capture cue_color and cue_kernel as the perceived PCV for the colour and kernel integrity attributes. Although Cox (1967) defined predictive and confidence values as two separate measures in their theory, empirical applications however allow for capturing these values as a single variable since it is the interaction of the two measures that lead to consumers' use of cues (Richardson, et al., 1994; Grunert, 2005). Specifically, we asked the respondents to rate on a scale of 1-5 the extent to which they believe that broken kernel and discoloration are important in judging the safety of maize they want to buy.

The variable $credibility\_gap$ is used as the proxy for the PCV for certification. We capture this variable as what Birol, et al., (2015) termed perceived credibility gap. Following the authors' approach, we asked respondents to state the probability that a maize that is certified safe will be safe for their consumption and repeated the same question for maize that is not certified. The difference between these subjective probabilities represent their perceived credibility gap. It indicates their judgment of the extent to which they believe that certification is credible as a cue for food safety. The variables $fg_{reliable}, sg_{reliable}, sg_{reliable}, private_{reliable}$ measure on a scale of 1-5 the respondents' perception of how reliable each of the respective certification authority is in implementing effective food safety certification. The use of the reliability measures to weight the credibility gap is necessary since literature is replete with evidences that perceived trust/reliability of certification authority matters in valuing certification labels (e.g (Banerji, et al., 2016; Wongprawmas & Canavari, 2017; Akinwehinmi, et al., 2022). The variable $safety\_risk$ captures the respondents' perceived maize safety risk (Steenkamp, 1990). Specifically, we asked respondents: *"How likely do you think that consuming maize contaminated with "aflatoxin" will harm your health?"*. Responses range from *"Not likely at all"* (0) to *"Likelihood very high"* (10).

4.4. Sampling procedures and data collection

We drew a sample of urban maize consumers who purchase Maize from typical informal unregulated markets in Ondo State, Nigeria. These markets are open market where foods are openly displayed. In sampling, we followed the current residential delineation of the study area to draw representative samples of low, middle and high income earning maize consumers. Residential locations in the study area are categorized in terms of density of household per unit of area of land. This classification gives rise to High-density residential zone (HDRZ), Medium-density residential zone (MDRZ) and Low-density residential zone (LDRZ) (Adeoye, 2016). The LDRZ, MDRZ, and the HDRZ mirror the high, middle, and low-income earners, respectively. There are residential areas (RA) within each zone. We selected two RA in the HDRZ and MDRZ but three in the LDRZ to match the quota for other zones.

Identifying a respondent begins with visit to streets in the selected RAs, although not all RAs have the streets laid out in a structured manner. On getting to a street, the enumerator approaches the first visible house and asks for a voluntary participation in the survey. As much as possible, enumerators were instructed to follow a systematic approach to selecting every third house to ensure sufficient spread. However, we cannot guarantee that this was possible on all occasions due to the structure of the streets. Respondents are randomized at two levels – first to treatment group (control or informed) and second to the choice experiment version (Block 1 or Block 2). Specifically, the enumerator starts with assigning the first two respondent to control and therein to block 1 and block 2 respectively. Thereafter, the next two respondents are assigned to a treated group and then to Block 1 and Block 2.

To start, the enumerator requests to interview the household head or the adult responding for food purchase, female. After securing consent to participate in the survey, screening questions that ask whether the respondent consumes Maize and also purchases the unprocessed Maize, either fresh or dried from the market, are posed to the consumer. On passing the screening, the flow of the questions and the version of the choice experiment subjected to depends on the treatment group and the choice experiment block respectively. The flow of the questions for the control and the treated group can be found in the appendix. The final composition of the sample by RA and zones can be found in the appendix. We sampled a total 360 adults responsible for household food purchase decisions, aged 42 on the average and mainly the female (70%). Out of 360 responses, we included observations from a total of 342 respondents for our estimation after removing 18 invalid responses.

5. Results

5.1. Sample Characteristics and Balance Test

The relevant socio-economic characteristics, maize purchase pattern and maize safety knowledge of the respondents are presented in Table 2. The full sample characteristics can be found in the Appendix. The sample, constituted mainly by female, is characterized by highly educated consumers whose average years of formal education is 15. The average monthly income of about USD 201 of the sample translates to about USD 6.7 per day. In terms of maize purchasing pattern, most (90%) of the consumers buy fresh (unshelled and unprocessed) Maize. About 60% stated they buy dried Maize from the market. To assess the current maize safety knowledge of the consumers, we asked a series of questions about the risk associated with maize contamination and the pathways (pre-harvest to post-harvest) through which Maize can be contaminated (see Appendix for the specific questions). They were also asked to rate themselves on a scale of 0-10 on how knowledgeable they are with possible sources of contamination in Maize. A few consumers (6.4%) have heard of the term "aflatoxin" despite being a sample that is highly educated. Only 16% of the sample have knowledge of the major health risks (especially liver cancer in adults and growth impairment in children) associated with Maize. Above half (64%) of the sample have objective knowledge of the pathways by which Maize gets contaminated from pre-harvest to consumption.

Table 2: Sample Summary Statistics

Variable	Pooled Mean (SD) / %	Control Mean (SD) / %	Treated Mean (SD) / %	Test p-value
Socio-economic				
Female	70%	71%	70%	0.7
Age	42 (13)	42 (13)	42 (12)	0.5
Married	77%	73%	82%	0.06*
Formal Education (Years)	15 (4.5)	15 (4.6)	15 (4.5)	0.9
Avg. Monthly Income (USD)	201.43 (203.77)	199.06 (225.86)	203.72 (180.5)	0.2
Low income	13%	15%	11%	0.3
Mid income	53%	55%	51%	0.5
High income	34%	30%	38%	0.14
Maize Purchase Pattern				
Buy fresh Maize	90%	91%	89%	0.4
Buy dried Maize	59%	59%	60%	0.9
Buy roasted Maize	77%	81%	74%	0.13
Knowledge				
Aflatoxin aware	6.4%	6.5%	6.3%	>0.9
Contamination pathway knowledge	64%	62%	66%	0.5
Maize safety risk knowledge	16%	14%	18%	0.3
Level of subjective knowledge	4.1 (2.2)	4.0 (2.0)	4.1 (2.4)	0.9

*Statistical significance markers: * p<0.1; ** p<0.05; *** p<0.01*

Consumers in the control and treated groups are statistically similar in all the sample characteristics presented in Table 2, except for marital status where we have statistically higher percentage of married in the treated group. Regardless, it is of more importance that consumers are statistically similar in characteristics such as awareness and knowledge, which are more likely to impact the effect of information. Since consumers in both groups are similar in terms of these more important variables, we consider our randomization to be successful and allow for pure test of the effect of information.

5.2. Mixed Logit Estimates

We report estimates of the basic model, Cue Models 1 and 2 respectively in Table 3. Attribute-specific Mean estimates for the control and the treated groups are presented for each of the Model. All estimates are presented as mean values with the robust standard errors in bracket. Basic Model is the benchmark model which does not account for cue component of the estimates. Cue models, specified according to our theoretical model, add shifters which account for the components of the estimate signaling value concerning maize safety. As mentioned earlier, the difference between Cue Model 1 and 2 is that later additionally account for the respondents' perceived safety risk. A statistically significant estimate of the shifter would imply that on the average consumers use the attribute as cue for food safety. A positive sign will mean that an improvement in the cue attribute signals a higher level of food safety to the consumer and vice versa.

In the basic model, all the attributes significantly influenced the choice of maize except the form of maize (fresh vs dried) and packaging attribute. In addition, Private certification was not significantly predicting choice of maize for the control group. The negative and statistically significant estimates for discoloration and broken kernels imply that increasing deterioration in these maize attributes reduce the likelihood of choosing maize. The positive signs for the certification attributes as observed for both control and treated groups show that maize certified by any of these certification types will increase the likelihood of choosing maize. As expected, increasing price of maize reduces the likelihood of choosing maize signified by the negative and statistically significant estimate of the price. The negative and statistically significant estimate for the "No buy" also signify the positive preference that respondents have for purchasing maize compared to not purchasing.

Table 3: Preference-Space Mixed Logit Models

	Basic Model		Cue Model 1		Cue Model 2	
	Control	**Treated**	**Control**	**Treated**	**Control**	**Treated**
Discoloration	-0.63 (0.07) ***	-0.67 (0.07) ***	-0.43 (0.22) **	-0.12 (0.25)	-0.55 (0.09) ***	-0.68 (0.14) ***
Broken Kernel	-0.53 (0.08) ***	-0.47 (0.07) ***	-0.66 (0.21) ***	-0.75 (0.22) ***	-0.41 (0.1) ***	-0.48 (0.13) ***
Certification_FG	0.59 (0.23) ***	0.96 (0.27) ***	0.5 (0.25) ***	0.34 (0.33)	0.54 (0.25) ***	0.4 (0.33)
Certification_SG	0.3 (0.18) **	0.65 (0.23) ***	0.37 (0.2) **	0.15 (0.26)	0.35 (0.2) **	0.22 (0.26)
Certification_LG	0.43 (0.18) ***	1.11 (0.21) ***	0.4 (0.2) ***	0.74 (0.24) ***	0.39 (0.2) ***	0.79 (0.25) ***
Certification_Private	0.09 (0.21)	1.2 (0.24) ***	0 (0.24)	0.9 (0.27) ***	-0.01 (0.23)	0.97 (0.28) ***
Fresh Form	-0.05 (0.16)	0.29 (0.19)	-0.05 (0.16)	0.25 (0.17)	-0.03 (0.16)	0.25 (0.16)
Yellow Maize	0.29 (0.1) ***	0.23 (0.12) **	0.29 (0.11) ***	0.21 (0.09) ***	0.28 (0.11) ***	0.2 (0.09) ***
Packaged	-0.04 (0.1)	-0.12 (0.13)	-0.02 (0.1)	-0.09 (0.1)	-0.05 (0.1)	-0.08 (0.1)
Price	-7.41 (0.73) ***	-7.14 (0.59) ***	-7.14 (0.57) ***	-7.54 (0.99) ***	-7.06 (0.63) ***	-7.3 (0.77) ***
No Buy	-4.65 (0.46) ***	-4 (0.46) ***	-4.72 (0.47) ***	-3.95 (0.48) ***	-4.58 (0.48) ***	-3.91 (0.45) ***
θ_Discolor			-0.24 (0.26)	-0.58 (0.28) ***	-0.18 (0.15)	0.02 (0.18)
θ_Broken			0.16 (0.24)	0.31 (0.25)	-0.28 (0.17) **	0.01 (0.18)

θ_FGN		0.33 (0.59)	1.34 (0.53) ***	0.38 (1.09)	1.6 (0.62) ***
θ_SG		-0.12 (0.55)	1.15 (0.46) ***	-0.32 (0.86)	1.23 (0.53) ***
θ_LG		0.63 (0.67)	0.9 (0.44) ***	0.35 (1.34)	1.03 (0.54) **
θ_Private		0.8 (0.78)	0.53 (0.41)	1.26 (1.12)	0.51 (0.51)
LL	-2756.47	-2747.86		-2750.37	
AIC	5662.93	5669.72		5674.74	
BIC	6115.33	6194.51		6199.52	

Turning to the Cue Models, as previously mentioned, these models allow us to identify if there is an association between the respondents' perceived predictive strength of intrinsic and certification cues and their valuation of the cues in their choices. The attributes expected to be used as cues include discoloration, broken kernel and the four certification attributes. We observe that in Cue Model 1, none of the cue parameters (θs, which capture the association) is significantly different from zero for the control group but for the treated group, the cue parameters are significantly different from zero except for broken kernel and private certification. Note that the mean estimates for the cue attributes for the control group were not affected by the inclusion of the cue shifters in terms of their statistical significance. But for the treated group, the inclusion of the cue shifters made the average estimates for discoloration, FG and SG no longer significant. However, average estimates for LG and Private certification attributes are still statistically significant even after including the cue shifters.

The results of Cue Model 1 imply that control group are not associating discoloration, broken kernel and any of the certification attributes with maize safety as they claimed. In the first place, we do not expect that consumers in the control know about the association between the intrinsic cue attributes and safety. It is also unlikely that consumers learn such association through product-related experience without such explicit information given to the treated group. This is because the dimension of food safety we examine in this study, aflatoxin contamination, is completely a credence attribute which may not be learned even after several times consuming maize. Moreover, in the study area, there is no known evidence of negative health consequences of consuming maize which may have signaled such safety issue to the consumers. Therefore, it seems that consumers in the control value both the intrinsic and certification attributes in the choice experiment for other reasons than as cues for maize safety, a behaviour contradicting their claim. An alternative interpretation is that they just consider these attributes as general quality cues such that any observed deterioration in the attributes only invoke emotional reactions which manifest in their behaviour.

The treated group on the other hand associated discoloration, FG, SG and LG as cues for maize safety as they have claimed. What is interesting is how FG and SG seem to be completely associated with maize safety in consumers' valuation while LG is only partially associated with safety but also being valued for other reasons that we cannot observe. In the case of the private certification attribute, it is valued by the treated group only for other reasons and not perceived maize safety. The notable difference we observe in the results of Cue Model 2 is that accounting for perceived importance of maize safety implies that consumers in the control group are more likely to use broken kernel as cue for maize safety the more they perceive that maize safety is important to their health. For the treated group, accounting for importance of maize safety makes the respondents to rely only on the FG, SG and LG as cues for maize safety disregarding discoloration, broken kernel and private certification.

6. Concluding Remarks and Policy Implications

In this paper, we derive a theoretical model showing how exogenous information about importance of a food safety risk and relative accuracies of cues for food safety can affect consumers' cue utilization for a credence food safety attribute. Existing studies (Rao & Monroe, 1988; Bredahl, 2003; Chocarro, et al., 2009; Grebitus, et al., 2011; Banovi´c, et al., 2012) of cue utilization in consumers' valuation of food quality attributes focus on the role of experience-based product knowledge in evaluation of experience food quality attributes. In this paper, we describe the context of cue utilization for a credence food attribute where experience-based product knowledge is insignificant making provision of expert information a feasible source of acquiring product knowledge. We tested the predictions of this model through a DCE among urban maize consumers who were randomized into a treated group that received health risks and cue accuracy information and a control group that did not receive the information.

The results from empirical test of the model confirm that information results in significant change in the way consumers use cues to infer a credence attribute. Consumers who gain product knowledge through the information are more likely to use cues accurately for food safety and offer higher premium for food safety certifications. This is consistent with the findings of the earlier cited studies that investigate the role of product knowledge in cue utilization. Our results show that failure to account for how consumers utilize cues in food choices with quality attributes may leave the researchers clueless as to what consumers are valuing in reality. Several food studies that use multi-attribute valuation techniques such as DCE report consumers' significant valuation of cue attributes without paying closer attention to consumers' motivation behind the use of the cues. This can lead to erronous conculsions about the effects of cue attributes in food choices.

One market implication of our finding is that current research agenda which focuses on using market mechanisms to incentivize trade of verified safe food will have to emphasize that efforts to enhance food safety must place equal if not greater importance on the enhancement of observable quality attributes, especially those related to visual cues. This is because food quality and food safety may continue to be inseparable concepts in the mind of the consumers (Rijswijk & Frewer, 2008). Therefore, one may not expect consumers to completely give up the use of the less accurate observable quality cues to judge food safety even if they are educated about the risk of misjudging using those cues. However, it is interesting to find that informed consumers in this study place higher relative value on certification. This shows the potential role of information in generating market premium to reward food suppliers' investment in FSC.

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