Aus dem Institut für Ernährungswirtschaft und Verbrauchslehre der Christian-Albrechts-Universität zu Kiel

# Three Essays on Modeling Consumer Preferences in the Presence of Hypothetical Bias and Attribute Non-Attendance in Food Choice Experiments

Dissertation

Zur Erlangung des Doktorgrades der Agrar- und Ernährungswissenschaftlichen Fakultät der Christian-Albrechts-Universität zu Kiel

vorgelegt von

M.Sc. Muhammad Baba Bello

aus Nigeria

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| Dekan: | Prof. Dr. Eberhard Hartung |
| 1.Berichterstatter: | Prof. Dr. Awudu Abdulai |
| 2. Berichterstatter: | Prof. Dr. Martin Schellhorn |
| Tag der mündlichen Prüfung: | 27. Januar, 2016 |

Gedruckt mit der Genehmigung der Agrar- und Ernährungswissenschaftlichen Fakultät
der Christian-Albrechts-Universität zu Kiel

Diese Arbeit kann als pdf-Dokument unter

http://eldiss.uni-kiel.de/

aus dem Internet geladen werden.

Dedicated to my parents

Alhaji Baba Bello and Hajiya Kaltume Bello

*For their Prayer and Guidance*

## Acknowledgement

Unto Allah Ta'ala the Most High I render all praises; for His special Grace and Sustenance. The realization of this great ambition in life was made possible by numerous individuals and institutions. I heartily acknowledge the inestimable support of my mentor Prof. Dr. Awudu Abdulai who supervised this work. His fatherly advice and encouragement has contributed immensely to the success of this study. Thanks also to members of my doctoral exam committee; Prof. Dr. Martin Schellhorn, Prof. Dr. Ulrich Orth and Prof. Dr. Dr. Christian H. Henning.

With gratitude, I acknowledge the financial support and opportunity afforded me by the management of Bayero University and the MacArthur Foundation. My appreciation also goes to colleagues at the Department of Agricultural Economics and Extension, Bayero University, for their moral support. Same goes to my colleagues at the University of Kiel; Dr. Rakhshanda Kousar, Dr. Silke Thiele, Dr. Rebecca Illichmann, Dr. Jan Dithmer, Dr. Christian Kulhgatz, Dr. Lukas Kornher, Dr. Linda Kleeman, Dr. Taiwo Osun, Dr. Victor Owusu, Dr. Kolawole Ogundari, Dr. Steffi Dierks, Abdul Nafeo Abdulai, Sohail Makhdum, Daniela Lueth, Anna Heller, Abdurrahman Awal, Issahaku Gazali, Marie Kamrad, Christian Levke, Jonas Peltner, Nelli Betke and Nicola Benecke.

I am eternally grateful for the prayers, understanding and unflinching support of my beloved parents, I beseech Allah (SWT) to reward them abundantly, Amin. To my brothers - Abdulkadir and Abubakar - I sincerely cherish your support and prayers. My dearest wife Nadiya have been a source of courage for which I extend my affection. My gratitude also goes to the entire Bello and Dankani families. I share with you all the joy and success of this noble work.

Kiel, im Januar 2016 Muhammad Baba Bello

**Abstract**

The identification of the market potentials of organic products is important in the drive towards a sustainable agricultural development in sub-Saharan Africa (SSA). However, available evidence shows that valuing attributes of credence goods (such as organic products) while using stated preference methods faces additional obstacles compared to other normal goods. In this study, consumers' preferences and willingness-to-pay (WTP) for health and environmental attributes of organic products in Nigeria is examined. A framework that jointly analyze the response to the stated choice component and the response to the attribute processing questions, while avoiding the potential endogeneity bias and measurement error problems arising from traditional methods is used. This research has made three broad contributions. First, in order to adequately capture the value of organic products, part of the heterogeneity across respondents is linked to differences in scale by making use of indicators of survey engagement. Second, using a between subject approach, the impact of *ex-ante* hypothetical bias mitigation methods (Cheap Talk and Honesty Priming) on respondents' attribute non-attendance (ANA) is investigated. Finally, sources of heterogeneous preferences (consumer segments) and market potentials for organic products' attributes in Nigeria is identified. The empirical results show that market for organic products exists in Nigeria, with reduction in pesticide residues attribute attracting the highest value, followed by the certification programme. In other words, consumers are willing to pay premium for both health and environmental gains achieved through organic production systems, although their quantitative valuation is higher for the health concerns. Furthermore, it is observed that increases in the latent engagement variable lead to a greater probability of agreement with statements relating to survey understanding and realism, and hence more substantive output. Similarly, incidence of ANA varies across the treatments in general, with significant difference in ANA rates between respondents exposed to the mitigation strategies (HP and CT) and the baseline group. The findings from this study also reveal that the low WTP values for HP task appear to correspond with the lowest ANA rates reported for all the attributes (especially price) and might reflect a more realistic valuation of the attributes. In addition, it is noted that individuals with stronger preferences for organic products tend to attach a global value to the certification program, whereas the valuation tends to be more restrictive among respondents that prioritize the status quo option (conventional alternative). In general, the results

indicated that differences in respondents' geographic location and level of awareness of organic food production characteristics (prior to the survey) have significant impact on consumers' choices.

# Abstrakt

Die Identifizierung der Marktpotenziale von Bio-Produkten ist wichtig im Hinblick auf eine nachhaltige Entwicklung der Landwirtschaft in Afrika südlich der Sahara (SSA). Bisherige Studien zeigen allerdings, dass die Bewertung der Attribute von Vertrauensgütern, wie z.B. Bio-Produkten, mit *Stated-Preference*-Methoden im Vergleich zu anderen normalen Gütern durch zusätzliche Hindernisse erschwert wird. In dieser Studie werden die Präferenzen der Verbraucher und ihre Zahlungsbereitschaft (WTP) für Gesundheits- und Umwelteigenschaften von Bio-Produkten in Nigeria untersucht. Dabei werden unter Vermeidung möglicher Verzerrungen durch Endogenität und Problemen mit Messfehlern, die die Anwendung herkömmlicher Methoden mit sich bringt, die Antwort auf die *Stated-Choice*-Komponente gemeinsam mit der Bewertung der Produktattribute untersucht. Diese Dissertation leistet drei wichtige methodische und inhaltliche Beiträge: Erstens wird, um den Wert von Bio-Produkten adäquat zu erfassen, ein Teil der Heterogenität zwischen den Befragten mit Unterschieden in ihren Aussagen zu Verständnis und Realismus der hypothetischen Kaufentscheidung verknüpft. Zweitens werden die Auswirkungen von hypothetischen Bias Minderungstechniken (*Cheap Talk* und *Honesty Priming*) auf die *Attribute Non-Attendance* (ANA) mit einem *Between-Subject*-Ansatz untersucht. Dies wird durch eine gemeinsame Untersuchung der Antworten auf die *Stated-Choice*-Komponente und die Bewertung der Produktattribute erreicht. Drittens werden die Quellen heterogener Präferenzen (Kundensegmente) und Marktpotenziale für Attribute von Bio-Produkten in Nigeria identifiziert. Die empirischen Ergebnisse zeigen, dass ein Markt für Bio-Produkte in Nigeria existiert. Das Attribut „Verringerung der Pestizidrückstände" hat dabei die größte Bedeutung, gefolgt von dem Zertifizierungsprogramm. Mit anderen Worten: Die Konsumenten besitzen eine Zahlungsbereitschaft für die durch organische Produktionssysteme erreichten Gesundheits- und Umweltgewinne, wobei die Zahlungsbereitschaft für Gesundheit höher ausfällt. Des Weiteren wird beobachtet, dass eine Zunahme der latenten Eingriffsgröße die Wahrscheinlichkeit der Zustimmung zu Aussagen zu Verständnis und Realismus der hypothetischen Kaufentscheidung erhöht. Das Auftreten von ANA variiert zwischen den Gruppen. Signifikante Unterschiede bestehen in den ANA-Raten zwischen Befragten, bei denen eine der Minderungsstrategien (*Cheap Talk* oder *Honesty Priming*) angewendet wurde und der Kontrollgruppe. Die Ergebnisse dieser Arbeit zeigen außerdem, dass die niedrigen

Zahlungsbereitschaften bei Anwendung der *Honesty Priming*-Strategie mit den niedrigsten ANA-Raten, die für alle Attribute (insbesondere Preis) angegeben wurden, korrespondieren. Dadurch wird möglicherweise eine realistischere Bewertung der Attribute erreicht. Darüber hinaus wird gezeigt, dass Personen mit stärkeren Präferenzen für Bio-Produkte dazu tendieren, dem Zertifizierungsprogramm höheren Wert beizumessen, während die Bewertung der Befragten, die den Status quo (konventionelle Alternative) priorisieren, niedriger ausfällt. Ebenso zeigten die Ergebnisse, dass Unterschiede in Region und Wissen über die Produktion von Bio-Lebensmitteln (vor der Erhebung) erhebliche Auswirkungen auf die Entscheidungen der Verbraucher haben.

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# Chapter 1

# Introduction and Summary

## 1.1 Introduction

Food security remains an issue of growing concern in sub-Saharan Africa (SSA), and in the drive to overcome this challenge, the tendency of governments in the region have been to formulate policies and design programmes to draw farmers into high-input technology (UNEP-UNCTAD 2008). As a result of this, the use of agrochemicals is now becoming an obvious part of current agriculture production systems in SSA (Sosan et al. 2008). In Nigeria, for instance, an estimated 125,000 to 130,000 Mt of pesticides are applied annually for agricultural pest control, the highest in West Africa (United Nations 2012).

A wide array of agrochemicals exist, all of which are potentially harmful and have been linked to adverse human health conditions and environmental problems (WHO, 1990). In developed countries, stringent laws and regulations on agrochemical use exists, and adherence is strictly enforced. However, in most SSA countries these laws are either non-existent or ineffective and, environmental pollution and other associated problems seem to continue unabated (Sosan et al. 2008). This situation is particularly true in the context of Nigeria, where the extent of pollution of the agrarian communities (which constitute over 60 percent of the population) by agrochemicals cannot be accurately estimated, as there are neither detailed research on the extent of environmental and health impact nor any effective monitoring process in place.

In light of these uncertainties, scholars and non-governmental organizations (NGOs) in Nigeria have being advocating for organic agriculture (OA) as a sustainable alternative farming system (Philip and Dipeolu 2010). OA is considered as one of the approaches that meet the objectives of sustainable agriculture. It is a holistic production management system that avoids the use of synthetic chemicals, growth hormones, antibiotics and gene manipulation, while promoting improved precise standards of production that are socially and economically sustainable (IFOAM 2012; UNEP-UNCTAD 2008). Like other SSA countries, there are a number of traditional farming systems that practice some organic techniques in Nigeria, however these systems do not fully meet the production standards for organic farming. Organic products are grown under a well-defined and unique set of certification procedures that gives consumers quality assurance and guarantee the products' integrity in the market (IFOAM 2012). According to the United Nations Conference on Trade and Development (UNCTAD) and United Nations Environment Program (UNEP) (2008), OA has the potential to offer a range of local and national sustainable development opportunities for Africa in that it integrates traditional farming methods, uses inexpensive locally available natural resources and has positive economic effects on farmers' productivity and income.

Although the Organic Agriculture initiative was introduced almost a decade ago in Nigeria, certified organic farming remains undeveloped, with very low adoption amongst farmers.[1] Several studies indicate that the potential for the development of certified OA in many African countries is significantly constrained by the general lack of domestic markets and the sole reliance on export (e.g., UNEP-UNCTAD 2008). Similarly, in addition to practicalities of certification, a number of risk factors are evolving as the future development of organic export from developing countries is being evaluated.

[1] Currently, of the 11,987 hectares of land under OA less than 60 hectares are recorded as fully certified organic farms and virtually all the organic products are for export (FAO 2011).

Many supplying countries and farmers of organic produce face huge challenges in entering and benefitting from organic exports in a sustainable way (e.g. Kleeman, Abdulai and Buss 2014; Oelofse, et al. 2010). Few of the identified barriers include: difficulties in creating reliable market links, cases of insecurity due to pirate raids (e.g. in East Africa), rising fuel prices, and the debate on carbon emission and food miles.

It is in this context that the need to diversify and explore domestic markets for organic products is now been considered in Nigeria to complement the international market access (FAO 2011). The availability of domestic market for certified organic products has the potential to open up more opportunities to farmers already in the business, as well as facilitate the adoption by others. Presently, the market features of organic products in the country shows that it is still in the introductory stage and the product attributes are not well familiar to consumers (Philip and Dipeolu 2010). The identification of market potentials of the organic product is important, given that future development of the sector will to a large extent depend on consumers' acceptance and demand. Market potentials for organic products are determined by consumers' preferences for the attributes; as reflected by the price premiums (or discounts) they are willing to pay (Chowdhury et al. 2011).

Discovering the right niche market is a complicated task, since preferences highly vary among consumers (Loureiro and Hine 2002). Studies on consumers' preferences in matured organic markets in Europe and North America are well documented in the literature (e.g. Van Loo et al. 2010). However, little information is available in the context of SSA where the organic markets are basically at early stages of development, or even non-existent. Few studies have investigated preferences for attributes of organic products among urban consumers in SSA and have used hypothetical stated preference (SP) approaches. Specifically, contingent valuation methods (CV) have been predominantly employed (e.g. Coulibaly et al. 2011; Philip and Dipeolu, 2010). Although the results from these studies provide some insight into the valuation of organic products, the underlying assumption of taste homogeneity has limited the validity of the estimated models (Train and Weeks, 2005).

The hypothetical choice experiment (CE) is now the most commonly used method in valuing consumer demand for attributes of nonmarket products (De-Magistris, Gracia and Nayga 2013). Concerns, however, persist that the willingness-to-pay (WTP) values obtained from this nonmarket valuation technique overstate individuals' true values of the good. Hypothetical bias is a well-known shortcoming of the state CE approach. [2] The lack of economic incentive is often suggested as one of the key source of hypothetical bias; given that a good is not actually paid for or delivered in hypothetical settings (Harrison, 2006), hence do not pose the same choice constraints as market experience.

Studies in the CE literature have employed the non-hypothetical choice experiment (RCE), which incorporates both an incentive compatible mechanism and real products. For instance, a number of extant literature have used non-hypothetical choice experiment (RCE) (e.g., Lusk and Schroeder 2004; Chowdhury et al. 2011) to compare results against hypothetical choice experiment (CE). The findings from these studies suggest that WTP values from RCE can be assumed to be the true values corresponding to actual payments in the marketplace.

On the other hand, De-Magistris, Gracia and Nayga (2013) highlight that due to administrative and fiscal reasons it is often difficult or even impossible to conduct a RCE. First, one needs the actual products to be able to properly conduct a RCE. Ideally, this

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[2] Hypothetical bias is described as the difference between values obtained through hypothetical methods (in the absence of product and real economic commitment) and the values obtained through non-hypothetical methods (Harrison 2006).

means that a researcher must possess all the product profiles presented in the choice sets. This can be challenging given that many product concepts that researchers want to test with CE are yet to be available on the market or even fully developed. Second, the RCE can be expensive and time-consuming to implement since subjects have to be paid a participation fee and actual transactions have to be made during the experiment.

In an effort to overcome these difficulties, over the years various authors have identified and proposed alternative mitigation strategies. Broadly, two strategies were developed to attenuate bias in hypothetical settings, namely: (i) an *ex ante* mitigation approach; and (ii) an *ex post* certainty scale calibration approach. The latter allows respondents to express their confidence about WTP with follow-up questions (e.g., Fifer, Rose and Greaves 2014; Moser, Raffaelli and Notaro 2014). However, Ready, Champ and Lawton (2010) reveal that this approach is highly complex in CE having more than two options per choice scenario (as is the case here), thus, the focus in this study is on the *ex-ante* mitigation approach.

Cheap talk script (CT) is a popular *ex-ante* mitigation method introduced by Cummings and Taylor (1999). The cheap talk script aims to increase the respondents' awareness about the presence of hypothetical bias prior to the administration of the valuation question. Although it has been extensively applied in CEs and the broader preference elicitation literature, empirical evidence about its effectiveness is still mixed. Several studies (Cummings and Taylor 1999; Chowdhury et al. 2011) demonstrate its usefulness by finding a lower marginal WTP in the cheap talk version of a survey. Chowdhury et al. (2011) reported for SSA that in the absence of a CT script, hypothetical bias is large, on average, participants overstated their WTP by a factor of more than two in hypothetical scenarios compared with real scenarios. They also reported that while CT mitigates hypothetical bias, it does not eliminate it. According to other studies, the script does not have any effect (List 2001; Brummet, Nayga and Wu 2007), or it actually increases the bias, depending on its context, length, structure, and the payment amount (Aadland and Caplan 2003). Moreover, it seems to work better with respondents who are less familiar with the product attributes being evaluated (List 2001; Lusk 2003). Similarly, augmenting the CT script with a short script on the opt-out option in the choice set has also been reported to reduce WTP estimates (Ladenburg and Olsen 2010). As concluded by Harrison (2006), Chowdhury et al. (2011) and Ladenburg and Olsen (2010), CT scripts seem to reduce the extent of hypothetical bias in many SP studies, even if it is yet to work in all contexts.

Literature in social psychology describes CT script as an explicit priming that could provide persuasive information to make respondents behave in the desired way to reveal their true preferences (Jacquemet et al. 2011). However, Joule, Bernard and Halimi-Falkowicz (2008) argued that persuasive information is a necessary but not sufficient condition to automatically trigger proper behavior; a gap usually exists between ideas and actions. In this case, Jacquemet et al. (2013) proposed a new and alternative *ex ante* technique taken from social psychology known as the “solemn oath” (HO). The authors employed the solemn oath as a truth-telling commitment device by asking bidders to swear on their honor to provide honest answers prior to participating in a second-price auction. The results confirm that the CT script had no effect on triggering sincere bidding, yet that the solemn oath improved the disclosure of true preferences, both in real, as well as hypothetical auctions.

Generally, due to the inconclusive results on the effectiveness of CT and the initial positive results on the use of the HO in reducing hypothetical bias ( e.g., Jacquemet et al. 2011), the approaches based on eliciting honest answers is now becoming an area of further research interest vis-à-vis the CT script. This argument is theoretically premised on the induced value theory (Smith 1976), which states that three conditions must be satisfied to solicit incentive-compatible behavior: monotonicity, salience, and dominance. Among these conditions, the most relevant criticism of hypothetical CE is the lack of the salience condition (De-Magistris, Gracia and Nayga 2013). That is, differences in decision-making exhibited in hypothetical surveys are linked to the notion of salience, and in stated preference context it is closely linked to the concept of incentive compatibility in experiments. A study is said to be incentive-compatible if it is in the best interest of the participant to reveal their true preferences (Moser et al. 2014).

According to De-Magistris, Gracia and Nayga (2013), given that a HO involves participants making a commitment, it is possible that some subjects may be bothered by this "heavy handedness'' or that the oath-taking may not be taken seriously by certain people for a variety of reasons (e.g., cultural background). These authors therefore proposed a new type of *ex ante* approach for eliciting "honest" answers, termed "honesty priming''(HP), in the same spirit as the honesty pledge of Jacquemet et al. (2011). Contrary to CT script, HP is an implicit warning based on Bargh (1990) auto-motive model. In this case, individuals are incidentally exposed to some cues or words related to the concept of honesty via a subliminal priming ''scrambled sentence'' test, these stimuli can activate different goals, thereby influencing subsequent decisions in an unconscious manner (Chartrand et al. 2008).

In recent studies HP have been argued to offer a powerful intervention to improve the validity of self-reported data in many different contexts (e.g., De-Magistris, Gracia and Nayga; Bargh et al. 2001). These priming effects involve cognitive and perceptual changes, such as how well people perform complex tasks, higher-level judgments (and candour) about many kinds of topics, and even the choice of actions or style of action. In general, although there is clear agreement that hypothetical bias exists, there is little consensus on the best mitigation strategy to adopt. Furthermore, while there is an extensive literature that examines the variation in WTP between the *ex-ante* mitigation strategies (e.g., De-Magistris, Gracia and Nayga 2013; Jacquemet et al. 2011), no previous study has provided insight into the mechanism that drive the differences across the hypothetical bias techniques.

Meanwhile a growing body of empirical evidence suggests that accounting for respondents' attribute processing strategy is of significance for both market share prediction and welfare estimates (e.g., Scarpa et al. 2013). In particular, findings show that respondents may follow a large variety of decision rules to simplify otherwise complex decisions (Hensher 2006).[3] Many of these simplified decision rules, or "heuristics," result in non-attendance to certain attributes (ANA). Within the contributions to date, some surveys include self-reported statements on ANA (e.g., Hensher 2006); others infer ANA behavior from the data through advanced model specifications (e.g., Hess and Hensher 2010).

Empirical evidence show that there is no one-to-one correspondence between stated processing strategies and actual (i.e. revealed) processing strategies (e.g. Hess and Hensher 2010). Drawing inference of ANA on observed choice responses represents a valuable alternative and is the focus of many studies (e.g. Hess and Hensher 2013; Scarpa et al. 2013). The motivation for steering clear of stated attribute processing strategies during model estimation is guided by three main reasons. First, there are arguably issues with endogeneity; that is, by conditioning the modeled choice process on

[3] There is accumulating evidence showing that in a multi-attribute context of choice the mere fact that information on attributes of choice alternatives is provided to survey respondents at the moment of choice is no guarantee that each single attribute is attended to by each respondent.

stated processing strategies, a correlation between respondent reported processing strategies and other unobserved components could lead to biased parameter estimates (Hess and Hensher 2013). Second, collecting additional data on stated non-attendance complicates survey design and lengthens survey duration and hence cost. Finally, such statements might be affected by respondent inaccuracies (measurement error) in perception and recall, and eventually be both uninformative and invalid (Scarpa et al. 2013).

Hess and Hensher (2013) however argued that the respondent reported data on processing strategies may still contain valuable information, but that such data should not be used deterministically as an error free measure of ANA. Rather, one should recognize that such data are simply a function of respondent-specific perceived attribute importance. In this respect, Hess and Hensher (2013) proposed a hybrid model framework which still allows the use of respondent reported information on processing strategies, while avoiding the risks arising from traditional methods. In particular, respondents' answers to information processing questions are treated as dependent rather than explanatory variables, that way preventing risks of endogeneity bias as well as avoiding the use of the answers as error free explanatory variables.[4]

In this thesis, recent survey data from Nigeria on consumers' preferences for organic products is used to investigate the impact of *ex-ante* hypothetical bias mitigation methods: CT (explicit approach) and HP (implicit approach), on respondents' attribute processing strategy (ANA) as well as to test whether there exist a statistically significant difference in welfare value estimates obtained from these different techniques in the

[4] The approach used here has similar aims to the work of Hensher (2008); Hole (2011) and Collins (2012) in that it aims to jointly model process and outcome, but in this study we used latent variables in the estimation.

context of SSA. Specifically, hybrid model framework is employed to explicitly address the potential endogeneity bias that may arise from correlation between respondent processing strategies and other unobservable components in ANA treatments, while exploring the effect of priming tasks on delivering WTP values for organic product attributes.[5]

Although few authors also recognized the limits of studies that deterministically handle stated ANA information. To overcome the potential endogeneity problem and yet still exploit stated ANA, some studies have employed sequential estimation (Hensher et al., 2007), while others have used the latent class (LC) structures (e.g., Hole, Kolstad and Gyrd-Hansen 2013; Collins 2012). Hensher, Rose and Bertoia (2007) proposed a two-stage estimation procedure that allows stated ANA to be handled stochastically rather than deterministically. First, a choice model was estimated, wherein the choices were the combinations of stated nonattendance across the attributes, as elicited from the respondent. The utility expressions were specified as a function of age, income, and the attribute levels of the choice tasks. The expected maximum utility (EMU) was calculated for each respondent, and sequentially introduced into a second model, where the choice alternatives were the alternatives of the choice task. Significant interactions were found between the EMU and the mean of two of the attributes. Model fit improved and the WTP increased once ANA was accounted for, where the difference in both the mean and

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[5] There are emerging views that the consideration of alternative behavioural paradigms on how respondents process attributes in a choice making context may well add greater value to the understanding of decision making than the advances made in sophisticated econometric choice models, however the combination of both may well deliver the best outcome (Hess and Hensher 2013). The contributions of this study to literature falls in this area.

variance of the measure was found to be significant. Whilst this approach does not assume that stated ANA is completely accurate, it is still reliant on sequential estimation.

A latent class approach is another analytical method that additionally leverages stated ANA responses. One analytical method that has gained traction in the literature as a way of inferring ANA is a variant of the LC model, which involves the censoring of taste coefficients to zero in certain classes. Here, a series of LC models, each of which tested for nonattendance to one of the attributes in the choice tasks is estimated (e.g., Hess and Rose 2007; Scarpa et al. 2009). Two classes are specified, and crucially, in one class, the taste coefficient for one of the attributes is constrained to zero, to represent nonattendance to the attribute. However, the shortcoming of this approach is that if all combinations of ANA across the attributes are to be modeled, then the number of parameters required for ANA assignment increases exponentially as attributes increases.

To this end, Hole (2011) proposed an alternative and more parsimonious approach for generating the final ANA assignment probabilities, called an 'endogenous attribute attendance' (EAA) model. Whereas the conventional approach estimates a single MNL model which generates the probability of each combination of ANA across the attributes, the EAA approach estimates a binary logit model for each of the attributes, and generates the probability of whether a single attribute is attended to or not. In its simplest form, each binary logit model contains a constant only, and thus the class assignment component of the model requires only as many parameters as there are attributes for which ANA is to be modeled. The final ANA assignment probability for each ANA combination is then the product of ANA assignment probabilities, each obtained from the binary logit models.

The EAA model is however limited by the homogeneous preference assumption, in which respondents who attend to an attribute are assumed to have identical preference for that attribute.[6] Hole, Kolstad and Gyrd-Hansen (2013) extended the EAA model by relaxing the homogeneity assumption, allowing for the utility parameters to vary across respondents. Thus termed mixed EAA (MEAA) model. The authors found that the MEAA models which controls for both non-attendance and preference heterogeneity outperforms the EAA models in terms of goodness of fit, and also have lower estimated ANA probabilities.[7] This may imply that respondents with low preferences are incorrectly classified as 'non-attenders' in the EAA model. Overall, they observed that the EAA and MEAA models outperform the standard logit and MMNL models.

The drawback of the EAA and MEAA specifications however, is that it is necessary to assume that the non-attendance probabilities are independent across attributes. Collins (2012), proposed a form of LC-MMNL model, termed random parameter ANA (RPANA) that relax this assumption. In particular, the model combines the LC approach for capturing ANA with the use of random parameters for representing preference heterogeneity, conditional on attendance to an attribute. Although, Collins' model is similar in construction and intent to MEAA and the LC-MMNL model implemented by Hess et al. (2013), however, RPANA do not completely rely on the assumption of independence of ANA across attributes, like the former models. The RPANA model may be specified in a parsimonious way, but unlike comparable models, this parsimony can

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[6] Hole (2011) noted that an extension to include random parameters would be "conceptually straightforward (but computationally intensive)".

[7] Hensher, Rose and Greene (2012) reported a marginal improvement in model fit with the introduction of random parameters to the fixed parameter LC-ANA model, due to confoundment between ANA and preference heterogeneity.

be eroded in a granular fashion, if the assumptions on which the parsimonious specification relies do not hold.[8] The motivation for such a model comes from the possibility that ANA is not independent across any attributes, and that failure to capture such correlation will likely be detrimental to model fit and the model outputs.[9] Nonetheless, Collins (2012) acknowledged that as currently formulated, the RPANA model cannot always handle ANA that vary across attributes, as it is found that the model is potentially susceptible to a number of identification problems, especially when choosing distributions. Likewise, estimating the model over all attributes may be very slow, and unstable, due to low incidence rates for some combinations of ANA. In fact, Hess et al. (2013) also reported stability problems with the random specification, which they abandoned for the independent form.[10]

All of the LC models discussed thus far treat the probability of ANA as being the same across respondents. To relax this assumption, these studies (e.g., Collins 2012;

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[8] There are currently two approaches to the specification of the latent classes in the LC approach to handling ANA. The most common approach estimates one parameter for every combination of ANA across the attributes, and so the number of parameters required increases exponentially as the number of attributes increases. Hole (2011) proposed an alternative approach, wherein the number of parameters required rises linearly, although this relies on the assumption that ANA is independent between all attributes. The proposed RPANA model allows for various specifications between these two extremes.

[9] In our dataset, evidence from the independence test as suggested by Collins (2012) shows that this is not the case.

[10] It is important to point out that unless this assumption is made the estimation problem becomes impractical, especially when including stated ANA in the model and allowing for preference heterogeneity. Also, in addition to slow specification search, the computational complexity of the model may make it outright infeasible, if the number of attributes is very large.

Hole, Kolstad and Gyrd-Hansen 2013) have handled the respondent-reported ANA information as covariates. Hole, Kolstad and Gyrd-Hansen (2013) included stated ANA as covariates in the binary logit models controlling the inferred ANA rate, thus allowing stated ANA to be handled probabilistically. While including stated ANA further improves the fit of these models, first, they found that self-reported non-attenders have a positive probability of attending to an attribute, suggesting some misreporting in the data. Second, they acknowledge that incorporating stated ANA dummies in the models may be problematic if these variables are endogenous. Furthermore, despite the fact that RPANA model is well placed to leverage the stated ANA information, and handle it probabilistically, whilst also capturing preference heterogeneity. However, the approach may still suffer from a problem of endogeneity.

Overall, it is worth noting that the hybrid choice models employed in this thesis are a generalization of standard discrete choice models where independent expanded models are considered simultaneously. Specifically, the model extension that accommodates a discrete choice kernel with latent explanatory variables is of particular interest. The empirical applications are consistent with the re-emerged trend in discrete choice modeling toward incorporating attitudinal factors into the behavioral representation of the decision process. Hybrid model represent integrated choice with latent variables that is written as a simultaneous system of structural equation models, where the latent variables are mapped using effect and causal indicators. Thus, offering an attractive improvement in modeling choice behavior, because choice model components form only a part of the underlying behavioral process, while incorporating individuals' attitudes and perceptions yield a more realistic econometric model. Moreover, the introduction of attitudes into a structural model of choice is supported by numerous theories in social psychology and cognitive science. Hence, if we omit the role of attitudes, which is the case in standard economic preference models, we may face problems related to endogeneity.

Furthermore, beside the methodological implications, this study has interesting applied contributions. The hybrid modeling approach is promising for studying behavioral intentions in choice situations where qualitative attributes or consumers' attitudes play major roles. Among these choice situations we can envision consumer response to new products, in this case certified organic products in SSA. Given that the adoption of new products depends not only on observable attributes but also on behavioral intentions, perceptions, attitudes and knowledge. Thus, when new products are developed it is important to forecast consumers' reactions in terms of purchase behavior not only for marketing plans aimed at introducing the new product in the market but also for policymaking.

In this thesis, therefore consumer preferences toward attributes of organic products are analyzed. The relevance of the choice situation employed comes from understanding the effects capacity of consumers' health and environmental concerns could have in redressing the failure of market to provide public goods. Using a hybrid choice model to explain purchase intentions by Nigerian consumers, this research shows that environmentally-conscious consumers are willing to pay for organic product attributes. Whereas standard demand models might have some challenges consistently representing ecofriendly behavior, the hybrid choice model is capable of modeling the consequent change in consumer behavior motivated by concerns for both health risk and environmental externalities of agricultural production.

In the following section, each chapter of this thesis is summarized, drawing attention to the methodological procedures employed as well as the empirical contributions.

## 1.2 Summary

### 1.2.1 Impact of Ex-Ante Hypothetical Bias Mitigation Methods on Attribute Non-Attendance in Choice Experiments

Progress has been made in developing techniques to estimate values of nonmarket goods through stated hypothetical CE. Concerns however persist that the monetary values obtained from such nonmarket valuation techniques overstate individuals' true values of the good. Hypothetical bias is a known drawback of CE approach, and studies have focused on the development of different *ex-ante* mitigation strategies; namely cheap talk script, which is considered an explicit approach, and honesty priming, an implicit technique. While there is an extensive literature that examines the variation in WTP between the *ex-ante* mitigation strategies (e.g., De-Magistris, Gracia and Nayga 2013; Jacquemet et al. 2011), no previous study has provided insight into the mechanism that drive the differences across the hypothetical bias techniques. Meanwhile a growing body of empirical evidence suggests that accounting for respondent's attribute processing strategy is of significance for both market share prediction and welfare estimates (e.g., Scarpa et al. 2013).

In this chapter, survey data from Nigeria on consumers' preferences for organic products is used to investigate the impact of *ex-ante* calibration methods (Cheap Talk and Honesty Priming) on respondents' attribute non-attendance (ANA). A framework that allows joint estimation of the response to the stated choice component and the response to the attribute processing questions, while avoiding the potential endogeneity bias and measurement error problems is employed. Using between-sample design, welfare estimates from respondents under cheap talk and honesty priming treatments are compared. Similarly, consistency between individual's observe behaviour in the stated choice components and respondent's provided information on attribute non-attendance and attribute ranking is investigated.

This study contributes to the literature by linking ANA to differences in the *ex-ante* hypothetical bias mitigation approaches, and by examining respondents' valuation of both environment- (public) and health-related (private) attributes of organic food products. This information is especially relevant to producers in identifying target markets and product pricing, particularly in SSA. Moreover, this work differs from previous studies on *ex-ante* mitigation of hypothetical bias (e.g., De-Magistris, Gracia and Nayga 2013; Jacquemet et al. 2011) in that in addition to observed choice responses, respondents' attribute processing strategies is also taken into account. Thus, providing additional behavioral insight as well as highlighting the implications of the use of respondents' adaptive decision strategies within the choice modeling structure.

### 1.2.2 Measuring Heterogeneity, Survey Engagement and Response Quality in Preferences for Organic Products in Nigeria

Over the last decade, a number of studies have focused on the nonmarket valuation of organic products' attributes. However, examining credence goods such as organic products' attributes is particularly challenging because many respondents are not well familiar with these attributes. Therefore, modeling solely the taste heterogeneity among respondents in a choice experiment, as has been done so far, might not be sufficient. In addition to investigating scale variation, accounting for preference heterogeneity in the response behavior is quite essential. On the other hand, approaches adopted in studies that model scale heterogeneity place emphasis on a deterministic treatment, relying erroneously on proxies as direct measure of individual's latent survey engagement that leads to scale differences.

In this chapter, recent household survey data from Nigeria is used to examine consumers' preferences and WTP for attributes of organic products, accounting for both scale and preference heterogeneity. A modeling approach is employed where data on both respondent-reported measures and analyst captured proxies for survey engagement are jointly modeled with respondent's answers to the stated choice questions, thus linking part of the heterogeneity to differences in scale without the risks encountered with traditional methods. Similarly, differences in survey engagement and the resulting scale heterogeneity is linked to the *ex ante* mitigation strategies used, as well as measured characteristics of the respondents. The approach in this chapter is appropriate to adequately capture the value of organic products, in that it considers heterogeneity in taste, differences in degree of choice determinism (i.e., scale heterogeneity), as well as the mitigation of hypothetical bias. This work continues an older tradition in the literature of understanding how consumers evaluate unfamiliar goods (e.g., Nelson 1970).

### 1.2.3 Identification of Consumer Segments and Market Potentials for Organic Products in Nigeria: A Hybrid Latent Class Approach

There is a growing interest in the potential of organic agriculture (OA) to correct environmental externalities in sub-Saharan Africa (SSA). However, presently, the market features of organic products in various parts of SSA reveal that it is still in the introductory stage and many consumers are unfamiliar with the concept of certified OA (e.g., Philip and Dipeolu 2010). Hence, the identification of market potentials of the organic product is important for the future development of the sector.

Discovering the right niche market is complicated task since preferences highly vary among consumers. Available empirical evidence indicate that preferences are indirectly affected by attitudes through the latent class to which the consumer belongs, and as such attitudinal data are quite important in explaining choice behavior (Swait 1994). Several studies making use of answers to attitudinal statements often directly incorporate the individual's responses as explanatory variables in the utility specification. However, proponents of hybrid latent class (HLC) approach (e.g., Ben-Akiva et al. 1999) query whether responses to attitudinal statements should be included directly as error free explanatory variables in a model. The authors argue that respondents' answers are mainly indicators of true underlying latent attitudes, hence incorporating these responses directly to a model could potentially lead to measurement error and endogeneity bias problems.

In this chapter, HLC model is used to investigate the sources of heterogeneity in preferences across classes of consumers and to estimate class-specific WTP values for the identified organic attributes. This model framework allows a joint examination of the response to the stated choice component as well as the response to the attitudinal questions, while avoiding the risks that arise from traditional methods. In this case, all sources of heterogeneity, including socioeconomic and attitudinal data are consistently incorporated. To the extent that the markets for organic products have shown potentials for growth, this study is designed to provide a better understanding of heterogeneous consumers' preferences for organic products in SSA and to derive implications for future development of the sector. Different market segments (classes) are identified based on consumers' socioeconomic and attitudinal data, as well as on observed choice behavior and product characteristics, potentially making the classes more directly relevant to management decision-making (e.g., Bechtold and Abdulai 2014).

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## Chapter 2

# Impact of Ex-Ante Hypothetical Bias Mitigation Methods on Attribute Non-Attendance in Choice Experiments

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published online 18/02/2016 in *American Journal of Agricultural Economics*
http://ajae.oxfordjournals.org/content/early/2016/02/17/ajae.aav098.short?rss=1

Abstract

In this article, we use survey data from Nigeria on consumers' preferences for organic products to investigate the impact of *ex-ante* hypothetical bias mitigation methods (Cheap Talk and Honesty Priming) on respondents' attribute non-attendance (ANA). We employ a framework that allows us to jointly examine the response to the stated choice component and the response to the attribute processing questions, while avoiding the potential endogeneity bias and measurement error problems arising from some ANA methods. Our results show that the incidence of ANA varies across the treatments in general, with significant difference in ANA rates between respondents exposed to the mitigation strategies (HP and CT) and the baseline group. We also find that the low WTP values for HP task appear to correspond with the lowest ANA rates reported for all the attributes (especially price) and might reflect a more realistic valuation of the attributes.

**JEL code:** C18, C25, D12

**Keywords** organic products, cheap talk, honesty priming, attribute non-attendance, hybrid model

## 2.1 Introduction

Food security remains an issue of growing concern in sub-Saharan Africa (SSA), and in the drive to overcome this challenge, the tendency of governments in the region have been to formulate policies and design programmes to draw farmers into high-input technology (UNEP-UNCTAD 2008). As a result of this, the use of agrochemicals is now becoming an obvious part of current agriculture production systems in SSA (Sosan et al. 2008). In Nigeria, for instance, an estimated 125,000 to 130,000 metric tons of pesticides are applied annually for agricultural pest control, the highest in West Africa (United Nations 2012).

A wide array of agrochemicals exist, all of which are potentially harmful and have been linked to adverse human health conditions and environmental problems (WHO 1990). In many SSA countries, stringent laws and regulations on agrochemical use are either non-existent or ineffective and, environmental pollution and other associated problems seem to continue unabated (Sosan et al. 2008). In light of these uncertainties, scholars and non-governmental organizations (NGOs) in Nigeria have being advocating for organic agriculture (OA) as a sustainable alternative farming system (Philip and Dipeolu 2010).

Although the Organic Agriculture initiative was introduced almost a decade ago in Nigeria, certified organic farming remains undeveloped. Some recent studies suggest that many supplying countries and farmers of organic produce face huge challenges in entering and benefitting from organic exports in a sustainable way (e.g. Kleeman, Abdulai and Buss 2014). It is in this context that the need to diversify and explore domestic markets for organic products is now being considered in Nigeria to complement the international market access (FAO 2011). The identification of market potentials of the organic product is important, given that future development of the sector will to a large extent depend on consumers' acceptance and demand. Market potentials for organic products are determined by consumers' preferences for the attributes; as reflected by the price premiums (or discounts) they are willing to pay (Chowdhury et al. 2011).

Studies on consumers' preferences in matured organic markets in Europe and North America are well documented in the literature (e.g., Van Loo et al. 2010). However, little information is available in the context of SSA where markets for organic products are basically at early stages of development. Few studies have investigated preferences for attributes of organic products among urban consumers in SSA and have used hypothetical stated preference (SP) techniques. In particular, contingent valuation methods (CV) have been predominantly employed (e.g., Coulibaly et al. 2011; Philip and Dipeolu 2010). Although the results from these researches provide some insight into the valuation of organic products, the underlying assumption of taste homogeneity has limited the validity of the estimated models (Train and Weeks 2005).

The hypothetical choice experiment (CE) is the most widely used method in valuing consumer demand for attributes of products that are yet to be available in the market place (de-Magistris, Gracia and Nayga 2013). Concerns, however, persist that the willingness-to-pay (WTP) values obtained from this nonmarket valuation technique overstate individuals' true values of the good (Harrison 2006). Hypothetical bias is a known drawback of CE approach, and studies have focused on the development of different *ex-ante* mitigation strategies.[11] For example, de-Magistris, Gracia and Nayga

[11] Broadly, two strategies have been developed to attenuate bias in hypothetical settings, namely: (i) an *ex ante* mitigation approach; and (ii) an *ex post* certainty scale calibration

(2013) proposed a new type of *ex ante* hypothetical bias mitigation approach termed "honesty priming'' (HP), along the same line as Jacquemet et al. (2011). Specifically, the authors compare the effect of a cheap talk script (CT) (Cumming and Taylor 1999) and HP on consumer's WTP for sustainability-related labels (''organic'' and ''food miles'') under hypothetical and non-hypothetical CE. While there is an extensive literature that examines the variation in WTP between the *ex-ante* mitigation strategies (e.g., de-Magistris, Gracia and Nayga 2013; Jacquemet et al. 2011), no previous study has provided insight into the mechanism that drive the differences across the hypothetical bias techniques.

Meanwhile a growing body of empirical evidence suggests that accounting for respondent's attribute processing strategy is of significance for both market share prediction and welfare estimates (e.g., Scarpa et al. 2013). In particular, findings show that respondents may follow a large variety of decision rules to simplify otherwise complex decisions (Hensher 2006). Many of these simplified decision rules, or "heuristics," result in non-attendance to certain attributes (ANA). Within the contributions to date, some surveys include self-reported statements on ANA (e.g., Hensher 2006); others infer ANA behavior from the data through advanced model specifications (e.g., Hess and Hensher 2010). Drawing inference on ANA from observed choice responses represents a valuable alternative and is the focus of many studies (e.g.,

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approach. The latter allows respondents to express their confidence about WTP with follow-up questions (e.g., Fifer, Rose and Greaves 2014). However, Ready, Champ and Lawton (2010) reveal that this approach is highly complex in CEs having more than two options per choice scenario; which is the case in our study. Thus, the focus in this article is on the *ex-ante* mitigation approach.

Hess and Hensher 2013; Scarpa et al. 2013). However, issues relating to potential endogeneity (e.g., Hensher, Rose and Bertoia 2007), measurement errors and survey costs (e.g., Scarpa et al. 2013) have been raised as shortcomings of approaches that condition the modeled choice process on stated ANA.

Hess and Hensher (2013), however argue that the respondent reported data may still contain valuable information, but that such data should not be used deterministically as an error free measure of ANA. In this spirit, they propose a hybrid model framework that still allows the use of respondent reported information on processing strategies, while avoiding the risks arising from traditional methods.

To overcome the potential endogeneity problem and yet still exploit stated ANA, some studies have employed sequential estimation (e.g., Hensher, Rose and Bertoia 2007), while others have used the latent class (LC) structures (e.g., Hole, Kolstad and Gyrd-Hansen 2013; Collins, 2012). Hensher, Rose and Bertoia (2007) proposed a two-stage estimation procedure that allows stated ANA to be handled stochastically rather than deterministically. Whilst this approach does not assume that stated ANA is completely accurate, it still relies on sequential estimation.

A latent class approach is another analytical method that additionally leverages stated ANA responses. The most common LC approach estimates one parameter for every combination of ANA across the attributes, and so the number of parameters required increases exponentially as the number of attributes increases (e.g., Hess and Rose 2007; Scarpa et al. 2009). On the other hand, Hole (2011) proposes an alternative and more parsimonious LC approach called an 'endogenous attribute attendance' (EAA) model, wherein the number of parameters required rises linearly, but homogeneous preference is assumed. Hole, Kolstad and Gyrd-Hansen (2013) extended the EAA model by relaxing the homogeneity assumption, allowing for the utility parameters $\beta$, to vary across respondents, resulting in a mixed EAA (MEAA) model. [12]

In this article, we use recent survey data on consumers' preferences for organic products in Nigeria to investigate the impact of *ex-ante* hypothetical bias mitigation methods: CT (explicit approach) and HP (implicit approach), on respondents' attribute processing strategies (ANA). We also test whether there exists a statistically significant difference in welfare value estimates obtained from these different techniques in the context of SSA. We employ the hybrid model framework to account for the potential endogeneity bias that may arise from correlation between respondent processing strategies and other unobservable components in ANA treatments, while exploring the effect of priming tasks on delivering WTP values for organic product attributes. Our study contributes to the literature by linking ANA to differences in the *ex-ante* hypothetical bias mitigation approaches, and by examining respondents' valuation of both environment- (public) and health-related (private) attributes of organic food products. This information is especially relevant to producers in identifying target markets and product pricing, particularly in SSA. Our work differs from previous studies on *ex-ante* mitigation of hypothetical bias (e.g., de-Magistris, Gracia and Nayga 2013; Jacquemet et al. 2011) in that in addition to observed choice responses, we also take into account respondents' attribute processing strategies. Thus, providing additional

[12] The authors found that the MEAA models which control for both non-attendance and preference heterogeneity outperforms the EAA models in terms of goodness of fit, and also have lower estimated ANA probabilities, implying that respondents with low preferences are incorrectly classified as 'non-attenders' in the EAA model.

behavioral insight as well as highlighting the implications of the use of respondents' adaptive decision strategies within the choice modeling structure.

## 2.2 Econometric Framework

The approach employed in this study follows the model proposed by Hess and Hensher (2013). In a standard specification of random utility model, $U_{int} = V_{int} + \varepsilon_{int}$, the deterministic component of the utility is given by a function of observed attributes $x$ and estimated taste parameters $\beta$, i.e $V_{int}(\beta) = h(x_{int}, \beta)$, where typically, a linear in parameters specification is employed.

The Mixed Multinomial Logit (MMNL) model, with random variations across respondents in $\beta$, and a type I extreme value distribution for the error term $\varepsilon$, is specified as:

$$P_{int}(\Omega) = \int_{\beta} P_{int}(\beta) f(\beta|\Omega) d\beta = \int_{\beta} \frac{e^{V_{int}(\beta)}}{\sum_{j=1}^{J} e^{V_{jnt}(\beta)}} f(\beta|\Omega) d\beta \qquad (1)$$

where $\beta \sim f(\beta|\Omega)$, with $\Omega$ representing a vector of parameters to be computed. We used repeated choice data, under an assumption of intra-respondent homogeneity, such that the likelihood of the actual observed sequence of choices for respondent $n$ is then expressed as:

$$L_n(\Omega) = \int_{\beta} \left[ \prod_{t=1}^{T} P_{i^*nt}(\beta) \right] f(\beta|\Omega) d\beta, \qquad (2)$$

where $i^*nt$ refers to the alternative chosen by respondent $n$ in choice scenario $t$.

As part of the survey, in addition to choice data, we captured answers to questions relating to information processing strategies. Specifically, with $K$ different attributes (and hence $K$ different associated $\beta$ parameters), we elicit data on respondents' stated ANA for each of these attributes, say $NA_{nk}, k = 1, \ldots\ldots, K$, where $NA_{nk}$ is equal to 1, if respondent $n$ states that he/she ignored attribute $x_k$ in making choices, while $A_{nk}$ equal to 1 if respondent $n$ attend to $x_k$. Therefore, let us further define $A_{nk} = 1 - NA_{nk} \; \forall \; k$ as answers to respondents' attribute attendance.

In a simplistic modeling approach, answers to questions relating to information processing strategies would normally be used as explanatory variables, where $\beta_k$ would be replaced by $A_{nk}\beta_k$. This implies that the parameter $\beta_k$ is set to zero for respondents that report ignoring attribute $x_k$. However, some studies have suggested that stated attribute non-attendance may simply equate to lower sensitivity (e.g., Campbell and Lorimer 2009; Hess and Hensher 2010), and rather than imposing a zero coefficient value for such respondents, separate coefficients are estimated, whereby $\beta_k$ is replaced by $NA_{nk}\beta_{k,na} + A\beta_{k,a}$. In this framework, $\beta_{k,a}$ is used to denote respondents who stated that they attended to attribute $k$, while $\beta_{k,na}$ is used for the remaining respondents. According to Hess and Hensher (2013), while this second approach departs from the assumption of absolute correctness of the stated non-attendance data, potential endogeneity is still an issue. Specifically, there is likely to be correlation between the respondent reported processing strategies and other factors not controlled for in the deterministic part of utility, resulting in potential correlation between $V_{int}$ and $\varepsilon_{int}$.

To account for this potential endogeneity problem, we follow the approach by Hess and Hensher (2013). First, we treat answers to information processing as dependent variables that are a function of the true underlying latent processing strategies. Second, we focus on the notion of attribute importance, hypothesizing that for every attribute $k$, each respondent has an underlying rating of attribute importance.[13] This attribute importance rating is unobserved, and is thus given by a latent variable $\alpha_{nk}$ for respondent $n$, with:

$$\alpha_{nk} = \varphi_k z_n + \eta_{nk} \ , \qquad (3)$$

where $z_n$ represents characteristics of the respondent, and $\eta_{nk}$ a random term assumed to follow a standard normal distribution across respondents and across the $K$ different attributes. The vector $\varphi_k$ explains the effect of $z_n$ on $\alpha_{nk}$. Also, for identification reasons, we constrained the variance of the random component in $\alpha_{nk}$. Third, we hypothesize that the answers to the attribute non-attendance questions can be modeled as a function of these latent variables. In particular, we employ a binary logit specification, in which conditional on a given value for the latent variable $\alpha_{nk}$, the probability of the actually observed value for $NA_{nk}$ is modeled as:

$$L_{NA_{nk}}(\kappa_k, \zeta_k | \ \alpha_{nk}) = \frac{NA_{nk} e^{\kappa_k + \zeta_k \alpha_{nk}} \ + \ A_{nk}}{1 + \ e^{\kappa_k + \zeta_k \alpha_{nk}}} \ , \qquad (4)$$

where $\kappa_k$ and $\zeta_k$ are parameters to be determined, capturing the mean value of $NA_{nk}$ in the sample population, and the impact of the latent variable ( $\alpha_{nk}$) on the probability of stated non-attendance, respectively. We then group the various latent variables together in $\alpha_n = < \alpha_{n1}, \dots., \alpha_{nk} >$, with the same definition for $\kappa$ and $\zeta$. With K different indicators, Equation 6 can be re-specified as:

$$L_{NA_n}(\kappa, \zeta | \alpha_n) = \prod_{k=1}^{K} \frac{NA_{nk} e^{\kappa_k + \zeta_k \alpha_{nk}} \ + \ A_{nk}}{1 + \ e^{\kappa_k + \zeta_k \alpha_{nk}}} \ . \qquad (5)$$

Beside adopting the latent variables to explain the answers to the non-attendance questions, we also use them as shrinkage factors inside the choice model component of the hybrid model, thus allowing for a continuous measure of importance (instead of a simple discrete complete attendance/non-attendance approach). In other words, we

13 It should be emphasized here that this is somehow different from a marginal sensitivity, as it does not relate to the actual value of the attribute in question.

employ the latent variable scaling approach, by scaling the coefficient of the latent variable rather than setting the estimate to zero at a certain threshold. Specifically, we replace the parameter $\beta_k$ by $e^{\lambda_k \alpha_{nk}} \beta_k$, by computing the attribute-specific scaling parameters $\lambda = < \lambda_1, \ldots, \lambda_K >$. To capture heterogeneity, we use two separate components, $\alpha_{nk}$ and $\beta_k$, to permit for the absence of a strict relationship between attribute importance and marginal sensitivities, thus capturing any unrelated random heterogeneity in $\beta_k$. Conditional on given values of $\alpha_n$ and $\beta$, and assuming linearity in attribute specification, the probability that respondent $n$ chooses alternative $i$, in choice situation $t$ is given as:

$$P_{int}(\beta, \lambda | \alpha_n) = \frac{e^{\sum_{k=1}^{K} e^{(\lambda_k \alpha_{nk})} \beta_k x_{k,int}}}{\sum_{j=1}^{J} e^{\sum_{k=1}^{K} e^{(\lambda_k \alpha_{nk})} \beta_k x_{k,jnt}}}, \qquad (6)$$

where $x_{k,int}$ is the $k$th component in $x_{int}$. Here, a positive estimate for $\lambda_k$ indicates that as the importance rating ($\alpha_{nk}$) rises in value, so does the marginal sensitivity to attribute $x_k$.

Equation 5 is dependent on a given value of $\alpha_n$, while Equation 6 is dependent on given values of $\beta$ and $\alpha_n$. Given that both are random components; an integral of the conditional probability in Equation 6 over all their possible values is required. Thus, we estimate the combined likelihood for respondent $n$, which relates to the stated choice component as well as the answers to the non-attendance questions. This is specified as a product of $T$ discrete choice probabilities:

$$L_n(\Omega, \lambda, \kappa, \zeta, \varphi) = \int_{\beta} \int_{\alpha_n} \left[ \prod_{t=1}^{T} P_{i^*nt}(\beta, \lambda | \alpha_n) \right] L_{NA_n}(\kappa, \zeta | \alpha_n) f(\beta | \Omega) \mathrm{g}(\alpha_n | \varphi, z_n) \mathrm{d}\beta \mathrm{d}\alpha_n, \qquad (7)$$

where $\alpha_n$ follows a $K$-dimensional normal distribution with an identity matrix used for the covariance matrix, and with the mean for $\alpha_{nk}$ being given by $\varphi z_n$. The maximization of the log-likelihood ($LL$), $\sum_{n=1}^{N} \ln(L_n(\Omega, \lambda, \kappa, \zeta, \varphi))$, for the hybrid model across the $N$ respondents entails the estimation of the component parameters.

We also collected information from respondents on attribute rankings. Let the mutually exclusive rankings for the $K$ attributes be given by $R_k$, $k = 1, \ldots, K$, where $1 \leq R_k \leq K, \forall\, k$. We make use of a rank exploded MNL model, by specifying:

$$\gamma_{nk} = \varsigma_k + \tau_k \alpha_{nk}, \forall k, \tag{8}$$

where we set $\varsigma_1 = 0$ for normalization purposes. The conditional probability is then given as:

$$v_{nr} = \sum_{k=1}^{K} \delta_{(R_{k,r})} \gamma_{nk}, r = 1, \ldots., K, \tag{9}$$

where $\delta_{(R_{k,r})}$ is equal to 1, if $R_k = r$, that is, if attribute $k$ has ranking $r$, and 0 otherwise. With $\varsigma$ and $\tau$ grouping together the individual elements $\varsigma_k$ and $\tau_k \forall k$ , respectively, the probability for the response to the ranking question is specified as:

$$L_{Rn}(\varsigma, \tau, \alpha_n) = \prod_{r=1}^{K-1} \frac{e^{v_{nr}}}{\sum_{s=r}^{K} e^{v_{ns}}}, \tag{10}$$

Thus, the values of the attribute ranking from Equation 10 is also jointly modelled with values of non-attendance $L_{NA_n}(\kappa, \zeta | \alpha_n)$ and the likelihood of the observed sequence of choices $P_{int}(\beta, \lambda | \alpha_n)$ from Equation 7. The $LL$ function for the hybrid model integrates the choice models with the measurement (latent variable) models. Equation 7 can then be rewritten as:

$$L_n(\Omega, \lambda, \kappa, \zeta, \varphi, \varsigma, \tau)$$

$$= \int_{\beta} \int_{\alpha_n} \left[ \prod_{t=1}^{T} P_{int}(\beta, \lambda | \alpha_n) \right] L_{NA_n(\kappa, \zeta | \alpha_n)}\, L_{R_n}\, (\varsigma, \tau | \alpha_n) f(\beta | \Omega) \mathrm{g}(\alpha_n | \varphi, z_n) \mathrm{d}\beta\, \mathrm{d}\alpha_n, \tag{11}$$

In comparison with Equation 7, we now need to estimate the two vectors, $\varsigma$ and $\tau$, from the attribute rankings in Equation 10.

It is worth noting that in Equation 6 in the choice model component, the five $\lambda$ parameters primarily play the role of attribute-specific scale parameters. Increases in the magnitude for the marginal utility of attribute $k$ can be captured in either the random distribution of $\beta_k$, or the scaling term, $e^{\lambda_k \alpha_n}$. The latent variable component which is interacted with $\lambda_k$ in the utility function is also used inside the additional component to model the response to the attribute non-attendance questions. This approach allows for the two components, $\lambda$ and $\beta$, to both be identified, thus addressing the limitations of the GMNL model highlighted by Hess and Rose (2012).

### 2.3 Survey Design and Data Description

Market data for sales of organic products are unavailable in Nigeria. We therefore, elicit primary data on consumer preferences using hypothetical CE. The data were drawn from a household survey conducted between July and October, 2013 in Kano State which lies in the North West geopolitical zone of Nigeria. The location occupies a strategic economic position as a commercial nerve centre and second most populous state in the country. The high population density, coupled with the socio-demographic heterogeneity and ethnic mix characterizing the location allowed for high degree of cross-sectional variation and representation in our dataset.

In the survey, we carried out face-to-face interviews with questionnaire, focusing on primary food buyers in the households and ensuring that respondents were generally representative. We sampled 900 respondents randomly from both urban and rural areas, using a multistage sampling approach. Our questionnaire centered on three areas of variation: individual socio-demographic data; choice experiment; and follow up questions on attribute processing strategies and attribute importance. As a tailpiece to the socio-demographic questions, we also probed respondents on their level of awareness of organic agriculture, and based on clarification regarding the meaning of organic concept, we proceeded with the CE task. We selected tomatoes as the organic product to analyze. The selection of a vegetable, in particular tomato, is guided by previous methodological and empirical suggestions on SSA (e.g., Coulibaly et al. 2011) and the acceptance by respondents as realistic. Furthermore, the attributes and their corresponding levels were identified through detailed review of the literature, discussions with scientific experts, focus groups, and pre-testing.

The choice sets were comprised of two experimentally-designed organic profiles and a 'status-quo' option.[14] The organic profiles were created following Scarpa, Campbell, and Hutchinson (2007), employing a three-stage Bayesian sequential technique. A pilot study based on an orthogonal fractional factorial design (Hensher, Rose and Greene 2005) was conducted to test the questionnaire and to provide Bayesian priors for the main design.[15] Then, using the approach described by Scarpa et al. (2013),[16] the design involved 36 choice tasks orthogonally arranged in four blocks of nine choice scenarios to reduce the probability of respondent fatigue. An even number of respondents were randomly assigned to each of these groups. As shown in Table 1,

[14] As pointed out by an anonymous reviewer, the absence of an opt-out implies that the model cannot be used to predict demand for tomatoes in Nigeria. Carlsson et al. (2007) report that no differences exist in marginal WTP among the specific attributes between the two surveys versions with and without an opt-out alternative.

[15] The design was derived assuming a multinomial logit probability specification, due to its simplicity and high performance in MMNL models (Bliemer and Rose 2010).

[16] The final design was generated using the Ngene software (version 1.0) and we accounted for uncertainty of priors by employing normally distributed Bayesian priors. The final design with the lowest Bayesian D-error (0.2534) was attribute-level balanced.

each organic alternative is described by four quality attributes and a price. The price attribute in the choice sets were the prices for 1kg basket of tomatoes, with three different price levels. The lowest price level represents the base price, which reflects the average retail market price; collected from the local markets immediately prior to the experiment. The remaining price levels reflect possible premium prices associated with the organic tomato products. These prices were derived on the basis of local market experts' opinion and focus group discussions.

Table 1: Attributes and Attribute Levels in the Choice Experiments

| Attributes | Description | Attribute Levels |
|---|---|---|
| Pesticide | Reduction in the level of pesticide residues content | 5%, 25% ,100% lower |
| Certification | Organic certification scenarios | Foreign, Foreign plus indigenous, Indigenous labels |
| Vitamin | Increase in vitamin A content | 5%, 25%, 100% higher |
| Price | Purchase price (in Naira) | ₦ 60, ₦ 80, ₦100 |
| Erosion | Reduction in the level of soil erosion | 5%, 25%, 100% lower |

Another attribute relates to the origin of the certifier of the organic product. Private voluntary certification of organic products has been shown to be an essential aspect of the OA initiative in developing countries (e.g., Kleeman, Abdulai and Buss 2014). In this application, we identified three organic certification scenarios. The first level corresponds with the scenario in which the organic tomato is certified by foreign certifiers only, while the second and third levels correspond to the scenarios with both foreign and indigenous third party certifiers, and indigenous certifiers only, respectively. The remaining three quality attributes of the organic choice options concern: higher vitamin A content; lower soil erosion and lower pesticide residues, and each were described by high, medium and low attribute levels.

A number of studies have indicated that organic farming leads to lower foodborne residues relative to conventional farming (Dangour et al. 2009). The first level (100% reduction) is related to the absence of residues, the second level (25% reduction) implies traces of residues from one component (<0.01mg/kg), and the third level (5% reduction) comprises of residues (>0.01mg/kg) from more than one component. Some studies have found higher amounts of carotenoid content in organic vegetables, which is a precursor and good source of vitamin A. Vitamin A can strengthen eye vision and the immune system (Chowdhury et al. 2011). Thus, the vitamin A content could be 5%, 25%, or 100% higher in organic tomato than in the conventional counterpart. Furthermore, OA helps to minimize soil degradation, as it improves soil organic matter content. Studies show that soil structure and water retention capacity on organic farming plots are higher than on conventional plots (e.g., Azadi et al. 2011). Thus, soil erosion could be 5%, 25%, or 100% lower on organic farms relative to conventional farms.

Following Lusk and Schroeder, (2004) in the CE procedure, we implemented different treatments and used a between-subject approach, whereby each respondent was randomly assigned to participate in only one of the three hypothetical CE treatments. In the first treatment, participants were not exposed to any of the *ex-ante* mitigation strategies. This treatment represents the baseline (N). The second treatment (CT) consisted of a CE with a cheap talk script, which was described to participants before responding to the CE questions. We used a generic, short, and neutral CT script, (Cummings and Taylor 1999; Silva et al. 2011), which were modified and developed in English and the local dialects. We refer to this as the cheap talk (CT) treatment. The third treatment (HP) consisted of a CE survey with an honesty priming script, which we also placed immediately before the CE questions. The HP script was the same as the one used by de-Magistris, Gracia and Nayga (2013), although we translated and implemented minor modifications after the validation exercise.

To ascertain true activation of honesty and manifestation of the priming effect, we followed the approach of Pashler, Rohrer and Harris (2013), and included debrief questions immediately after the survey. We observed that none of the participants in the HP treatment showed any evidence of having inferred the purpose of the study. Specifically, no participant noted the presence of honesty-related words in the semantic task, nor did any reveal any awareness of our hypothesis, we therefore consider this as evidence of honesty activation.

After completion of the nine choice tasks (instead of the entire survey), respondents were immediately presented with follow-up questions capturing information on attribute processing. In particular, each respondent was asked to rank the five attributes in order of importance, and then to indicate whether they had ignored any of the five attributes in making their choices. [17]

[17] Following Scarpa et al. (2013), we elicited attribute attendance statements based on an ordinal scale with 5 levels. Respondents were asked to indicate on a frequency scale how much they felt they attended to each attribute in their sequence of responses. The expressions used in the scale were "never," "rarely," "sometimes," "often," and "always." However, after experimenting with different options we recorded as "attribute non-attendance" all those who either stated "never" or "rarely" (NA=1), while the selection of the other three options was considered as full attendance (NA=0). As noted by Scarpa et

Table 2: Distribution of Stated Attribute Non-Attendance across Treatments

| Attributes | Baseline | Honesty priming | Cheap talk | Hypothesis test |
|---|---|---|---|---|
| Pesticide | 540 (20%) | 81 (3%) | 243 (9%) | $\chi^2 = 421.3, p < 0.001$ |
| Certification | 405 (15%) | 135 (5%) | 243 (9%) | $\chi^2 = 156.7, p < 0.001$ |
| Vitamin | 621 (23%) | 108 (4%) | 270 (10%) | $\chi^2 = 471.1, p < 0.001$ |
| Price | 621 (23%) | 54 (2%) | 216 (8%) | $\chi^2 = 645.4, p < 0.001$ |
| Erosion | 459 (17%) | 81 (3%) | 297 (11%) | $\chi^2 = 287.5, p < 0.001$ |

Note: the null hypothesis of equality in the rates of ANA incidences for each attribute across treatments is rejected.

Table 2 reveals the respondent-reported ANA information. The results show that the rate of stated ANA varies across the treatments in general, with respondents under the HP treatment reporting the lowest ANA rates followed by CT, and then N treatments. As shown in the table, there are also significant differences in ANA rates between respondents exposed to the mitigation strategies (HP and CT) and the baseline (N) group. In particular, the price attribute in the HP and CT treatments has the lowest ANA rate, while it is second highest in the N treatment.

Table 3 reports the socio-demographic characteristics of the participants in the three treatments. To allow for comparison of the results, we employed a stratified random sampling technique to select our participants in the sub-locations. We then used a chi-square test to determine if there are significant differences in socio-demographic profiles across treatments. The results of the tests show that the null hypothesis of

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al. (2013), the first two options are most likely to fit a pattern of choice resulting in zero, or low influence of selected attribute coefficients in the utility function.

equality between the socio-demographic characteristics across treatments cannot be rejected at

Table 3: Sample Characteristics, Percentages

| Variable Definition | Baseline | Honesty priming | Cheap talk |
|---|---|---|---|
| *Gender* | | | |
| Female | 18.41 | 18.67 | 17.67 |
| $\chi^2$ (2) = 0.9749 | | | |
| $p$ = 0.614 | | | |
| *Age* | | | |
| Between 18 and 40 years | 24.07 | 24.0 | 23.33 |
| Between 41 and 60 years | 59.59 | 59.67 | 59.67 |
| More than 60 years | 16.33 | 16.33 | 17.0 |
| $\chi^2$ (4) = 0.8625 | | | |
| $p$ = 0.930 | | | |
| *Level of Education* | | | |
| None | 10.89 | 12.0 | 12.0 |
| Primary | 20.44 | 18.33 | 18.33 |
| Secondary | 65.33 | 66.0 | 66.33 |
| Tertiary | 33.33 | 3.67 | 3.33 |
| $\chi^2$ (6) = 6.9180 | | | |
| $p$ = 0.329 | | | |
| *Ave. Monthly Income (₦)* | | | |
| Low income (≤ 30,000) | 14.56 | 13.67 | 14.56 |
| Medium income (30,001 – 150,000) | 57.67 | 58.0 | 57.67 |
| High income (> 150,000) | 27.78 | 27.33 | 27.78 |
| $\chi^2$ (4) = 0.6985 | | | |
| $p$ = 0.952 | | | |
| *Awareness of organic* | | | |
| Aware | 21.96 | 22.33 | 22.33 |

| | | | |
|---|---|---|---|
| $\chi^2$ (2) = 0.1429 | | | |
| $p$ = 0.931 | | | |
| *Food-related Disease* | | | |
| Incidence | 13.07 | 13.67 | 13.33 |
| $\chi^2$ (2) = 0.4117 | | | |
| $p$ = 0.814 | | | |
| *Household size* | | | |
| Less than 4 persons | 29.11 | 29.33 | 28.67 |
| Between 4 and 10 persons | 55.07 | 54.33 | 54.0 |
| More than 10 persons | 15.82 | 16.33 | 17.33 |
| $\chi^2$ (4) = 2.4645 | | | |
| $p$ = 0.651 | | | |

the 5% significance level for gender, age, education, income, and household size variables. Similar test results were obtained for the perceptual indicators: whether participants have previous awareness of organic products and whether there is any known recent incidence of food-related disease among relatives and friends. These results suggest that our randomization was successful in equalizing the characteristics of participants across the treatments.

### 2.4 Empirical Specification

Each respondent was faced with nine choice tasks, and for the analysis, we made use of a sample of 2,700 observations from 300 respondents, each in the HP, CT and N treatments, as well as a pooled sample of 8,100 observations from the 900 respondents. Four different model specifications were estimated. These include the hybrid models and robustness checks including the mixed multinomial logit models (MMNL), endogenous attribute attendance (EAA) and mixed EAA. The later three models are primarily included for illustrative purposes, given their past use in previous studies (e.g.

de-Magistris, Gracia and Nayga 2013; Hole, Kolstad and Gyrd-Hansen 2013). We estimated the hybrid and MMNL models using 250 Halton draws per respondent and per random term in simulation based estimation, while for the MEAA models we used 500 Halton draws (Halton 1960).

In the MMNL models, we assume full attribute attendance and thus do not use the respondent reported processing strategies, and no attempt was made to additionally incorporate deterministic effects linked to the respondent reported attribute rankings. In the hybrid model, we make use of the non-attendance data as well as the ranking data, with likelihood functions given in Equations 5 and 10, and the overall log-likelihood as defined in Equation 11. We also extend on Hess and Hensher (2013) hybrid model by including socio-demographic interactions in the latent variable specification in Equation 3. Constants were included to capture the conventional alternatives in the MMNL and hybrid models. Furthermore, in the three model specifications where the marginal utility coefficients were specified to vary randomly across respondents, a correlated lognormal distribution was used.

In comparison with the MMNL models, the hybrid models (HYBRID) make use of 30 additional parameters, 5 of them in the choice model component (the $\lambda$ terms), with the remaining 25 used in the measurement model. This latter model is appropriately normalized and this is the most parsimonious suitable specification, such that there is no risk of over-fitting. The five $\lambda$ parameters quantify the effect of the latent variables inside the choice model, as shown in Equation 6. While $\alpha$ follows a standard normal distribution, the $\beta$ parameters in the hybrid model still follow a lognormal distribution, just as in the base models. The remaining sets of parameters ($\kappa, \zeta, \varsigma$ $and$ $\tau$) follow the approach set out in Equations 5 and 8 to 10, with $\varsigma_{Price}$ normalized to zero.

Similar to the hybrid models, the EAA and MEAA models are also essentially a joint model of choice process and outcome, thus simultaneous estimation of all model components are used (Hensher 2008). The probability that decision-maker $n$ takes attribute $k$ into account takes the form of a product of several binary logit probabilities specified as exp $(\gamma^{\iota} z_{nk})$/ [1 + exp $(\gamma^{\iota} z_{nk})$], where $z_{nk}$ is a vector of individual-level observed characteristics and $\gamma_k$ is a vector of parameters to be estimated. This probability can be specified to depend on the respondents' stated ANA by including a dummy variable for having reported to ignore attribute $k$ in $z_{nk}$. In the EAA model, the respondents who attend to an attribute are assumed to have identical preferences for that attribute, hence the mean is estimated, while this assumption is relaxed in the MEAA model by allowing $\beta$ to vary across respondents, hence capturing both mean and standard deviation.

## 2.5 Empirical Results

We first tested the hypothesis of equality across treatments using the likelihood ratio test. Table 4 reports the likelihood values for the pooled and segmented samples (treatments), as well as for each combination of the three treatments. The results indicate that the null hypotheses of equality between the pooled and segmented treatments is rejected, suggesting that comparing the estimated parameters from the various treatments is appropriate when estimating the models separately.

The maximum likelihood estimates for the choice models are summarized in tables 5, 6 and 7.[18] They relate to model statistics and the estimates of the discrete

[18] The models were coded and estimated using a mixture of Biogeme (Bierlaire 2003) for hybrid models and Stata for the EAA specifications (Hole 2011).

choice component of the models.[19] It is important to note that the fit of the hybrid model cannot be compared to that of the MMNL models, because the latter are estimated on the stated

Table 4: Hypothesis Tests of Equality across Treatments

| Hypothesis Tests of Equality | Number of Observations | MMNL Models | HYBRID Models |
|---|---|---|---|
| | | *LL* | *LL* |
| Pooled[a] | 8,100 | -4.684.443 | -11,771.204 |
| Baseline | 2,700 | -1,334.180 | -3,845.301 |
| Honesty priming | 2,700 | -1,193.733 | -3,754.168 |
| Cheap talk | 2,700 | -1,992.791 | -3,913.119 |
| $H_{0_1}$ = *Test of equality across treatments* | | 327.478*** | 517.232*** |
| Pooled[b] | 5,400 | -3,386.033 | -7,815.675 |
| $H_{0_2}$ = *Test of equality between baseline and honesty priming treatments* | | 1,716.240*** | 432.412*** |
| Pooled[c] | 5,400 | -3,555.253 | -7,829.726 |
| $H_{0_3}$= *Test of equality between baseline and cheap talk treatments* | | 456.564*** | 142.612*** |
| Pooled[d] | 5,400 | -3,249.275 | -7,804.581 |
| $H_{0_4}$ = *Test of equality between cheap talk and honesty priming treatments* | | 125.502*** | 274.588*** |

Note: *** denotes significance at the1% level.

[a] Indicates all treatments ; [b] Indicates baseline and HP treatments; [c] Indicates baseline and CT treatments; [d] Indicates HP and CT treatments

choice data alone, while the former models the responses to the non-attendance and the attribute ranking questions, in addition to the choice information. This is reflected in the greater null log-likelihood (LL) for the hybrid model (Hess and Hensher 2013). Similarly,

[19] To conserve space, the MLE for the pooled treatments are reported can be found in the supplementary online appendix.

in contrast to hybrid models, stated ANA information are used endogenously in both the MEAA and EAA specifications.[20]

[20] The information criteria indicate that the EAA and MEAA models with stated ANA covariates outperform the benchmark models across all treatments. A comparison of the model fit can be found in the supplementary online appendix.

Table 5: Maximum Likelihood Estimates and ANA Probabilities from Benchmark Models

| | Baseline | | | | | | Honesty priming | | | | | | Cheap talk | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Resp. | 300 | | 300 | | | | 300 | | 300 | | | | 300 | | 300 | | | |
| Obser. | 2,700 | | 2,700 | | | | 2,700 | | 2,700 | | | | 2,700 | | 2,700 | | | |
| LL(0) | -2,159.54 | | -1,836.59 | | | | -1,950.12 | | -1702.72 | | | | -1,990.11 | | -2,025.33 | | | |
| LL | -1,731.89 | | -1,606.27 | | | | -1,717.21 | | -1514.64 | | | | -1,566.43 | | -1,545.20 | | | |
| Par. | 10 | | 15 | | | | 10 | | 15 | | | | 10 | | 15 | | | |
| | **EAA** | | **MEAA** | | | | **EAA** | | **MEAA** | | | | **EAA** | | **MEAA** | | | |
| Var. | Est. | t-Ratio | Est. | t-Ratio | SD | t-Ratio | Est. | t-Ratio | Est. | t-Ratio | SD | t-Ratio | Est. | t-Ratio | Est. | t-Ratio | SD | t-Ratio |
| $\beta_{price}$ | -2.631 | -16.18 | -1.099 | -12.04 | -0.698 | -3.31 | -1.337 | -14.63 | -1.131 | -11.33 | -0.981 | -0.41 | -3.875 | -11.76 | -2.548 | -13.61 | 0.135 | 0.10 |
| $\beta_{pesticide}$ | 0.411 | 16.30 | 0.513 | 16.72 | 0.141 | 6.86 | 0.517 | 13.91 | 0.547 | 16.41 | 0.128 | 2.97 | 0.419 | 17.25 | 0.954 | 14.28 | 0.162 | 6.87 |
| $\beta_{certification}$ | 0.785 | 11.78 | 0.107 | 9.19 | 0.103 | 3.83 | 0.049 | 4.57 | 0.451 | 2.81 | 0.311 | 4.30 | 0.246 | 3.45 | 0.189 | 8.13 | 0.175 | 9.60 |
| $\beta_{vitamin}$ | 0.160 | 14.16 | 0.301 | 7.26 | 0.032 | 0.57 | 0.245 | 13.98 | 0.332 | 11.60 | 0.057 | 3.44 | 0.175 | 9.16 | 0.869 | 9.42 | 0.681 | 6.49 |
| $\beta_{erosion}$ | 0.308 | 6.03 | 0.185 | 7.15 | 0.121 | 4.07 | 0.254 | 11.72 | 0.307 | 7.19 | -0.238 | -1.77 | 0.131 | 4.53 | 0.724 | 8.28 | 0.193 | 4.79 |
| **ANA Probabilites** | | | | | | | | | | | | | | | | | | |
| | Prob. | t-Ratio | Prob. | t-Ratio | | | Prob. | t-Ratio | Prob. | t-Ratio | | | Prob. | t-Ratio | Prob. | t-Ratio | | |
| $\beta_{price}$ | 0.519 | 24.30 | 0.334 | 4.76 | | | 0.213 | 15.30 | 0.087 | 2.18 | | | 0.266 | 34.31 | 0.124 | 2.36 | | |
| $\beta_{pesticide}$ | 0.232 | 8.88 | 0.050 | 9.94 | | | 0.126 | 9.80 | 0.028 | 1.42 | | | 0.219 | 6.44 | 0.081 | 2.67 | | |
| $\beta_{certification}$ | 0.632 | 34.56 | 0.186 | 1.01 | | | 0.112 | 1.10 | 0.051 | 0.41 | | | 0.273 | 10.70 | 0.037 | 0.34 | | |
| $\beta_{vitamin}$ | 0.436 | 7.49 | 0.148 | 3.91 | | | 0.215 | 4.49 | 0.068 | 1.74 | | | 0.150 | 3.59 | 0.108 | 1.05 | | |
| $\beta_{erosion}$ | 0.491 | 1.00 | 0.274 | 0.59 | | | 0.201 | 3.75 | 0.065 | 1.06 | | | 0.204 | 3.00 | 0.092 | 1.70 | | |

The estimates in Table 6 reveal that the estimated ANA probabilities for each attribute based on EAA models are substantially higher than those based on MEAA models, implying that lower sensitivity is captured when heterogeneity is controlled for (e.g., Campbell and Lorimer 2009). However, despite the reduction in the ANA probabilities, the probability of ignoring the attributes are still significantly different from zero among the attenders. This suggests that although accounting for preference heterogeneity reduces the influence of ANA, it does not completely eliminate it (Hess et al. 2013). The results also indicate that the stated ANA rates are lower than the inferred ANA probabilities derived from the models, reflecting a lack of concordance. The gaps are however substantially less among the respondents exposed to the mitigation strategies (HP and CT). For example, in the case of price attribute, the gap between inferred and stated nonattendance rates is estimated at 4 percent under both the HP and CT treatments, while for the baseline group, the two rates are widely divergent, with a margin of over 35 percent. Likewise, across the two models (EAA and MEAA), the inferred ANA probabilities under the HP treatment are lower and more consistent with stated ANA reported relative to the estimates obtained under the CT treatment.

The estimates in table 7 show that the magnitudes and (negative) signs of the constants indicate some inertia towards the conventional (or status quo) alternative (Hess and Hensher 2013). Furthermore, the five log-normally distributed[21] mean parameters are all statistically significant across all six models, with the expected negative

[21] We also estimated the models with normally distributed coefficients, but these were found to have lower goodness of fit.

Table 6 : Maximum Likelihood Estimates and ANA Probabilities from Models with Stated ANA Covariates

| | Baseline | | | | | | Honesty priming | | | | | | Cheap talk | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Resp. | 300 | | 300 | | | | 300 | | 300 | | | | 300 | | 300 | | | |
| Obser. | 2,700 | | 2,700 | | | | 2,700 | | 2,700 | | | | 2,700 | | 2,700 | | | |
| LL(0) | -1,878.31 | | -2,038.08 | | | | -1,487.63 | | -1,459.87 | | | | -1,640.75 | | -1,610.48 | | | |
| LL | -1,629.84 | | -1,594.07 | | | | -1,283.56 | | -1,250.96 | | | | -1,316.13 | | -1,260.09 | | | |
| Par. | 15 | | 20 | | | | 15 | | 20 | | | | 15 | | 20 | | | |
| | **EAA** | | **MEAA** | | | | **EAA** | | **MEAA** | | | | **EAA** | | **MEAA** | | | |
| Var. | Est. | t-Ratio | Est. | t-Ratio | SD | t-Ratio | Est. | t-Ratio | Est. | t-Ratio | SD | t-Ratio | Est. | t-Ratio | Est. | t-Ratio | SD | t-Ratio |
| $\beta_{price}$ | -1.236 | -12.16 | -2.097 | -14.64 | 1.732 | 4.93 | -1.256 | -15.28 | -1.342 | -13.83 | 0.337 | 1.57 | -1.820 | -18.16 | -1.874 | -13.43 | -0.833 | -0.48 |
| $\beta_{pesticide}$ | 0.461 | 18.07 | 0.726 | 14.68 | 0.159 | 5.02 | 0.608 | 18.05 | 0.646 | 17.29 | 0.123 | 2.69 | 0.725 | 16.62 | 0.950 | 15.30 | 0.303 | 8.57 |
| $\beta_{certification}$ | 0.121 | 6.34 | 0.178 | 6.36 | 0.182 | 8.19 | 0.163 | 3.37 | 0.506 | 2.88 | 0.284 | 3.08 | 0.121 | 3.47 | 0.186 | 11.54 | 0.167 | 7.45 |
| $\beta_{vitamin}$ | 0.251 | 5.81 | 0.375 | 5.26 | 0.620 | 4.24 | 0.255 | 9.50 | 0.299 | 8.69 | 0.017 | 1.03 | 0.248 | 13.77 | 0.644 | 9.04 | 0.504 | 2.15 |
| $\beta_{erosion}$ | 0.180 | 10.44 | 0.438 | 7.92 | 0.336 | 3.06 | 0.293 | 11.99 | 0.292 | 9.67 | 0.047 | 2.38 | 0.345 | 15.06 | 0.517 | 9.04 | 0.146 | 3.73 |

**ANA Probabilites**

| | Baseline | | | | | | Honesty priming | | | | | | Cheap talk | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **EAA** | | | **MEAA** | | | **EAA** | | | **MEAA** | | | **EAA** | | | **MEAA** | | |
| | Att. | Non-att | Diff. | Att. | Non-att | Diff. | Att. | Non-att | Diff. | Att. | Non-att | Diff. | Att. | Non-att | Diff. | Att. | Non-att. | Diff. |
| $\beta_{price}$ | 0.407 | 0.760 | -0.352 | 0.323 | 0.586 | -0.263 | 0.041 | 0.149 | -0.108 | 0.046 | 0.063 | -0.017 | 0.247 | 0.563 | -0.315 | 0.087 | 0.121 | -0.035 |
| | (5.78) | (5.46) | (-17.0) | (3.35) | (22.5) | (-4.45) | (2.82) | (12.1) | (-9.16) | (2.00) | (6.28) | (-2.43) | (4.19) | (14.7) | (-14.6) | (3.08) | (4.23) | (-2.97) |

| | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\beta_{pesticide}$ | 0.150 | 0.430 | -0.280 | 0.075 | 0.553 | -0.478 | 0.069 | 0.178 | -0.120 | 0.031 | 0.110 | 0.080 | 0.258 | 0.368 | 0.110 | 0.070 | 0.095 | -0.025 |
| | (2.48) | (2.59) | (-0.57) | (3.46) | (11.0) | (-0.38) | (1.81) | (5.71) | (-1.11) | (1.78) | (12.8) | (0.46) | (2.89) | (10.1) | (5.20) | (2.60) | (6.29) | (-1.53) |
| $\beta_{certification}$ | 0.026 | 0.441 | -0.416 | 0.040 | 0.109 | -0.070 | 0.125 | 0.140 | -0.015 | 0.039 | 0.069 | -0.030 | 0.189 | 0.351 | 0.162 | 0.053 | 0.061 | -0.008 |
| | (0.19) | (1.16) | (-0.62) | (0.52) | (1.47) | (-0.60) | (3.42) | (10.2) | (-4.47) | (5.34) | (3.60) | (-5.29) | (1.35) | (1.19) | (0.29) | (0.09) | (0.86) | (-1.96) |
| $\beta_{vitamin}$ | 0.404 | 0.539 | -0.136 | 0.234 | 0.474 | -0.240 | 0.059 | 0.320 | -0.262 | 0.028 | 0.055 | -0.027 | 0.081 | 0.354 | -0.272 | 0.061 | 0.328 | -0.267 |
| | (1.05) | (2.53) | (-1.38) | (2.05) | (3.47) | (-5.56) | (3.60) | (6.85) | (-5.81) | (0.83) | (5.48) | (-6.45) | (3.24) | (11.6) | (-12.2) | (2.85) | (14.7) | (-6.28) |
| $\beta_{erosion}$ | 0.497 | 0.536 | -0.039 | 0.152 | 0.407 | -0.255 | 0.137 | 0.285 | -0.432 | 0.012 | 0.0822 | -0.070 | 0.097 | 0.449 | -0.353 | 0.087 | 0.344 | -0.258 |
| | (0.90) | (0.86) | (-1.22) | (2.57) | (10.5) | (-4.65) | (3.97) | (4.05) | (-11.7) | (1.00) | (1.20) | (-1.90) | (2.44) | (3.33) | (-11.2) | (2.15) | (2.04) | (-5.05) |

Notes: Att., self-reported attribute attenders; Non-att., self-reported attribute non-attenders; Diff., difference in ANA probability between the two groups.

Figures in parentheses are t-Ratios.

signs for parameters of price attributes[22], and the high preference for increase in the remaining four attributes of the organic profile. Similarly, from the Cholesky matrix, we observe that majority of the estimates of the diagonal elements are statistically significant, indicating heterogeneity in preferences for the identified organic attributes among respondents.

The next set of estimates shown on table 7 relate to the $\lambda$ parameters, which have the role of a scaling parameter on the marginal utilities. It can be observed that for all five attributes, consistent with Hess and Hensher (2013), increases in the associated latent variable tend to increase the sensitivity of the concerned attribute, a finding that is in line with the interpretation of the five latent variables as underlying importance ratings for the attributes. The $\varphi_k$ parameters, which capture the impact of socio-demographics on the latent attribute importance ratings reveal that participants with higher importance ratings for the identified attributes (in both treatments) are more likely to be older and more educated, and with previous awareness of organic products. Moreover, in the HP treatments, this group are more likely to have experienced a food-related disease within the last 24 months.

We next turn to the two additional measurement components of the hybrid model that allow the use of the $e^{\lambda_k \alpha_{nk}}$ term, that is, the model for the response to the non-attendance questions and the model for the response to ranking question. All the estimates for the $\kappa$ parameters are negative, indicating that the stated non-attendance

[22] Given that the lognormal distribution produces positive parameter value which may be contrary to a priori expectation for the price attribute, we reverse the sign of the price attribute by defining the negative of the attribute prior to model estimation.

Table 7: Maximum Likelihood Estimates for Baseline, Honesty Priming and Cheap Talk Treatments

| | $MMNL_{N}$ | | $HYBRID_{N}$ | | $MMNL_{HP}$ | | $HYBRID_{HP}$ | | $MMNL_{CT}$ | | $HYBRID_{CT}$ | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Respondents | 300 | | 300 | | 300 | | 300 | | 300 | | 300 | |
| Observations | 2,700 | | 2,700 | | 2,700 | | 2,700 | | 2,700 | | 2,700 | |
| LL(0) | -3,376.557 | | -4,330.199 | | -3,157.503 | | -4,092.202 | | -3,452.158 | | -4,213.039 | |
| LL | -1,334.180 | | -3,845.301 | | -1,193.733 | | -3,754.168 | | -1,992.791 | | -3,913.119 | |
| Par. | 11 | | 41 | | 11 | | 41 | | 11 | | 41 | |
| Variable | Est. | *t*-Ratio | Est. | *t*-Ratio | Est. | *t*-Ratio | Est. | *t*-Ratio | Est. | *t*-Ratio | Est. | *t*-Ratio |
| $\beta_{price}$ | -6.4866 | -17.21 | -0.9335 | -14.73 | -3.1568 | -9.16 | -1.2527 | -18.34 | -3.8294 | -16.33 | -0.7161 | -13.33 |
| $\beta_{pesticide}$ | 1.1302 | 17.89 | 0.6985 | 17.10 | 2.1025 | 12.50 | 1.0201 | 21.94 | 0.6772 | 12.10 | 0.4372 | 12.10 |
| $\beta_{certification}$ | 0.0046 | 0.12 | -0.1102 | -2.36 | 0.4273 | 7.46 | 0.0997 | 2.43 | 0.2147 | 6.50 | 0.0624 | 1.88 |
| $\beta_{vitamin}$ | 0.4376 | 9.95 | 0.3761 | 1.25 | 0.3270 | 5.44 | 0.2420 | 5.43 | 0.2170 | 5.41 | 0.2321 | 6.46 |
| $\beta_{erosion}$ | 0.5133 | 11.75 | -0.4366 | -0.51 | 0.4857 | 7.98 | 0.3241 | 7.28 | 0.2807 | 7.94 | 0.2785 | 7.63 |
| Constant | -17.6277 | -16.32 | -2.0057 | -16.90 | -16.4829 | -8.72 | -2.5313 | -17.88 | -16.3698 | -16.23 | -1.3033 | -15.70 |
| $S_{(\beta_{Price})}$ | -0.2014 | -2.44 | 0.0142 | 0.56 | 0.6681 | 2.52 | -0.0099 | -4.40 | 0.2888 | 2.16 | -0.0030 | -6.22 |
| $S_{(\beta_{Pesticide}),(\beta_{price})}$ | -0.3611 | -1.86 | 0.2333 | 1.82 | -0.1773 | -1.64 | 0.0140 | 1.47 | 0.6299 | 0.52 | 0.0192 | 0.88 |
| $S_{(\beta_{Pesticide})}$ | -0.4529 | -5.95 | -0.0407 | -1.67 | 1.1966 | 8.43 | 0.0416 | 1.64 | 0.3440 | 3.29 | 0.0137 | 1.01 |
| $S_{(\beta_{Certification}),(\beta_{Price})}$ | -0.4771 | -1.77 | -0.0378 | -0.73 | -0.2721 | -1.75 | -0.0496 | -0.09 | -0.6905 | -1.09 | -0.0183 | -0.99 |
| $S_{(\beta_{Certification}),(\beta_{Pesticide})}$ | -0.2395 | -4.11 | -0.0176 | -1.06 | 0.2580 | 7.37 | -0.0525 | -1.91 | -0.7205 | -1.57 | -0.0360 | -0.08 |
| $S_{(\beta_{Certification})}$ | 0.0269 | 0.69 | -0.0075 | -3.41 | 0.1582 | 2.28 | -0.0125 | -1.09 | 0.0721 | 0.88 | 0.0125 | 1.63 |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $S_{(\beta_{Vitamin}),(\beta_{Price})}$ | 0.1200 | 4.41 | 0.1007 | 0.59 | 0.1590 | 3.42 | -0.0230 | -8.10 | 0.5672 | 4.33 | -0.0336 | -0.55 |
| $S_{(\beta_{Vitamin}),(\beta_{Pesticide})}$ | 0.1608 | 7.89 | 0.1052 | 2.15 | -0.1392 | -8.73 | 0.0407 | 1.23 | 0.6142 | 6.15 | 0.1032 | 1.29 |
| $S_{(\beta_{Vitamin}),(\beta_{Certification})}$ | 0.1150 | 2.83 | 0.1180 | 1.35 | -0.1422 | -3.85 | 0.0432 | 0.20 | -0.6021 | -1.70 | 0.0807 | 1.35 |
| $S_{(\beta_{Vitamin})}$ | 0.2556 | 4.77 | 0.0352 | 1.25 | -0.2292 | -3.61 | -0.0061 | -2.20 | -0.1945 | -2.08 | -0.0168 | -3.81 |
| $S_{(\beta_{Erosion}),(\beta_{price})}$ | -0.0339 | -5.32 | 0.1690 | 0.84 | 0.0603 | 3.57 | 0.2711 | 0.22 | -0.6280 | -4.91 | 0.2695 | 1.91 |
| $S_{(\beta_{Erosion}),(\beta_{Pesticide})}$ | -0.1765 | -7.39 | -0.1995 | -0.63 | -0.3030 | -8.59 | -0.1987 | -1.30 | 0.5514 | 6.04 | -0.0672 | -10.99 |
| $S_{(\beta_{Erosion}),(\beta_{Certification})}$ | 0.2720 | 4.19 | 0.2141 | 0.24 | 0.1077 | 4.99 | 0.0630 | 0.15 | -0.5594 | -1.92 | 0.0796 | 1.21 |
| $S_{(\beta_{Erosion}),(\beta_{Vitamin})}$ | -0.0684 | -1.09 | -0.0015 | -1.23 | -0.2250 | -0.62 | 0.1130 | 6.28 | 0.5673 | 0.34 | 0.0137 | 1.88 |
| $S_{(\beta_{Erosion})}$ | 0.3447 | 5.91 | -0.0147 | -0.51 | -0.2914 | -4.47 | -0.0178 | -2.53 | -0.2243 | -2.42 | 0.0401 | 1.81 |
| $\lambda_{Price}$ | - | - | 0.6461 | 10.02 | - | - | 0.5678 | 11.65 | - | - | 0.9489 | 8.69 |
| $\lambda_{Pesticide}$ | - | - | 0.9014 | 11.01 | - | - | 0.5142 | 14.42 | - | - | 1.0071 | 8.19 |
| $\lambda_{Certification}$ | - | - | -0.2713 | -0.90 | - | - | 1.7056 | 2.25 | - | - | 3.3604 | 1.84 |
| $\lambda_{Vitamin}$ | - | - | 0.1322 | 1.74 | - | - | 0.3873 | 2.64 | - | - | 0.4747 | 2.68 |
| $\lambda_{Erosion}$ | - | - | 0.3091 | 3.59 | - | - | 0.4781 | 4.62 | - | - | 0.6278 | 4.74 |
| $\varphi_{Age}$ | - | - | 0.0566 | 1.03 | - | - | 0.3213 | 6.91 | - | - | 0.2717 | 5.37 |
| $\varphi_{Male}$ | - | - | 0.4186 | 8.70 | - | - | 0.5945 | 13.01 | - | - | 0.3279 | 6.09 |
| $\varphi_{Educ}$ | - | - | 0.3502 | 11.90 | - | - | 0.3014 | 11.10 | - | - | 0.1633 | 5.59 |
| $\varphi_{H/hsize}$ | - | - | 0.0087 | 2.71 | - | - | 0.0132 | 5.08 | - | - | -0.0902 | -3.81 |
| $\varphi_{Disease}$ | - | - | -0.2101 | -4.25 | - | - | 0.0948 | 1.66 | - | - | -0.2128 | -4.36 |
| $\varphi_{Aware}$ | - | - | 0.6407 | 12.59 | - | - | 0.6288 | 14.95 | - | - | 0.5486 | 10.98 |
| $\kappa_{Price}$ | - | - | -2.2257 | -3.80 | - | - | -1.1221 | -18.20 | - | - | -1.8554 | -3.18 |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\kappa_{Pesticide}$ | - | - | -2.1482 | -4.80 | - | - | -2.4568 | -4.48 | - | - | -2.5823 | -6.30 |
| $\kappa_{Certification}$ | - | - | -3.8785 | -7.59 | - | - | -3.6238 | -5.90 | - | - | -3.3259 | -6.45 |
| $\kappa_{Vitamin}$ | - | - | -3.4855 | -5.14 | - | - | -4.0187 | -8.08 | - | - | -3.6021 | -8.24 |
| $\kappa_{Erosion}$ | - | - | -3.2621 | -7.32 | - | - | -3.7787 | -7.81 | - | - | -3.6343 | -1.86 |
| $\zeta_{Price}$ | - | - | -0.8736 | -3.81 | - | - | -0.5765 | -23.07 | - | - | -0.6206 | -23.33 |
| $\zeta_{Pesticide}$ | - | - | -0.3480 | -10.88 | - | - | -0.1085 | -4.01 | - | - | -0.0447 | -1.50 |
| $\zeta_{Certification}$ | - | - | 0.3266 | 7.33 | - | - | -0.5151 | -14.68 | - | - | -0.6357 | -16.42 |
| $\zeta_{Vitamin}$ | - | - | 0.6401 | 24.19 | - | - | 0.8940 | 30.57 | - | - | 0.8671 | 25.51 |
| $\zeta_{Erosion}$ | - | - | 0.2550 | 9.37 | - | - | 0.3061 | 8.92 | - | - | 0.4339 | 12.82 |
| $\varsigma_{Price}$ | - | - | 0 | - | - | - | 0 | - | - | - | 0 | - |
| $\varsigma_{Pesticide}$ | - | - | 0.2384 | 3.21 | - | - | -0.1931 | -1.95 | - | - | 0.4260 | 6.81 |
| $\varsigma_{Certification}$ | - | - | -0.7354 | -10.17 | - | - | -0.8131 | -10.24 | - | - | -0.6853 | -11.73 |
| $\varsigma_{Vitamin}$ | - | - | -2.3133 | -23.94 | - | - | -2.3151 | -20.67 | - | - | -1.0475 | -18.77 |
| $\varsigma_{Erosion}$ | - | - | -1.3722 | -18.92 | - | - | -0.6433 | -6.72 | - | - | -2.5194 | -27.11 |
| $\tau_{Price}$ | - | - | 0.6382 | 20.85 | - | - | 0.9579 | 29.08 | - | - | 0.4068 | 11.09 |
| $\tau_{Pesticide}$ | - | - | 0.4163 | 8.34 | - | - | 0.2496 | 3.89 | - | - | 0.3793 | 7.25 |
| $\tau_{Certification}$ | - | - | -0.2429 | -4.04 | - | - | 0.2043 | 3.87 | - | - | 0.2608 | 5.18 |
| $\tau_{Vitamin}$ | - | - | 0.0178 | 0.38 | - | - | 0.3075 | 5.94 | - | - | -0.2706 | -5.72 |
| $\tau_{Erosion}$ | - | - | 0.2286 | 4.83 | - | - | -0.0764 | -1.82 | - | - | -0.5170 | -7.10 |

rates were below 50 % for each of the five attributes. The $\varsigma$ terms for the ranking component play a similar role, with $\varsigma_{Price}$ normalized to zero. The remaining negative estimates reflect the overall highest ranking for the price attribute, followed by low pesticide and then soil attributes in the HP treatment. The low pesticide attribute is ranked highest among participants in the CT treatment, ahead of price and certification attributes.

For the remaining parameters, the rule of thumb is that a negative estimate for $\zeta_k$ implies that as the latent variable $\alpha_{nk}$ increases, the probability of respondent $n$ indicating that he/she ignored attribute $k$ decreases. Similarly, a positive value for $\tau_k$ implies that as $\alpha_{nk}$ increases, the probability of respondent $n$ ranking attribute $k$ highly increases (Hess and Hensher 2013).

Although $\zeta_{pesticide}$ in the CT treatment is not statistically significant, we observe the expected signs for the $\zeta$ and $\tau$ parameters for price, low pesticide residue and certification attributes in the two treatments. For each attribute, an increase in the associated latent variable is associated with a lower probability of stated non-attendance for that attribute, and an increased probability of higher ranking for the attribute. At the same time, the estimates for the $\lambda$ parameters (all being positive and significant) in the choice model component show that such increases in the latent variables also lead to higher sensitivity to the associated attributes in the utility functions. This indicates consistent results across the three model components ($\lambda$ ,$\zeta$, $\varsigma$) for these three attributes (i.e., price, pesticide residue and certification), and as such justifies the interpretation of the latent variable as an underlying attribute importance rating.

A different view however unfolds for vitamin A and erosion attributes. For instance, in the CT treatment, while the estimate for $\zeta_{Vitamin}$ and $\zeta_{Erosion}$ are positive, and the estimate for $\tau_{Vitamin}$ and $\tau_{Erosion}$ are negative, the estimate for $\lambda_{Vitamin}$ and $\lambda_{Erosion}$ in the choice model is once again positive, implying that increases in the latent variable lead to increased marginal disutilities for higher vitamin A and low soil erosion attributes. In other words, increases in the latent variables $\alpha_{n,Vitamin}$ and $\alpha_{n,Erosion}$, which lead to higher marginal utility for vitamin A and erosion attributes, also counter-intuitively result in a higher probability of stated non-attendance for these attributes, and increased probability of a lower ranking for the attributes. Similarly, in the HP treatment, even though, $\lambda_{Erosion}$ and $\lambda_{Vitamin}$ are both positive as expected, we observe contrasting signs for $\zeta_{Vitamin}$ and $\zeta_{Erosion}$ as well as for $\tau_{Erosion}$ estimates.

The findings for vitamin A and soil erosion attributes are consistent with the results of Hess and Hensher (2013), who also reported lack of consistency between the behaviour in the stated choice components and the respondent provided information on attribute non-attendance and attribute ranking. It also further confirms the usefulness of the modelling framework proposed by Hess and Hensher (2013), since it allows for such discrepancies to be identified without relying on deterministic approaches treating respondent provided information as error free measures of attribute non-attendance and attribute rankings.

Tables 8 and 9 summarize the results from the estimation of trade-off between the attribute coefficients. Table 8 reports the estimates for the benchmark models, while table 9 presents those for the models with stated ANA. The results relate to sample population level distributions, taking into account the distributions of the latent variables $\alpha$ and parameters of the attributes $\beta$. In particular, we calculate the monetary valuations for the four attributes. The $\beta_k$ parameters in the MEAA and MMNL models and the $e^{\lambda_k \alpha_{nk}}\beta_k$

Table 8 : Implied Trade-Off and Monetary Valuations (Estimates from Benchmark Models )

| | **Baseline** | | | **Honesty priming** | | | **Cheap talk** | | |
|---|---|---|---|---|---|---|---|---|---|
| | $MMNL_{N}$ | $EAA_{N}$ | $MEAA_{N}$ | $MMNL_{HP}$ | $EAA_{HP}$ | $MEAA_{HP}$ | $MMNL_{CT}$ | $EAA_{CT}$ | $MEAA_{CT}$ |
| **Mean** | | | | | | | | | |
| Lower Pesticide residue | 19.72 | 15.61 | 15.55 | 14.49 | 12.90 | 12.08 | 16.58 | 16.23 | 12.47 |
| | (7.50, 21.23) | (14.01, 17.38) | (13.41, 18.25) | (9.03, 18.00) | (10.86, 15.29) | (10.46, 14.18) | (12.89, 17.71) | (13.80, 19.37) | (11.53, 13.53) |
| Certification | 9.82 | 14.91 | 12.82 | 15.97 | 3.63 | 6.64 | 9.08 | 6.35 | 7.43 |
| | (4.77, 18.52) | (12.97, 16.90) | (9.10, 17.07) | ( 5.25, 16.23) | (2.06, 5.32) | (1.95, 12.01) | (7.40, 12.27) | (2.61, 10.51) | (6.03, 8.83) |
| Higher Vitamin A content | 9.55 | 11.70 | 13.69 | 11.22 | 9.51 | 9.04 | 8.52 | 10.11 | 9.75 |
| | (7.79, 11.87) | (8.20, 15.05) | (10.25, 17.38) | (9.96, 15.13) | (7.78, 11.49) | (6.66, 11.75) | (5.98, 12.44) | (5.79, 14.82) | (7.11, 13.31) |
| Lower Soil Erosion | 10.40 | 6.06 | 8.42 | 12.81 | 9.15 | 8.39 | 9.06 | 9.04 | 8.87 |
| | (6.04, 18.42) | (5.16, 7.07) | (6.14, 11.01) | (9.79, 18.35) | (7.71, 10.81) | (7.72, 12.37) | (7.11, 11.75) | (7.02, 11.40) | (7.41, 10.30) |
| **Coefficient of variation** | | | | | | | | | |
| Lower Pesticide residue | 2.56 | | 3.38 | 13.30 | | 3.72 | 7.10 | | 2.00 |
| Certification | 17.43 | | 5.58 | 10.08 | | 3.59 | 3.74 | | 2.80 |
| Higher Vitamin A content | 5.40 | | 4.99 | 4.63 | | 3.64 | 9.46 | | 6.20 |
| Lower Soil Erosion | 14.37 | | 3.41 | 3.91 | | 3.32 | 6.40 | | 2.89 |

Note: 95% confidence intervals (CIs) calculated using the Krinsky and Robb (1986) method in parentheses. The CIs are based on 10, 000 replications.

Table 9: Implied Trade-Off and Monetary Valuations (Estimates from Models with Stated ANA )

| | **Baseline** | | | **Honesty priming** | | | **Cheap talk** | | |
|---|---|---|---|---|---|---|---|---|---|
| | $EAA_N$ | $MEAA_N$ | $HYBRID_N$ | $EAA_{HP}$ | $MEAA_{HP}$ | $HYBRID_{HP}$ | $EAA_{CT}$ | $MEAA_{CT}$ | $HYBRID_{CT}$ |
| **Mean** | | | | | | | | | |
| Lower Pesticide residue | 18.65 | 13.86 | 13.05 | 12.10 | 12.04 | 7.93 | 13.28 | 12.67 | 7.57 |
| | (15.83, 22.28) | (12.41, 15.47) | (11.82, 14.52) | (10.89, 13.50) | (10.84, 13.46) | (4.69, 13.53) | (9.10, 21.79) | (11.60, 13.92) | (4.85, 11.86) |
| Certification | 9.81 | 8.48 | 7.26 | 3.24 | 6.28 | 3.16 | 6.65 | 9.89 | 5.20 |
| | (6.94, 12.87) | (6.12, 10.96) | (5.78, 9.26) | (1.35, 5.20) | (1.99, 10.91) | (1.92, 5.15) | (3.04, 10.22) | (8.34, 11.64) | (3.35, 8.11) |
| Higher Vitamin A content | 10.16 | 11.98 | 9.45 | 7.78 | 7.44 | 3.64 | 9.49 | 8.59 | 6.16 |
| | (6.75, 13.87) | (7.51, 16.55) | (8.74, 10.29) | (6.58, 9.11) | (5.92, 9.02) | (2.27, 5.79) | (8.41, 10.65) | (7.02, 10.20) | (5.69, 6.63) |
| Lower Soil Erosion | 7.28 | 10.45 | 10.03 | 9.04 | 7.26 | 3.95 | 6.83 | 6.90 | 6.46 |
| | (5.73, 9.13) | (8.38, 12.53) | (8.52, 12.24) | (7.01, 11.32) | (5.67, 9.08) | (2.35, 6.57) | (6.02, 7.70) | (5.69, 8.17) | (5.63, 9.95) |
| **Coefficient of variation** | | | | | | | | | |
| Lower Pesticide residue | | 4.28 | 1.50 | | 2.62 | 3.25 | | 2.32 | 1.15 |
| Certification | | 3.39 | 1.03 | | 3.19 | 2.29 | | 1.66 | 1.04 |
| Higher Vitamin A content | | 6.33 | 8.08 | | 3.10 | 1.64 | | 3.18 | 2.50 |
| Lower Soil Erosion | | 2.91 | 2.36 | | 3.41 | 2.84 | | 2.48 | 3.07 |

Note: 95% confidence intervals (CIs) calculated using the Krinsky and Robb (1986) method in parentheses. The CIs are based on 10, 000 replications.

parameters in the hybrid model all follow lognormal distributions.[23] The tables first report the mean WTP and the bounds at 95% confidence interval (CI) for the attributes under different modeling strategies and for each treatment. The means and CIs represent empirical distributions, which we compute based on the parametric bootstrap procedure introduced in Krinsky and Robb (1986). [24] The results reveal that respondents are willing to pay a premium for the certifications as well as the identified health- and environment-related attributes of organic products, indicating the presence of a market for organic products in Nigeria.

Tables 8 and 9 also present estimates of the implied coefficient of variation (or noise-to-signal ratio). While the calculation of the mean and standard deviation account for correlation between individual distributions, they are also used to estimate the noise-to-signal ratio. The hybrid models exhibit lower noise relative to the MEAA and MMNL models. The differences between the hybrid models ($HYBRID_{HP}$ and $HYBRID_{CT}$) are relatively modest. However, we observe lower (and arguably more realistic) values in the monetary valuations of attributes in the hybrid models than is the case in MMNL and MEAA models, under the HP and CT treatments. Also noteworthy is the fact that for the majority of trade-offs, we see reduced variability in the hybrid model, which is a reflection of the greater ability of the model to accommodate the heterogeneity across

[23] We take into account the random nature of the parameters in our WTP specifications. The estimation procedure for the welfare values can be found in the supplementary online appendix.

[24] We take advantage of the properties of maximum likelihood and simulate multiple datasets by drawing 10,000 observations from a multivariate normal distribution parameterized by the means and covariances that arise from the estimations.

respondents by linking the values to underlying attribute importance ratings. This is not possible in MMNL models, which may be attributed to inability of the MMNL to use additional information about the attribute processing strategy. Likewise, in the MEAA models stated ANA are handled as covariates rather than as dependent variables. These findings highlight the limitations in models that condition choice responses on the assumption of respondents' full attendance to the presented attributes as well as models that do not account for potential endogeneity bias problem in stated ANA.

We also test whether there exist a statistically significant difference in welfare value estimates obtained from the two alternative priming tasks (HP and CT) applied in the hypothetical CE.  Table 10 reports the differences between the marginal WTP estimates across the treatments. Also presented in the table are the significance levels from statistical tests on the differences in the empirical distributions, based on the complete combinatorial approach (Poe, Girard, and Loomis 2005). This approach compares the differences between every combination of data points in the empirical distributions that arise from the bootstrapping procedure.[25] Based on the results, the null hypotheses of equality in WTP estimates is rejected, especially for the hybrid estimators, indicating that hypothetical CE under different priming task gives different WTP values. Furthermore, across the three model specifications, the HP task

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[25] For iterations of the bootstrapping procedure, the Poe, Girard, and Loomis (2005) method considers differences. Thus, for a bootstrap procedure with 10,000 iterations, this would imply $10,000^2$ = 100,000,000 differences. To make these computations tractable, we reduced the number of data points from 10,000 down to 1,000 for the complete combinatorial test.

consistently leads to lower WTP values by nearly a factor of two relative to CT task, for three of the four attributes identified.[26]

Table 10: Difference in Implied Trade-Off for Attributes from Models with Stated ANA

| | EAA | | | MEAA | | | HYBRID | | |
|---|---|---|---|---|---|---|---|---|---|
| | ΔWTP | | | ΔWTP | | | ΔWTP | | |
| | (HP-N) | (CT-N) | (HP-CT) | (HP-N) | (CT-N) | (HP-CT) | (HP-N) | (CT-N) | (HP-CT) |
| Lower Pesticide residue | -6.55* | -5.37*** | -1.18* | -1.82** | -1.19 | -0.63 | -5.11** | -5.48* | 0.37* |
| Certification | -6.57** | -3.16** | -3.41** | -2.20** | 1.41* | -3.61** | -4.10*** | -2.06** | -2.05* |
| Higher Vitamin A content | -2.38* | -0.67 | -1.71 | -4.54** | -3.39* | -1.15** | -5.81* | -3.29** | -2.52* |
| Lower Soil Erosion | 1.76* | -0.45 | 2.21* | -3.19* | -3.55* | 0.36 | -6.08* | -3.57* | -2.51* |

Note: The values are the differences between the marginal WTP estimates across the treatments, and the significance levels from statistical tests on the differences in empirical distribution based on the complete combinatorial approach (Poe, Girard, and Loomis, 2005).

***, **,* Significance at the1%, 5% and 10% levels, respectively.

Moreover, in comparison to the WTP values obtained from the baseline treatment (N), the results reveal that the HP task is better able to mitigate potential upward bias in WTP values in hypothetical CE relative to CT treatment. As indicated by Hess et al. (2013), in models that account for ANA, it is expected that the WTP for an attribute will increase, as the number of respondents that implicitly ignore the price attribute increases. Thus, the low values for HP task might reflect a more realistic valuation of the attributes. It is significant to note that the WTP values are highest in the N treatment,

[26] For the sake of brevity, the results on test of equality in implied trade-off and monetary valuations from other alternative ANA models for each attribute across the treatments can be found in the supplementary online appendix.

followed by the CT and then the HP group across all the models.[27] This variation in WTP also corresponds to the order of prevalence of non-attendance among respondents across treatments, particularly for the price attribute, and as such could help explain the differences in the estimates. This finding might explain the mechanism that drives the differences across the hypothetical bias techniques.

Generally, consumers are willing to pay a price premium for each attribute of the organic tomato product, although significant differences exist between the premiums for the attributes. Our results reveal a pronounced preference ordering, with respondents revealing higher preferences for health-related attributes relative to attributes of environmental concerns, across treatments. For example, under the HP group, we observe that consumers are willing to pay higher premiums for the reduction of pesticide residues (₦7.93) than for lower soil erosion (₦ 3.95) at the 5% significance level.

The observed differences in the extent of ANA rates across treatments show the importance of accounting for *ex ante* mitigation methods in improving the validity of WTP estimates. We note that implementing the mitigation strategies tend to reduce non-attendance, irrespective of the ANA model employed, although ordering of the attributes for respondents in a given *ex ante* treatment remains relatively consistent. In comparing

[27] We also assessed the robustness of these test results by specifying utility in the WTP space (de-Magistris, Gracia and Nayga 2013), such that there is one extended utility function for each pair of the HP, CT and N treatments. Given that we use the second WTP values as the reference levels, the estimated parameters are all negative and mainly significant, hence lending support to the results obtained using the Poe, Giraud, and Loomis (2005) test. The estimates can be found in the supplementary online appendix.

the effect on welfare estimates, evidence from the pattern of our results suggest that estimates derived from models when mainly controlling for hypothetical bias are lower relative to values obtained when solely accounting for stated ANA. However, more substantial effect on WTP estimate is attained by jointly accounting for ANA as well as adopting measures to mitigate upward bias. Based on these findings, we infer that incorporating indicators of stated ANA in models is likely to provide more reliable WTP values in instances where hypothetical bias mitigation methods are incorporated in CE. Lastly, it is worth noting that in this empirical application, we find that hybrid models that account for potential endogeneity bias and measurement error problems yield the lowest WTP values. However, it is significant to mention that the effect of correcting for endogeneity bias is still being debated in the literature, as some studies argue that endogeneity is more likely to be a product of model misspecification, and correcting for it may be difficult, or even counter-productive (e.g., Balcombe et al. AJAE forthcoming; Chorus and Kroesen 2014).

### 2.6 Conclusion

The need to diversify and explore domestic markets for organic products is now been considered in Nigeria to complement international market access. Discovering the right niche market is a complicated task, since preferences vary among consumers. The identification of market potentials for organic food product is important, given that future development of the sector will to a large extent depend on consumers' acceptance and willingness to pay for the products.

In this article, we are the first to investigate the impact of *ex-ante* hypothetical bias mitigation methods (CT (explicit approach) and HP (implicit approach)), on respondents' attribute processing (ANA) as well as to test whether there exist a statistically significant difference in welfare value estimates obtained from these different techniques in the context of organic products in sub-Saharan Africa. To explore the effects of the priming tasks on respondents' ANA vis-à-vis their WTP values, we estimated hybrid models that account for potential endogeneity and measurement errors as well as the commonly used mixed multinomial logit (MMNL), endogenous attribute attendance (EAA) and mixed EAA models, as robustness checks.

Our results reveal that respondents are willing to pay a premium for the certifications as well as the identified health- and environment-related attributes of organic products, especially with lower pesticide residue attracting the highest value in the treatments. This implies that potential market for organic products exists in Nigeria, and since consumers are highly inclined towards health concerns, this could serve as an important entry point for marketing.

The estimates from the stated ANA information show that the incidence of ANA varies across the treatments in general, with respondents under the HP treatment reporting lowest ANA rates followed by CT, and then baseline treatments. More so, we observe significant differences in ANA rates between respondents exposed to the mitigation strategies (HP and CT) and the baseline (N) group. For example, the price attribute in the HP and CT treatments has the lowest ANA rate, while it is highest in the baseline treatment. This suggests that the use of *ex-ante* hypothetical bias mitigation methods elevate the congruence between inferred and stated ANA.

Furthermore, our findings show that hypothetical CE under different priming tasks generally result in different WTP values. In particular, the HP task resulted in lower WTP values by nearly a factor of two relative to CT task, for three of the four attributes identified. Similarly, in comparison to the WTP values obtained from the baseline treatment, the results revealed that in a hypothetical CE setting, the HP task is better able to mitigate potential upward bias in WTP values relative to CT treatment. Thus, the low WTP values for HP task appear to correspond with the lowest ANA rates reported for all the attributes (especially price) and might reflect a more realistic valuation of the attributes. We further observe that when hypothetical bias mitigation strategies are employed, there is a high degree of consistency between the respondent-reported answers to processing questions for most of the attributes identified, and the marginal utilities for these attributes in the choice model.

From a policy perspective, the finding that consumer's previous awareness effectively advances the potential demand for organic products indicates that initiating effective sensitization programs may be significant for the successful development of sustainable organic sector in Nigeria. Similarly, given consumers' valuation of the certification attributes, institutionalizing third party certification for organic food products would be an appropriate policy strategy.

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## Appendix

TABLE A1: Maximum Likelihood Estimates for the Pooled Data

| | MMNL<sub>POOLED</sub> | | HYBRID<sub>POOLED</sub> | |
|---|---|---|---|---|
| Respondents | 900 | | 900 | |
| Observations | 8,100 | | 8,100 | |
| LL(0) | -9,938.836 | | -13,086.079 | |
| LL | -4,684.443 | | -11,771.204 | |
| Par. | 11 | | 41 | |
| Variable | Est. | *t*-Ratio | Est. | *t*-Ratio |
| $\beta_{price}$ | -3.8288 | -25.46 | -0.9503 | -27.35 |
| $\beta_{pesticide}$ | 1.2635 | 28.98 | 0.6785 | 30.04 |
| $\beta_{certification}$ | 0.2192 | 10.07 | 0.0426 | 1.91 |
| $\beta_{vitamin}$ | 0.2770 | 11.09 | 0.2878 | 13.08 |
| $\beta_{erosion}$ | 0.3452 | 15.55 | 0.3242 | 14.39 |
| Constant | -14.9848 | -19.56 | -1.8651 | -28.84 |
| $S_{(\beta_{Price})}$ | 1.6263 | 10.40 | -0.0774 | -1.65 |
| $S_{(\beta_{Pesticide}),(\beta_{price})}$ | 0.0395 | 5.82 | 0.0365 | 0.69 |
| $S_{(\beta_{Pesticide})}$ | 0.6940 | 16.50 | 0.0459 | 0.34 |
| $S_{(\beta_{Certification}),(\beta_{Price})}$ | 0.2799 | 10.18 | 0.0757 | 0.59 |
| $S_{(\beta_{Certification}),(\beta_{Pesticide})}$ | -0.2555 | -10.97 | 0.0316 | 0.38 |
| $S_{(\beta_{Certification})}$ | 0.0357 | 1.07 | -0.0064 | -4.22 |
| $S_{(\beta_{Vitamin}),(\beta_{Price})}$ | -0.2380 | -10.60 | -0.0099 | -1.26 |
| $S_{(\beta_{Vitamin}),(\beta_{Pesticide})}$ | 0.0064 | 15.74 | 0.1760 | 0.68 |
| $S_{(\beta_{Vitamin}),(\beta_{Certification})}$ | 0.0479 | 4.00 | 0.0157 | 1.13 |
| $S_{(\beta_{Vitamin})}$ | -0.1491 | -4.45 | 0.0174 | 1.10 |
| $S_{(\beta_{Erosion}),(\beta_{price})}$ | -0.0494 | -10.67 | 0.1644 | 0.85 |
| $S_{(\beta_{Erosion}),(\beta_{Pesticide})}$ | 0.0696 | 15.64 | 0.1475 | 0.15 |
| $S_{(\beta_{Erosion}),(\beta_{Certification})}$ | 0.2011 | 3.09 | 0.1651 | 0.53 |

| | | | | |
|---|---|---|---|---|
| $S_{(\beta_{Erosion}),(\beta_{Vitamin})}$ | -0.1950 | -1.22 | 0.0292 | 0.46 |
| $S_{(\beta_{Erosion})}$ | -0.0887 | -2.93 | 0.0074 | 0.48 |
| $\lambda_{Price}$ | - | - | 0.6956 | 18.26 |
| $\lambda_{Pesticide}$ | - | - | 0.7345 | 19.92 |
| $\lambda_{Certification}$ | - | - | 3.3724 | 1.85 |
| $\lambda_{Vitamin}$ | - | - | 0.2535 | 4.23 |
| $\lambda_{Erosion}$ | - | - | 0.5547 | 8.57 |
| $\varphi_{Age}$ | - | - | 0.2699 | 9.49 |
| $\varphi_{Male}$ | - | - | 0.3967 | 14.48 |
| $\varphi_{Educ}$ | - | - | 0.2808 | 17.53 |
| $\varphi_{H/hsize}$ | - | - | 0.0674 | 3.73 |
| $\varphi_{Disease}$ | - | - | -0.1500 | -5.14 |
| $\varphi_{Aware}$ | - | - | 0.5791 | 21.67 |
| $\kappa_{Price}$ | - | - | -1.7061 | -3.53 |
| $\kappa_{Pesticide}$ | - | - | -2.2947 | -6.82 |
| $\kappa_{Certification}$ | - | - | -3.7556 | -10.04 |
| $\kappa_{Vitamin}$ | - | - | -3.7212 | -12.60 |
| $\kappa_{Erosion}$ | - | - | -3.5224 | -11.41 |
| $\zeta_{Price}$ | - | - | -0.7771 | -3.70 |
| $\zeta_{Pesticide}$ | - | - | -0.5280 | -27.54 |
| $\zeta_{Certification}$ | - | - | 0.7246 | 23.35 |
| $\zeta_{Vitamin}$ | - | - | 0.5261 | 22.96 |
| $\zeta_{Erosion}$ | - | - | 0.0544 | 2.48 |
| $\varsigma_{Price}$ | - | - | 0 | - |
| $\varsigma_{Pesticide}$ | - | - | 0.2836 | 6.53 |
| $\varsigma_{Certification}$ | - | - | -1.6779 | -3.22 |
| $\varsigma_{Vitamin}$ | - | - | -1.0678 | -25.26 |
| $\varsigma_{Erosion}$ | - | - | -0.0343 | -0.80 |
| $\tau_{Price}$ | - | - | 0.7153 | 39.60 |
| $\tau_{Pesticide}$ | - | - | 0.0291 | 1.04 |
| $\tau_{Certification}$ | - | - | -0.1520 | -4.42 |

| | | | | |
|---|---|---|---|---|
| $\tau_{Vitamin}$ | - | - | 0.1295 | 4.56 |
| $\tau_{Erosion}$ | - | - | 0.1064 | 3.71 |

Table A2: Comparison of Information Criteria

| | | Obser. | LL | Par. | AIC | AIC/N | 3AIC | 3AIC/N |
|---|---|---|---|---|---|---|---|---|
| Baseline | | | | | | | | |
| 1 | EAA | 2,700 | -1,731.89 | 10 | 3483.8 | 1.290 | 3493.8 | 1.294 |
| 2 | EAA + ANA | 2,700 | -1,629.84 | 15 | 3289.7 | **1.218** | 3304.7 | **1.224** |
| 3 | MEAA | 2,700 | -1,606.27 | 15 | 3242.5 | 1.201 | 3257.5 | 1.206 |
| 4 | MEAA + ANA | 2,700 | -1,594.07 | 20 | 3228.1 | **1.196** | 3248.1 | **1.203** |
| Honesty Priming | | | | | | | | |
| 1 | EAA | 2,700 | -1,717.21 | 10 | 3454.4 | 1.279 | 3464.4 | 1.283 |
| 2 | EAA + ANA | 2,700 | -1,283.56 | 15 | 2597.1 | **0.962** | 2612.1 | **0.967** |
| 3 | MEAA | 2,700 | -1,514.64 | 15 | 3059.3 | 1.133 | 3074.3 | 1.139 |
| 4 | MEAA + ANA | 2,700 | -1,250.96 | 20 | 2541.9 | **0.941** | 2561.9 | **0.949** |
| Cheap Talk | | | | | | | | |
| 1 | EAA | 2,700 | -1,566.43 | 10 | 3152.9 | 1.168 | 3162.9 | 1.171 |
| 2 | EAA + ANA | 2,700 | -1,316.13 | 15 | 2662.3 | **0.986** | 2677.3 | **0.992** |
| 3 | MEAA | 2,700 | -1,545.20 | 15 | 3120.4 | 1.156 | 3135.4 | 1.161 |
| 4 | MEAA + ANA | 2,700 | -1,260.09 | 20 | 2560.2 | **0.948** | 2580.2 | **0.956** |

Table A3: Difference in implied trade-off for benchmark models

| | EAA | | | MEAA | | |
|---|---|---|---|---|---|---|
| | | ΔWTP [a] | | | ΔWTP | |
| | (HP-N) | (CT-N) | (HP-CT) | (HP-N) | (CT-N) | (HP-CT) |
| Lower Pesticide residue | -2.71* | 0.62 | -3.33* | -3.47* | -3.08* | -0.39* |
| Certification | -11.28* | -8.56** | -2.72* | -6.18** | -5.39* | -0.79** |
| Higher Vitamin A content | -2.19* | -1.59 | -0.60 | -4.65* | -3.94* | -0.71* |
| Lower Soil Erosion | 3.09* | 2.98* | 0.11 | -0.03 | 0.45 | -0.48 |

Table A4: Tests of Equality between the implied trade-off across treatments

| | Baseline | | | | | Honesty Priming | | | | | Cheap talk | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $HYBRID_{N}$ vs. | | | | | $HYBRID_{HP}$ vs. | | | | | $HYBRID_{CT}$ vs. | | | | |
| **Attributes** | $EAA_1$ | $EAA_2$ | $MEAA_1$ | $MEAA_2$ | MMNL | $EAA_1$ | $EAA_2$ | $MEAA_1$ | $MEAA_2$ | MMNL | $EAA_1$ | $EAA_2$ | $MEAA_1$ | $MEAA_2$ | MMNL |
| Lower Pesticide residue | 0.042 | 0.008 | 0.013 | 0.021 | 0.001 | 0.039 | 0.008 | 0.001 | 0.100 | 0.000 | 0.030 | 0.000 | 0.081 | 0.097 | 0.059 |
| Certification | 0.012 | 0.017 | 0.003 | 0.042 | 0.061 | 0.033 | 0.006 | 0.055 | 0.014 | 0.009 | 0.072 | 0.066 | 0.053 | 0.018 | 0.011 |
| Higher Vitamin A content | 0.017 | 0.004 | 0.070 | 0.009 | 0.021 | 0.002 | 0.006 | 0.035 | 0.018 | 0.001 | 0.103 | 0.009 | 0.001 | 0.010 | 0.002 |
| Lower Soil Erosion | 0.001 | 0.070 | 0.014 | 0.007 | 0.002 | 0.001 | 0.001 | 0.000 | 0.000 | 0.000 | 0.028 | 0.030 | 0.019 | 0.025 | 0.005 |

Table A5: Implied trade-off and monetary valuation in WTP space.

| Tests | Estimates | *t*-Ratio |
|---|---|---|
| **ΔWTP** [a] | | |
| **(Honesty Priming – Baseline)** | | |
| Pesticide × $HP_{treat}$ | -1.4054*** | -10.32 |
| Certification × $HP_{treat}$ | -0.3929*** | -3.47 |
| Vitamin A × $HP_{treat}$ | -0.0811 | 0.68 |
| Erosion × $HP_{treat}$ | -0.3555*** | -3.41 |
| *Obser.* = 5,400 | | |
| *Resp.* = 600 | | |
| *LL(0)* =3,684.077 | | |
| *LL* = 3,474.032 | | |
| *Par.* = 20 | | |
| **ΔWTP** | | |
| **(Cheap Talk –Baseline)** | | |
| Pesticide × $CT_{treat}$ | -0.9177*** | -7.72 |
| Certification × $CT_{treat}$ | -0.3127*** | -2.85 |
| Vitamin A × $CT_{treat}$ | -0.3433*** | -3.15 |
| Erosion × $CT_{treat}$ | -0.0338 | -0.33 |
| *Obser.* = 5,400 | | |
| *Resp.* = 600 | | |
| *LL(0)* =3,671.502 | | |
| *LL* = 3, 428.170 | | |
| *Par.* = 20 | | |
| **ΔWTP** | | |
| **(Honesty Priming –Cheap Talk)** | | |
| Pesticide × $HP_{treat}$ | -0.6839*** | -5.68 |
| Certification × $HP_{treat}$ | -0.1511 | -1.49 |
| Vitamin A × $HP_{treat}$ | -0.1950** | -2.01 |
| Erosion × $HP_{treat}$ | -0.3987*** | -3.97 |
| *Obser.* = 5,400 | | |
| *Resp.* = 600 | | |

| |
|---|
| *LL(0)* =3,814.786 |
| *LL* = 3,588.848 |
| *Par.* = 20 |

[a] Denotes the effects of the *ex-ante* treatments ($HP_{treat}$ and $CT_{treat}$) on marginal WTP estimates.

***, ** Significance at the1% and 5% levels, respectively.

**Empirical specification for the WTP estimations.**

Given that we specified our models to allow for more complex error component structures, describe heterogeneous behaviour as well as take panel effects into account, the WTP measures are specified as random distributions. To address the challenge of calculating the confidence intervals (CI) for random parameter models estimated in preference space, we applied the Krinsky and Robb parametric bootstrapping procedure (1986). First, we compute the Cholesky decomposition of the covariance matrix, yielding a lower triangular matrix. Second, we take simulated draws (10,000 Halton) from a multivariate normal distribution for each of the estimated four structural parameters, which then results in a lognormal distribution for both price and the specific quality attribute considered. For example, to calculate the marginal WTP for lower pesticide residue, we specified the marginal utility coefficients for price and pesticide attributes as:

$\theta_{price}$= exp $(\beta_{price} + S_{(\beta_{Price})} \times N)$

$\theta_{pesticide}$= exp $\left(\beta_{pesticide} + (S_{(\beta_{Pesticide}).(\beta_{Price})} \times N + S_{(\beta_{Pesticide})} \times N) \times N\right)$

where $N$ has a standard normal distribution.

Third, from these two distributions we again take simulated draws (10,000 Halton) and compute the WTP ratios, $\theta_{pesticide} / \theta_{price}$, for each draw. Finally, we estimate the welfare values by taking expectation of the WTPs, and also compute the 95% confidence intervals by taking the 0.025 and 0.975 percentiles. Overall, our WTP estimations for the random coefficient models involve a Monte Carlo simulation in six dimensions that takes into account the coefficient estimates, the variances of the estimated parameters as well as the covariances. In other words, we derive our WTP values based on random parameters using all the information in the distributions. This is consistent with the procedure proposed in Hensher and Greene (2003) and implemented in Sillano and Ortúzar (2005), Michaud, Llerena and Joly (2013) and Bliemer and Rose (2013).

# Chapter 3

## Measuring Heterogeneity, Survey Engagement and Response Quality in Preferences for Organic Products in Nigeria

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published 2016 in *Applied Economics*, 48 (13): 1159-1171

Abstract

The identification of the market potentials of organic products is important in the drive towards a sustainable agricultural development in sub-Saharan Africa (SSA). However, available evidence shows that valuing attributes of credence goods (such as organic products) while using stated preference methods faces additional obstacles compared to other normal goods. In this study, we examine consumers' preferences and willingness-to-pay (WTP) for health and environmental attributes of organic products in Nigeria. We employ an approach that allows us to adequately capture the value of organic products by linking part of the heterogeneity across respondents to differences in scale, while making use of indicators of survey engagement, without risks of endogeneity bias and measurement error that arise from the deterministic methods. The empirical results show that market for organic products exists in Nigeria, with reduction in pesticide residues attribute attracting the highest value, followed by the certification programme. Furthermore, we observe that increases in the latent engagement variable lead to a greater probability of agreement with statements relating to survey understanding and realism, and hence more substantive output.

**JEL code** Q56, Q17, N97, C93

**Keywords** organic products, SSA**,** survey engagement, random scale

## 3.1Introduction

Although the use of agrochemicals offers significant economic benefits by enhancing agricultural production in sub-Saharan Africa (SSA), the discovery of pesticide residues in various sections of the environment has raised serious concerns (e.g., Sosan *et al.,* 2008). Agrochemicals not only have the potential to cause diseases in humans, but can also be highly toxic to the aquatic life and soil microflora. The increase in soil degradation is a serious biophysical problem that has threatened food production systems in developing countries (especially in SSA), where about 10 million hectares of crop land are lost annually (e.g., Azadi, *et al.,* 2011). According to a joint report by World Health Organization (WHO) and United Nations Environment Program (UNEP), around 3 million people are poisoned each year by pesticides, with a vast majority (95%) of the cases from developing nations (WHO/UNEP, 1990). For example, studies have shown that farmers in SSA often abuse, misuse and overuse pesticides (e.g., Lund *et al.,* 2010).

Overcoming this predicament has generally been acknowledged to require a wide range of creative sustainable agricultural systems that provide food, and also factor in health and environmental concerns. It is against this background that organic agriculture (OA) as a sustainable alternative farming system is now being advocated in Nigeria (Philip and Dipeolu, 2010). OA is a holistic production management system that avoids the use of synthetic chemicals, growth hormones, antibiotics and gene manipulation, while promoting improved precise standards of production, which are socially and economically sustainable (United Nations Conference on Trade and Development; United Nations Environment Programme (UNEP-UNCTAD), 2008). Like other African countries, there are a number of traditional farming systems that practice some organic techniques in the country. However, these systems do not fully meet the production standards for organic farming (e.g., Kleeman and Abdulai, 2013). Organic products are grown using a well-defined and unique set of certification procedures that give consumers quality assurance and guarantee the products' integrity on the market (International Federation of Organic Agriculture Movements (IFOAM), 2012).

Although OA initiative was introduced almost a decade ago in Nigeria, general lack of domestic markets and the sole reliance on export has constrained the adoption amongst farmers (IFOAM, 2012).[28] Available evidence show that in addition to practicalities of certification, a number of risk factors evolve as the future development of organic export in developing countries is being evaluated (e.g., Oelofse, *et al.,* 2010). Also, many supplying countries and farmers of organic produce have been confronting huge challenges to enter and benefit from organic export in a sustainable way (e.g., Kleeman and Abdulai, 2013). Few of the identified hindrances to organic export include: difficulties in creating reliable market links, cases of insecurity due to pirate raids (e.g. in East Africa), rising fuel prices and the debate on carbon emission and food miles (e.g., UNEP-UNCTAD, 2008). It is in this context that the need to diversify and explore domestic markets for organic products is now being considered to complement the international market access. The identification of market potentials of the organic product is important, given that future development of the sector will to a large extent depend on consumers' acceptance and demand.

Few studies have investigated preferences for attributes of organic products among urban consumers in SSA and have used hypothetical stated preference (SP) approaches. Specifically, contingent valuation methods (CV) have been predominantly employed (e.g. Philip and Dipeolu, 2010). Although the results from these studies provide some insight into the valuation of organic products, the underlying assumption

[28] Currently, of the 11,987 hectares of land under OA less than 60 hectares are recorded as fully certified organic farms and virtually all the organic products are for export.

of taste homogeneity has limited the validity of the estimated models (Train and Weeks, 2005). The hypothetical choice experiment (CE) is now the most commonly used method for valuing consumer demand for attributes of nonmarket products. The variation in taste across people has been widely addressed by means of discrete choice specifications. Among these, the mixed multinomial logit model (MMNL) has been a workhorse, particularly for its flexibility to accommodate different forms of parameterization (McFadden and Train, 2000; Greene and Hensher, 2013). However, a debated issue in the choice modeling literature is the confounding role of the scale parameter of the Gumbel error (Louviere and Eagle, 2006). Although several approaches have been implemented to distinctly accommodate variation in taste and in scale (e.g., Fiebig *et al.,* 2010),[29] Hess and Rose (2012) argued that in a typical linear-in-parameter specification the two components of random heterogeneity cannot be separately identified.

Nevertheless, the variation in scale remains as an integral part of the behavioural and decision-making processes reflected in the response patterns of stated preference studies (Lundhede *et al.,* 2009). In particular, understanding the role of scale heterogeneity in the overall findings, as well as its determinants, is considered to be conceptually relevant (Hess and Stathopoulos, 2013). Some studies have focused on the effect of exogenous variables in driving scale heterogeneity, often in relation to the task environment (e.g., Swait and Adamowicz, 2001). Others have shown that the capacity-difficulty gap and respondent's level of survey engagement are more important (e.g.,

[29] The underlying perception is that variations in scale across respondents constitutes a significant share of the heterogeneity in random coefficients models, rather than differences in sensitivities.

Heiner, 1983);[30] which they control deterministically. Meanwhile, hypothetical bias is a well-known shortcoming of CE approach, and studies have focused on the development of different *ex ante* mitigation strategies; such as honesty priming (HP) (de-Magistris, *et al.,* 2013) and cheap talk (CT) (Cumming and Taylor, 1999) scripts.[31] Although, there is general agreement that hypothetical bias exists, there is little consensus on the best mitigation strategy to adopt. We are not aware of any previous study that examines the impact of *ex ante* mitigation strategies on respondents survey engagement vis-à-vis response scale. Yet this seems to be an important issue to address, as it has implications for survey design and operation.

In this study, we examine consumers' preferences and willingness-to-pay (WTP) for health and environmental attributes of organic food product in Nigeria. We employ a hybrid model framework proposed by Hess and Stathopoulos (2013), in which data on indicators of survey engagement are jointly modeled with respondent's answers to the stated choice questions. This approach distinctly accounts for scale heterogeneity caused by potentially different levels of engagement among the respondents, while also overcoming the problems of endogeneity bias and measurement errors. Also, we explore the effect of *ex ante* mitigation strategies (i.e., CT, an explicit approach and HP, an implicit technique) on respondent's survey engagement.

The emphasis in this article on respondent's survey engagement is especially relevant in the context of SSA, given that empirical evidence show that valuing attributes

[30] They consider individual differences in the ability to deal with complexity, arising due to variations in demographic variables; such as literacy, age, experience and cognitive ability, among others.

[31] Ready *et al.,* (2010) reveals that *ex post* approach is highly complex in CEs having more than two options per choice scenario; which is the case in our study.

of credence goods (such as organic products) while employing stated preference methods faces additional obstacles compared to valuing other normal goods (e.g., Giannakas, 2002). For example, presently, the market features of organic products in Nigeria reveal that it is still in the introductory stage and many of the respondents are unfamiliar with the concept of certified OA, and as such lack adequate information about the intrinsic quality attributes of organic products (e.g., Philip and Dipeolu, 2010). As a result, choices made among various alternative options in CEs may not only be characterized by differences in preferences, but also be prone to anomalies. Therefore, our approach in this article is appropriate to adequately capture the value of organic products, in that it considers heterogeneity in taste, differences in degree of choice determinism (i.e., scale heterogeneity), as well as the mitigation of hypothetical bias. Our work continues an older tradition in the literature of understanding how consumers evaluate unfamiliar goods (e.g., Nelson, 1970).

The remainder of this article is organized as follows. The next section outlines the econometric framework adopted in the study, followed by a description of the survey methodology and the data in section 3. The empirical specification employed in the study is presented in section 4, while the results of the analysis are discussed in section 5. Finally, we briefly summarize the key findings of the article in Section 6.

### 3.2 Econometric Framework

In a standard specification of random utility model, the deterministic component of utility is given by a function of observed attributes $x$ and estimated parameters, $\beta$ , i.e $V_{int}(\beta) = f(x_{int}, \beta)$ , where typically, a linear-in-parameters specification is adopted. As indicated previously, we follow the model structure of Hess and Stathopoulos (2013). We assume that the standard deviation of unobserved utility (i.e., the scale parameter) varies across respondents as a function of survey engagement, and using a linear in attributes specification, the utility function is expressed as

$$V_{int} = \Gamma_n \beta_n x_{int}, \qquad (1)$$

where $\Gamma_n$ is the scale parameter for respondent $n$, $\beta_n$ is a vector of taste parameters and $x_{int}$ is a vector of attributes for alternative $i$ as faced by respondent $n$ in choice scenario $t$.

However, as noted earlier, the random heterogeneity in $\Gamma_n$ cannot be identified separately. In addition, while the measured variables and proxies for survey engagement can contain valuable information, linking them deterministically to explain scale heterogeneity or to decompose scale, may be erroneous (Hess and Stathopoulos, 2013).

In line with Hess and Stathopoulos (2013), we control these issues in the specifications. To address the endogeneity problem, we note that survey engagement itself is unobserved and that its indicators are simply functions of this underlying level of engagement. Thus, we consider respondent's engagement as a latent variable, which is specified as

$$\alpha_n = h(m_n, \varphi) + \eta_n, \qquad (2)$$

where $h(m_n, \varphi)$ represents the deterministic component of $\alpha_n$, with $m_n$ as a vector of covariates related to respondent $n$ (including an *ex ante* mitigation strategy dummy variable and other respondent-related characteristics), and $\varphi$ a vector of parameters. The random term $(\eta_n)$, follows a normal distribution across respondents, and for identification reasons, we set the mean $\mu_\alpha = 0$ and standard deviation $\sigma_n = 1$.

We then rewrite Equation (1) as

$$V_{int} = e^{\tau\alpha_n}\beta_n x_{int} , \quad (3)$$

where $\Gamma_n$ is substituted by $e^{\tau\alpha_n}$, $\tau$ measures the impact of the latent variable $\alpha_n$ on the scale of utility and the exponential to guarantee that the scale remains positive. However, Equation (3) is a random scale specification subject to the limitations outlined by Hess and Rose (2012). To expand on this base model, we include an additional component that allows us to address these issues, as well as to use supplementary information (i.e. indicators), while avoiding measurement error and endogeneity bias problems.

For the specification, we employ a set of $K$ such indicator variables, which contain a mixture of ordered indicators collected using a Likert-type scale (1-5) and continuous indicators. We then explain the observed values for $I_{kn}, k = 1, \ldots, K$ on the basis of $\alpha_n$. To examine the subjective descriptions (ordered responses); the level of realism, importance and understanding, $I_k$, we employ an ordered logit model, with the likelihood of the observed values specified as

$$L_{I_{kn}} = \sum_{s=1}^{S} \psi_{(I_{kn}=s)} \left[\frac{e^{\omega_{k,s}-\lambda_k\alpha_n}}{1+e^{\omega_{k,s}-\lambda_k\alpha_n}} - \frac{e^{\omega_{k,s-1}-\lambda_k\alpha_n}}{1+e^{\omega_{k,s-1}-\lambda_k\alpha_n}}\right], \quad (4)$$

where $\psi_{(I_{kn}=s)}$ is 1 if $I_{kn} = s$ and 0 otherwise, $S$ is the number of levels, $\omega_{k,s}$ are estimated threshold parameters and $\lambda_k$ measures the impact of $\alpha_n$ on indicator $I_{kn}$. For identification reasons, we set $\omega_{k,S}$ to $+\infty$, and $\omega_{k,0}$ to $-\infty$, such that the probability for indicator values of 1 and S are denoted as $\left(e^{\omega_{k,1}-\lambda_k\alpha_n}\right)/\left(1 + e^{\omega_{k,1}-\lambda_k\alpha_n}\right)$, and $1 - (e^{\omega_{k,s-1}-\lambda_k\alpha_n})/(1 + e^{\omega_{k,s-1}-\lambda_k\alpha_n})$, respectively.

Furthermore, we use participants' response times for the completion of stated choice component (rather than the entire survey) , $I_k$. Since time response is continuous, we centre the indicator on zero prior to estimation, i.e. $I_{kn}^{*} = I_{kn} - \overline{I_{kn}}$, , and then use a normal density:

$$L_{I_{kn}} = \frac{1}{\sigma_{I_k}\sqrt{2\pi}} \; . \, e^{-\frac{(I_{kn}^{*}-\lambda_k \alpha_n)^2}{2\sigma_{I_k}^2}} \quad , \tag{5}$$

where $\sigma_{I_k}$ and $\lambda_k$ are estimated.

The log-likelihood ($LL$) function of the hybrid model then consists of two different components that include the probability of the observed sequence of choices and the probability of the responses to the attitudinal questions. In the model, we let $L(y_n|\beta_n, \tau, \alpha_n)$ denote the likelihood of the observed sequence of choices ($y_n$) for respondent $n$, conditional on the vector of taste coefficients $\beta_n$, the parameter $\tau$, and the latent variable $\alpha_n$, which itself is a function of the *ex ante* mitigation strategies and other respondent-related characteristics, $\varphi$ and its random term. This likelihood will therefore be a product of $T$ discrete choice probabilities. Next, we let $L(I_n|\lambda_I, \sigma_I, \omega_I, \alpha_n)$ denote the probability of observing the actual values for the different indicator variables, conditional on $\lambda_I$ vector of parameters, $\sigma_I$ vector of standard deviations for continuous indicators, $\omega_I$ vector of threshold parameters for ordered indicators, and $\alpha_n$ for the latent variable, which is again a function of $\varphi$. This likelihood is then given by $L(I_n|.) = \prod_{k=1}^{K} L_{I_{kn}}$, where each element in this product potentially make use of a blend of specifications from Equations (4) and (5).

Given that both $L(y_n|\beta_n, \tau, \alpha_n)$ and $L(I_n|\lambda_I, \sigma_I, \omega_I, \alpha_n)$ are conditional on the specific realization of the random latent variable, $\alpha_n$, this approach integrates choice models with latent variable models over the distribution of $\eta_n$, and the randomly distributed vector of taste coefficients $\beta_n$, with $\beta_n \sim z(\beta_n|\Omega)$; where $\Omega$ is the vector of parameters. Hence, the $LL$ function across the $N$ respondents is expressed as

$$LL(\Omega, \varphi, \tau, \lambda_I, \sigma_I, \omega_I) = \sum_{n=1}^{N} \ln \int_{\beta} \int_{\eta} L(y_n|.)L(I_n|.)\mathrm{r}(\eta)\mathrm{z}(\beta|\Omega)\mathrm{d}\,\eta\mathrm{d}\beta, \qquad (6)$$

Generally, the advantage of using a latent variable approach is to overcome the bias inherent in direct incorporation of indicators as explanatory variables in the utility function, rather than treating them as dependent variables.

### 3.3 Survey Design and Data Description

Given that market data for sales of organic products are unavailable in Nigeria, we elicit primary data on consumer preferences using hypothetical CE. [32]The data were drawn from a recent household survey conducted between July and October, 2013 in Kano State, North-Western Nigeria. The location occupies a strategic economic position as commercial nerve centre and second most populous state in the country. The high population density, coupled with the socio-demographic heterogeneity and ethnic mix characterizing the location allowed for high degree of cross-sectional variation and representation in the dataset.

In our survey, we conducted face-to-face interviews with questionnaire, and ensured that subjects were generally representative, and had experience with buying food items. The target population was therefore the primary food buyers in the households. We sampled participants using a multistage sampling approach. First, two

[32] We are unable to conduct a non-hypothetical stated preference approach (i.e., the experimental auction method) due to the fact that the organic product concepts tested in this study are yet to be available on the market. More so, auction methods are more expensive and time-consuming to implement as subjects have to be paid a participation fee and actual transactions have to be made during the experiment. Studies have shown that ideally, an analyst must possess all the product profiles presented in the choice sets in order to properly execute an experimental auction, given that it involves the exchange of real money for actual products (e.g., Harrison, 2006).

highly heterogeneous local government areas (LGAs) were selected (based on national census data; NPC, 2006). Second, twelve districts were randomly selected, that is, three from each LGA. Finally, we sampled a proportionate number of households across socio-demographic strata from these districts. For the present study, our sample consist of 600 respondents.

Following Hess and Stathopoulos (2013), our questionnaire focused on three areas of variation: individual socio-demographic data; choice experiment; and follow up questions. Part of the follow up questions is bordered on subjective descriptions of the level of realism, understanding and importance of the choice tasks. These questions were scored on five-point scales from *do not agree* (1) to *fully agree* (5). Specifically, the three questions used the following wording: $I_1$: "The scenarios I was presented with were realistic"; $I_2$: "I was able to fully understand the tasks I was faced with"; $I_3$: "All the attributes of the choice alternatives were important in my choice decision". The answers to these three questions were collected at the end of the CE aspect of the survey and thus do not relate to a respondent's overall impression of the survey.[33] Then we recorded the time taken by a respondent to complete the stated choice component alone (instead of the entire survey).

Furthermore, in addition to basic information on socio-demographics, the questionnaire contain some attitudinal statements - such as questions about the respondent's household buying habits, their attitudes and beliefs concerning the environment; including their conservation practices. Next, respondents were probed on their level of awareness of OA, and based on a common understanding of organic

[33] Exploratory factor analysis was employed to test the reliability and internal consistency of the indicators. The value of Cronbach's alpha (0.733) confirms reliability of using these indicators as a common construct.

production; we proceeded with the CE task. We also attempted to attenuate hypothetical bias by exposing respondents to *ex ante* mitigation treatments; cheap talk script and HP. Following Lusk and Schroeder, (2004) in the CE procedure, we implemented different treatments and used a between-subject approach, by randomly assigning each respondent to participate in only one of two hypothetical CE treatments. The first treatment (CT) consisted of a CE with a cheap talk script, which was described to participants before responding to the CE questions. We used a generic, short, and neutral CT script, (Cummings and Taylor, 1999), which were modified and developed in English and the local dialects. We refer to this as the cheap talk (CT) treatment. The second treatment (HP) consisted of a CE survey with an HP script, which we also placed immediately before the CE questions.

The choice sets, comprised of two experimentally-designed organic profiles and a 'status-quo' option. The organic profiles were created following Scarpa, Campbell and Hutchinson (2007), using a three-stage Bayesian sequential approach. A preliminary pilot study based on an orthogonal fractional factorial design was carried out to test the questionnaire and to provide Bayesian priors for the main design. Our final design involved 36 choice tasks orthogonally arranged in four blocks of nine choice scenarios each to reduce the probability of respondent fatigue.[34] An even number of respondents were randomly assigned to each of these groups. As shown in Table 1, we describe each organic alternative by four quality attributes and a price. The selection of vegetable, in particular tomato, is guided by previous methodological and empirical suggestions on SSA

[34] The final design was generated using the Ngene software (version 1.0) and we accounted for uncertainty of priors by employing normally distributed Bayesian priors. The final design with the lowest Bayesian D-error (0.2534) was attribute-level balanced.

Table 1: Attributes and Attribute Levels in the Choice Experiments

| Attributes | Description | Attribute Levels |
|---|---|---|
| Pesticide | Reduction in the level of pesticide residues content | 5%, 25% ,100% lower |
| Certification | Organic certification scenarios | Foreign, Indigenous, Foreign plus indigenous labels |
| Vitamin | Increase in vitamin A content | 5%, 25%, 100% higher |
| Price | Purchase price (in Naira) | ₦ 60, ₦ 80, ₦100 |
| Erosion | Reduction in the level of soil erosion | 5%, 25%, 100% lower |

(e.g., Coulibaly et al. 2011) and the acceptance by respondents as realistic. [35]The pricing were derived from local market experts' opinion and focus group discussions. The price

[35] Tomato production plays an important role in enhancing food security in Nigeria, as it provides food and raw materials for industries, income from sales, and employment for smallholder households in urban and peri-urban areas. The demand for tomato is universal in the country, it serves as an excellent source of good amount of vitamin C and beta-carotene, and also there are no cultural / religious barriers against it. Tomato makes up about 18% of the average daily consumption of vegetables in Nigerian homes. Furthermore, Nigeria is ranked the largest producer of tomato in SSA and thirtieth largest in the world with an annual total area of one million hectares used for tomato cultivation and about 1.701 million tonnes of tomatoes produced annually, at an average of 25-30 tonnes per hectare (FAO, 2010). However, tomato being a perishable product remains susceptible to location- and cultivar-specific pests and diseases. Thus, as farmers attempt to meet growing demand and are faced with strong pest pressure, they increasingly rely on synthetic pesticides to reduce the risk of harvest and income loss (e.g., Lund, et al., 2010).

attribute in the choice sets were the prices for 1kg basket of tomatoes, with three different price levels. The lowest price level represents the base price, which reflects the average retail market price; collected from the local market places immediately prior to the experiment. The remaining price levels reflect possible premium prices associated with the organic tomato products.

Another attribute relates to the origin of the certifier of the organic product. Private voluntary certification of organic products has been shown to be an important aspect of the OA initiative in developing countries (e.g., Kleeman and Abdulai, 2013).[36] In this study, we identified three organic certification scenarios. The first level (base) corresponded with the scenario in which the organic tomato is certified by foreign certifiers only, while the second (medium) and third (high) levels correspond to the scenarios with both foreign and indigenous third party certifiers, and indigenous certifiers only, respectively. The remaining three quality-attributes of the organic choice options concern: higher vitamin A content, lower soil erosion and lower pesticide residues. These attributes were described by high, medium and low levels.

Several studies have indicated that organic farming leads to lower usage of pesticide relative to conventional farming (e.g., Dangour *et al.,* 2009). The high level (100% reduction) is related to the absence of residues, the medium level (25% reduction) implies traces of residues from one component (<0.01mg/kg), and the base level (5% reduction) comprises residues (>0.01mg/kg) from more than one component. Some studies have found higher amounts of carotenoid content in organic vegetables, which are precursor and good source of vitamin A. Vitamin A can strengthen eye vision and the immune system (Chowdhury *et al.* 2011). Hence, the vitamin A content could be

[36] In principle, organic certification can improve producers' environmental performance, even in countries where state regulation is weak.

5% (base level), 25 % (medium) or 100% (high) higher in organic tomato than in the conventional counterpart. Similarly, OA contributes positively to the process of encountering soil degradation, as it improves soil organic matter content. Studies show that the water retention capacity on organic farming plots is higher than on conventional plots (e.g., Azadi, *et al.,* 2011). Thus, soil erosion could be 5% (low), 25% (medium), or 100% (high) lower on organic plots relative to conventional farms.

To assess if our randomization was successful in equalizing the characteristics of participants across the two treatments, we use a chi-square test. The results of the tests show that the null hypothesis of equality between the socio-demographic characteristics across treatment samples cannot be rejected at the 5% significance level (see Table A1). We present information on the socioeconomic characteristics of the sample households used in the econometric modeling in Table 2. Each respondent was randomly assigned to participate in only one of two hypothetical CE treatments. The results indicate that

Table 2: Sample Socio-demographics

| Variables | Definition | Mean | S.D. | Min | Max |
|---|---|---|---|---|---|
| Age | Age of household head in years | 43.34 | 11.7 | 17 | 75 |
| Male | Dummy(1=if household head is male, 0 otherwise) | 0.82 | 0.39 | 0 | 1 |
| Education | Years of formal education of the household head | 7.29 | 4.13 | 0 | 26 |
| Income | Average monthly income in Naira (₦ '000) | 47.73 | 75.42 | 9 | 800 |
| Household Size | Number of members of the household | 9.88 | 2.66 | 4 | 15 |
| Awareness | Dummy(1=if previously aware of organic products, 0 otherwise) | 0.24 | 0.42 | 0 | 1 |
| Disease | Dummy(1=if incidence of food disease in 24months, 0 otherwise) | 0.17 | 0.38 | 0 | 1 |
| Urban | Dummy(1=if urban dweller, 0= if rural dweller) | 0.52 | 0.50 | 0 | 1 |
| Recycling | Dummy(1=if food waste is often recycled, 0 otherwise) | 0.46 | 0.49 | 0 | 1 |
| HPtreat | Dummy(1=if honesty priming, 0 = if cheap talk ) | 0.50 | 0.50 | 0 | 1 |

majority (82%) of the households are male-headed, with an average household size of about 10 members. Household's average monthly income was estimated at around ₦ 47,000. On average, respondents have less than 8 years of formal education. Similarly, awareness of organic products is low among the sampled respondents; only 25% reported previous knowledge of certified organic farming. Furthermore, environmental conservation practices, such as the recycle of food waste, are undertaken by 46% of the respondents.

### 3.4 Empirical Specification

Each respondent was faced with up to nine choice tasks, and for the analysis, we made use of a sample of 5400 observations from the 600 respondents.[37] Two different models were estimated on the data, a MMNL and the hybrid model (HYBRID) shown in Equation (6). The MMNL model is primarily included for illustrative purposes. The two models were coded in Biogeme (Bierlaire, 2003), using 250 Halton draws per respondent and per random term in simulation based estimation (Halton, 1960). [38] For the hybrid model, simultaneous estimation of all model components was used (Hess and Stathopoulos, 2013).

In both the MMNL and hybrid models, the alternative specific constants were not statistically significant; as such we only considered the effects of the five identified attributes. The four quality attributes were all dummy coded, with the base levels set to zero. [39] The final models were specified to vary randomly across respondents, with a full

[37] A sample of 2700 observations from 300 respondents, each in the HP and CT treatments were used for the analysis.

[38] Increasing the draw to 500 and 1000, did not have marked impact on our results.

[39] In estimating the models, we observe that the medium level of the attributes were not statistically significant from zero, thus for the reason of parsimony, the medium and

covariance matrix being computed for all the elements in marginal utility coefficients $\beta$ (e.g., Hess and Rose, 2012).[40] Both taste parameters ($\beta$) and scale parameters ($\Gamma$) were specified to follow lognormal distributions, in order to prevent any mismatch and allow for more tractability.[41]

For more behavioural insight, we link some socio-demographic interactions as shifts in the mean distributions of the attributes. Our final specification includes shifts in the sensitivity to certification attribute based on respondents' household size, geographic location (region) and awareness of organic products. Similarly, for the specification of the latent engagement variable $\alpha_n$ in Equation (2), we include interactions with the treatment dummy (set to 1 for respondents under HP treatment and 0 for the CT group) and five socio-demographic variables. We identify the related parameters as: $\varphi HPtreat$, $\varphi Income$, $\varphi Educ$, $\varphi Age$, $\varphi Recycle$ and $\varphi Disease$.

The final component of the hybrid model is given by the measurement equations for the attitudinal indicators. We use four indicators, with the first three, $I_1$–$I_3$, relating to the survey engagement statements as described previously, and the survey response time, $I_4$. We employ an ordered logit specification (in Equation 4) to estimate the thresholds for each of the three indicators, but the specific distribution of the responses led to our merging of the first three and last two levels for all indicators. We further

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base levels were effectively collapsed to form a single base level (e.g., Collins, *et al.,* 2012).

[40] For example, the Cholesky terms, $S_{(\beta_{Pesticide}),(\beta_{price})}$ and $S_{(\beta_{Pesticide})}$ give the two components of the Cholesky matrix relating to the pesticide coefficient, the first being off-diagonal, the second being the diagonal element, while e.g. $\beta_{Pesticide}$ gives the mean distribution for the pesticide coefficient.

[41] We also estimated the models with normally distributed coefficients, but these were found to have lower goodness of fit.

simplify the model by constraining the estimates of the indicators in Equation (4) to 1. As such, any differential impact of the latent variable on the three indicators was plugged into the estimates for the thresholds. A continuous specification as shown in Equation (5), is used for the respondent's survey duration.

As highlighted in section 2, the $LL$ function of the hybrid model is composed of two components. The first component $L(y_n|.)$ which gives the likelihood of observed choices, is a product of MNL probabilities. The second component $L(I_n|.)$ denoting the probability of responses to the attitudinal questions is a product of three ordered logit terms (for $I_1$–$I_3$) and one continuous term (for $I_4$) from Equations (4) and (5), respectively. The distribution of the random latent variable, r($\eta$), is univariate normal, with zero mean and a standard deviation of one, whereas the distribution of the random attributes, z($\beta|\Omega$), is a multivariate normal, with five elements and a full covariance matrix. Both $\beta$ and $\Gamma$ are exponentiated to obtain a Lognormal distribution. We use a simultaneous estimation (Equation 8), with the integration over $\eta$ and $\beta$, and reflecting the repeated choice nature of our data (Revelt and Train, 1998). For the MMNL model, we also estimate simultaneously although without the $L(I_n|.)$ component and integration over $\eta$, or the multiplication of the utility functions by $e^{\alpha_n}$ in Equation (6) (Hess and Stathopoulos, 2013).

### 3.5 Empirical Results

In this section, we first discuss the results of the choice model components on preferences for the organic product attributes, before we proceed to present the measurement model and structural equation of the latent variable. Finally, we present the welfare value measures for the attributes.

Table 3 shows the statistics and the maximum likelihood estimates of the choice model component of the two models, with the results on the lower part mainly describing the hybrid model; the additional model components were not estimated in the MMNL model. The hybrid model jointly explains choices and the indicators, as reflected in the higher null log-likelihood ($LL$). Therefore, a comparison of model fit between the two specifications is not possible. Further, it should also be noted that following the suggestion in Hess and Rose (2012), we specified a full covariance matrix and allowed for all the parameters to vary randomly (lognormally distributed) in both models. [42]

The results from the choice model component reveal that there are high preferences for organic product attributes among consumers in Nigeria. The five mean estimates are all statistically significant across the two models, with the expected negative sign for the price attribute and preferences for increase in the remaining four attributes of the organic profile.[43] Similarly, from the Cholesky matrix, we observe that majority of the estimates of the diagonal elements are statistically significant, indicating heterogeneity in preferences for the attributes among respondents. Next, for the effect of the socio-demographic variables, we observe that across both models, the sensitivity to

[42] However, in our final model specification, no significant alternative specific constants were recovered, and we thus limited ourselves to the effects of five explanatory variables.

[43] For the negative price attribute, given that the lognormal distribution produces positive parameter value which may be contrary to a priori expectation, we follow the literature and reverse the sign by defining the negative of the attribute prior to model estimation.

Table 3: Maximum likelihood estimates of the choice models

| | MMNL | | HYBRID | |
|---|---|---|---|---|
| Respondents | 600 | | 600 | |
| Observed choices | 5400 | | 5400 | |
| Observed indicator measurements | 0 | | 1046 | |
| Log-likelihood | -1,460.359 | | - 2,505.830 | |
| Par. | 13 | | 28 | |
| Variable | Est. | $t$-Ratio | Est. | $t$-Ratio |
| $\beta_{price}$ | -0.1958 | -27.36 | -0.1173 | -10.57 |
| $\beta_{pesticide}$ | 1.0856 | 21.92 | 0.8197 | 19.50 |
| $\beta_{certification}$ | 0.4114 | 13.67 | 0.2762 | 12.52 |
| $\beta_{vitamin}$ | 0.4396 | 12.14 | 0.2242 | 7.32 |
| $\beta_{erosion}$ | 0.3305 | 12.26 | 0.3084 | 12.98 |
| $S_{(\beta_{Price})}$ | -0.0730 | -11.68 | 0.0668 | 8.20 |
| $S_{(\beta_{Pesticide}),(\beta_{price})}$ | 0.1233 | 2.44 | -0.2077 | -1.47 |
| $S_{(\beta_{Pesticide})}$ | 0.0394 | 0.85 | 0.1299 | 3.20 |
| $S_{(\beta_{Certification}),(\beta_{Price})}$ | -0.0675 | -12.33 | -0.1332 | -1.36 |
| $S_{(\beta_{Certification}),(\beta_{Pesticide})}$ | -0.2045 | -7.86 | 0.0669 | 2.17 |
| $S_{(\beta_{Certification})}$ | 0.7102 | 11.31 | 0.0082 | 12.52 |
| $S_{(\beta_{Vitamin}),(\beta_{Price})}$ | -0.2049 | -2.28 | 0.1725 | 0.99 |
| $S_{(\beta_{Vitamin}),(\beta_{Pesticide})}$ | 0.0787 | 0.39 | -0.1901 | -0.28 |
| $S_{(\beta_{Vitamin}),(\beta_{Certification})}$ | -0.1720 | -8.82 | -0.1064 | -1.59 |
| $S_{(\beta_{Vitamin})}$ | 0.0169 | 0.45 | 0.1113 | 7.32 |
| $S_{(\beta_{Erosion}),(\beta_{price})}$ | 0.0313 | 3.52 | -0.1453 | -6.78 |
| $S_{(\beta_{Erosion}),(\beta_{Pesticide})}$ | 0.2521 | 4.91 | 0.0946 | 6.13 |
| $S_{(\beta_{Erosion}),(\beta_{Certificatin})}$ | -0.2810 | -10.29 | -0.0188 | -3.90 |

| | | | | |
|---|---|---|---|---|
| $S_{(\beta_{Erosion}),(\beta_{Vitamin})}$ | 0.2125 | 4.75 | 0.0802 | 5.65 |
| $S_{(\beta_{Erosion})}$ | -0.2717 | -4.82 | -0.2179 | -5.44 |
| | | | | |
| $\Delta_{H/hsize.\beta_{certification}}$ | -0.4465 | -3.25 | -0.1747 | -1.42 |
| $\Delta_{Urban_{\beta_{certification}}}$ | 0.7138 | 4.33 | 0.0440 | 0.37 |
| $\Delta_{Aware.\beta_{certification}}$ | 0.1055 | 0.79 | 0.5407 | 3.69 |
| $\tau$ | - | - | 0.5851 | 5.62 |
| | | | | |
| $\varphi_{HPtreat}$ | - | - | 1.0707 | 5.46 |
| $\varphi_{Income}$ | - | - | 1.0307 | 5.49 |
| $\varphi_{Educ}$ | - | - | 0.4202 | 5.38 |
| $\varphi_{Age}$ | - | - | -0.0963 | -3.06 |
| $\varphi_{Recycle}$ | - | - | 1.7161 | 5.62 |
| $\varphi_{Disease}$ | - | - | 0.5056 | 5.02 |
| | | | | |
| $\omega_{I_1,1,2\&3}$ | - | - | -3.1695 | -22.97 |
| $\omega_{I_1,4\&5}$ | - | - | -0.0321 | -4.63 |
| $\omega_{I_2,1,2\&3}$ | - | - | -2.6665 | -20.40 |
| $\omega_{I_2,4\&5}$ | - | - | -0.0159 | -3.42 |
| $\omega_{I_3,1,2\&3}$ | - | - | -3.0334 | -21.05 |
| $\omega_{I_3,4\&5}$ | - | - | -0.0165 | -3.29 |
| $\lambda_{I_4}$ | - | - | 0.0843 | 5.65 |
| $\sigma_{I_4}$ | - | - | 1.1894 | 10.32 |

certification attribute is higher among urban households who are previously aware of organic products. Lastly, for the hybrid model we consider the parameter $\tau$, which describes the effect of the latent variable ($\alpha_n$) on the scale parameter, with $\Gamma = e^{\tau\alpha_n}$. As expected, the estimate is positive and statistically significant, suggesting that increases in the latent survey engagement variable lead to higher model scale. This implies an increase in the ability of the model to better explain consumers' choice behaviors.

Estimates of the structural equation parameters for the latent variable and the parameters of the measurement component are also presented in Table 3. For the interactions in Equation (2), our results reveal that the treatment dummy, ( $HPtreat$) is positive and significantly different from zero, indicating that the level of survey engagement is higher among respondents that were exposed to the HP treatment. Also, for the other socio-demographic interactions, the value of the latent variable (and hence level of survey engagement) is more likely to be higher amongst younger and more educated middle-income households, who often participate in environment-friendly activities, such as food waste recycling, and had recent (within last 24 months) incidence of food-related disease. The high and positive value of the education parameter estimate is intuitive, when considered in light of higher survey understanding (e.g., Hess and Stathopoulos, 2013; De Silva and Pownall, 2014). Moreover, the educational level correlate positively with cognitive capabilities, and thus becomes relevant when hypothetical CE technique is applied in a developing country setting.

For the measurement model, we observe increasing values in the threshold of the three ordered indicators. This implies that increases in the latent engagement variable ($\alpha_n$) are associated with a higher probability of stronger agreement with the three statements describing the indicators. More so, we see a positive estimate for $\lambda_{I_4}$, indicating that increases in the latent engagement variables are also linked with a higher probability of increases in survey response time. Although no overly long time was encountered, we observe some variations ($\sigma_{I_4}$) in the duration of the survey across respondents.

Generally, these estimates reveal that a respondent with more positive value for the latent variable ($\alpha_n$) is more probable to demonstrate more deterministic behaviour when making choice decisions, that is, less noise or higher scale (Hess and Stathopoulos, 2013). As stated previously, such a respondent is more likely to have been exposed to the honesty priming (HP) task and have taken longer to complete the survey, which can be considered as an indication of a more thorough inspection of each choice situation. Also, the respondent may probably express that he/she found the survey to be realistic and understandable, and considers basically all the organic profile attributes to be important. Thus, these findings substantiate the conception of the variable as a latent engagement variable.

Table 4: Heterogeneity in individual coefficients

| | $\beta$(MMNL) | $\beta$(HYBRID) | $\Gamma.\beta$(HYBRID) | Change (%) | Part due to Γ (%) |
|---|---|---|---|---|---|
| $\beta_{Price}$ | 2.64 | 2.75 | 2.94 | +11.23 | 6.92 |
| $\beta_{Pesticide}$ | 2.60 | 2.16 | 2.31 | +12.49 | 6.92 |
| $\beta_{Certification}$ | 4.31 | 3.24 | 3.46 | -19.56 | 6.90 |
| $\beta_{Vitamin}$ | 8.20 | 7.33 | 7.84 | -4.45 | 6.92 |
| $\beta_{Erosion}$ | 10.07 | 8.91 | 9.52 | -5.41 | 6.90 |

Table 4 presents the implied sample level distributions (i.e., coefficients of variation) of the marginal utility coefficients, $\beta$, across the models.[44] Our results show discernible differences in heterogeneity between $\beta$ in the MMNL model to the $\Gamma\beta$ in the hybrid model, with increases in heterogeneity for the price and pesticide coefficients, and a decline in heterogeneity for the certification, vitamin A and soil erosion

[44] Here, we use the same draws as those used in estimation, and incorporate the socio-demographic shifts applicable to each respondent (e.g., Hess and Stathopoulos 2013).

coefficients. These outcomes lend credence to the argument in Hess and Rose (2012) in terms of heterogeneity, that the treatment of scale heterogeneity within the hybrid model framework can yield considerably varied parameter estimates in the choice model component (Hess and Stathopoulos, 2013). We observe that a bulk of the heterogeneity lies in the variation in $\beta$, as differences in scale constitute only about 6% of the heterogeneity in marginal utility coefficients in the hybrid model.

Lastly, we present the implied sample level WTP distributions in Table 5. The results show the mean WTP and the bounds at 95% confidence interval (CI) for each attribute. The means and CIs represent empirical distributions, which we compute based on the parametric bootstrap procedure introduced in Krinsky and Robb (1986). [45] The results reveal that respondents are willing to pay a premium for the certifications as well as the identified health- and environment-related attributes of organic products, with lower pesticide residue attracting the highest value in both treatments. For example, our results show that respondents are willing to pay an additional ₦ 14 for organic tomatoes over the base retail price (₦ 60) for one kilogram basket of conventional tomatoes. This extra value corresponds to 25% premium over the typical market prices results reported for conventional tomatoes during the peak seasons in Nigeria. These findings indicate presence of a market for organic products in Nigeria.[46]

[45] We take advantage of the properties of maximum likelihood and simulate multiple datasets by drawing 10,000 observations from a multivariate normal distribution parameterized by the means and covariance that arise from the estimations.

[46] Our survey data bordered mainly on consumers' observed choices and follow-up questions on their engagement, we did not capture information on organic production factors and input costs. Thus, the analysis of production data for organic tomato is beyond the scope of our study. Nevertheless, the WTP for organic products attributes found in this research is clearly within the range of price premiums identified by other

We also test whether there exist a statistically significant difference in welfare value estimates obtained from the two models using the complete combinatorial approach (Poe, *et al.,* 2005). [47] Based on the results, the null hypotheses of differences in WTP estimates cannot be rejected, as we observe lower values in three of the four attributes.

Table 5 also reports estimates of the implied coefficient of variation (or noise-to-signal ratio). The hybrid models exhibit lower noise relative to the MMNL models. We note significant reductions in heterogeneity patterns in the WTP estimates, for each of the five measures. This could have led to erroneous inferences and conclusions, if the model were to be used to provide outputs for policy recommendation. These results indicate that the hybrid model leads to different and more realistic outcomes in terms of the implied distribution of individual sensitivities, as well as welfare value estimates.

However, at this point, it is important to note that the random scale component ($e^{\tau\alpha_n}$) in the hybrid model has no effect on the WTP patterns since all $\beta$s are affected uniformly. Therefore, variations between the two models can be attributed solely to any effects that the supplementary variables on survey engagement have on the remaining

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studies. Although evidence from developing countries is limited, the review by Yirdidoe et al. (2005) suggests an average WTP premium for organic certified goods of about 30%, and Coulibaly et al. (2011) on their study of private households in urban Ghana and Benin, calculate a premium for organic certification of 57–66% for cabbage and 50–56% for tomatoes.

[47] This approach compares the differences between every combination of data points in the empirical distributions that arise from the bootstrapping procedure. For iterations of the bootstrapping procedure, the Poe, *et al.,* (2005) method considers differences. Thus, for a bootstrap procedure with 10 000 iterations, this would imply 10 000$^2$ = 100 000 000 differences. To make these computations tractable, we reduced the number of data points from 10 000 down to 1 000 for the complete combinatorial test.

model parameters, especially the differential impacts on individual $\beta$ (Hess and Stathopoulos, 2013).

Table 5: Implied trade-offs and monetary valuation

| | MMNL | HYBRID | *p-value*[a] |
|---|---|---|---|
| **Mean** | | | |
| Lower Pesticide residues | 13.75 | 4.18 | 0.002 |
| | (10.80,16.70) | (3.81,4.55) | |
| Certification | 8.83 | 3.34 | 0.001 |
| | (5.88,11.78) | (2.96,3.80) | |
| Higher Vitamin A | 4.68 | 3.23 | 0.041 |
| | (2.28,7.08) | (2.86,3.60) | |
| Lower Soil Erosion | 4.76 | 3.18 | 0.011 |
| | (1.60,7.92) | (2.78,3.58) | |
| **Coefficient of variation** | | | |
| Lower Pesticide residues | 3.37 | 1.15 | |
| Certification | 6.52 | 3.82 | |
| Higher Vitamin A | 5.58 | 2.43 | |
| Lower Soil Erosion | 20.03 | 12.38 | |

Note: 95% confidence intervals calculated using the Krinsky and Robb (1986) method in parentheses. The CIs are based on 10, 000 replications.

[a] The *p-value* are from the statistical tests on the differences in empirical distribution and is based on the complete combinatorial approach (Poe, *et al.,* 2005).

### 3.6 Conclusion

Over the last decade, a number of studies have focused on the nonmarket valuation of organic products' attributes. However, examining credence goods such as organic products' attributes is particularly challenging because many respondents are not well familiar with these attributes. Therefore, modeling solely the taste heterogeneity among respondents in a choice experiment, as has been done so far, might not be sufficient. In addition to investigating scale variation, accounting for preference heterogeneity in the response behaviour is quite essential. On the other hand, approaches adopted in studies that analyse scale heterogeneity tend to place emphasis on a deterministic treatment, relying erroneously on proxies as direct measure of an individual's latent survey engagement, leading to scale differences.

In this study, we used recent household survey data from Nigeria to investigate consumers' preferences and WTP for certification, as well as health- and environmental-related attributes of organic products, accounting for both scale and preference heterogeneity. We employed an approach in which data on survey engagement is modeled jointly with respondent's answers to the stated choice questions, thus allowing us to link part of the heterogeneity to differences in scale without the risks encountered with traditional methods. We also linked differences in survey engagement and the resulting scale heterogeneity to the *ex ante* mitigation strategies employed, as well as measured characteristics of the respondents.

Our empirical results show that market for organic products exists in Nigeria, as respondents are willing to pay a premium for the attributes of organic products identified, with lower pesticide residue attracting the highest value in both treatments followed by the certification attributes. These findings reveal participants' inclination towards health concerns and could serve as an important entry point for marketing. More so, the premium values the certification attributes attract underscores the potential of organic products to improve farmers' environmental performance by creating financial incentive for them to meet certification standards.

The results also show that increases in the latent engagement variable tend to raise respondents' probability of agreement with statements relating to survey understanding and realism, as well as the likelihood of longer survey duration, and higher model scale. Furthermore, we observed that the level of survey engagement is likely to be higher among respondents that were exposed to the HP treatment, with a higher value for younger and more educated respondents. These results lend support to the idea of the importance of *ex ante* calibration methods, particularly HP, in triggering proper behaviour and candor from respondents in a hypothetical CE setting.

The findings generally show that institutionalizing third-party certification for organic food products would be an appropriate policy strategy in promoting organic products. Further, since consumer's previous awareness effectively advances the potential demand for organic products, the adoption of effective sensitization programmes would be essential for the successful development of a sustainable organic sector in Nigeria. Moreover, the findings suggest that a consumer-oriented approach to understanding OA in Nigeria is important not only in its own right, but also in terms of response to the increasing significance of organic food products and the anticipated growth in the future market for such products.

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## Appendix

TABLE A1: Sample Characteristics, Percentages

| Variable Definition | Honesty priming | Cheap talk |
|---|---|---|
| **Gender** | | |
| Female | 18.67 | 17.67 |
| Male | 81.33 | 82.33 |
| Chi-Square (1) = 2.1576 | | |
| *p-value* = 0.142 | | |
| **Age** | | |
| Between 18-40 years | 24.0 | 23.33 |
| Between 41-60 years | 59.67 | 59.67 |
| More than 60 years | 16.33 | 17.0 |
| Chi-Square (2) =1.8402 | | |
| *p-value* = 0.398 | | |
| **Level of Education** | | |
| None | 12.0 | 12.0 |
| Primary | 18.33 | 18.33 |
| Secondary | 66.0 | 66.33 |
| Tertiary | 3.67 | 3.33 |
| Chi-Square (3) = 1.1553 | | |
| *p-value* = 0.764 | | |
| **Ave. Monthly Income (₦)** | | |
| Low income (≤ 30,000) | 13.67 | 14.56 |
| Medium income (30,001 – 150,000) | 58.0 | 57.67 |
| High income (> 150,000) | 27.33 | 27.78 |
| Chi-Square (2) = 2.6755 | | |
| *p-value* = 0.262 | | |
| **Awareness of organic** | | |
| Aware | 22.33 | 22.33 |

| | | |
|---|---|---|
| Unaware | 77.76 | 77.76 |
| Chi-Square (1) = 0.3403 | | |
| *p-value* = 0.560 | | |
| **Food-related Disease** | | |
| Incidence | 13.67 | 13.33 |
| No-incidence | 86.33 | 86.67 |
| Chi-Square (1) = 1.1696 | | |
| *p-value* = 0.279 | | |
| **Household size** | | |
| Less than 4 persons | 29.33 | 28.67 |
| Between 4 – 10 persons | 54.33 | 54.0 |
| More than 10 persons | 16.33 | 17.33 |
| Chi-Square (2) = 1.9810 | | |
| *p-value* = 0.371 | | |

# Chapter 4

## Identification of Consumer Segments and Market Potentials for Organic Products in Nigeria: A Hybrid Latent Class Approach

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**Abstract**

In this study, we employ a hybrid latent class approach to examine sources of heterogeneous preferences for organic products' attributes among consumers in Nigeria. The approach allows us to jointly analyze responses to stated choice and assignment to latent classes, while avoiding measurement error problems. Our results reveal that consumers are willing to pay premium for both health and environmental gains achieved through organic production systems, although their quantitative valuation is higher for the health concerns. Furthermore, we note that individuals with stronger preferences for organic products tend to attach a global value to the certification program, whereas the valuation tends to be more restrictive among respondents that prioritize the status quo option (conventional alternative). We also observe that differences in respondents' geographic location and level of awareness of organic food production characteristics (prior to the survey) have significant impact on consumers' choices.

**JEL code** D12, Q13, Q18, Q56

**Keywords** organic products, consumer segments, environmental and health attitudes, hybrid latent class

## 4.1 Introduction

The increase in soil degradation is a serious biophysical problem that threatens food production systems in developing regions of the world (particularly sub-Saharan Africa), where about 10 million hectares of crop land are lost annually (e.g., Azadi *et al.* 2011). Available empirical evidence stress the role played by resource-poor farmers in human-induced natural resource degradation (e.g., Reardon and Vosti 1997). This situation has generated concern over which environmental externalities of agricultural production should be encouraged and which should be corrected. The prevailing economic explanation for the continuing trend toward resource degradation is that economic incentives often encourage degradation and discourage conservation (e.g., Heath and Binswanger 1996).

In light of this challenge, there is a growing interest in the potential of organic agriculture (OA) to correct environmental externalities in sub-Saharan Africa (SSA). OA is one of the approaches that meet the objectives of sustainable agriculture. According to the United Nations Conference on Trade and Development (UNCTAD) and United Nations Environment Program (UNEP) (2008), OA has the potential to offer a range of local and national sustainable development opportunities for Africa in that it integrates traditional farming methods, uses inexpensive locally available natural resources and has positive economic effects on farmers' productivity and income. Furthermore, like other ''green'' labeling initiative, OA is considered a mechanism for the private provision of public goods.[48] This is premised on the

[48] This is based on the assumed relationship between the reduction in environmental pollution associated with organic production practices, which is a public (non-excludable) attribute, and an intrinsic product quality (health), which is a private attribute.

notion that the joint production of public and private characteristics in a good might mitigate the crowding-out effect in the private provision of public goods (e,g,, Cornes and Sandler 1984). Implying that the capacity of consumers' acceptance and demand for the attributes of organic products could redress the failure of the market to provide public goods. However, presently, the market features of organic products in various parts of SSA reveal that it is still in the introductory stage and many consumers are unfamiliar with the concept of certified OA (e.g., Philip and Dipeolu 2010). Hence, the identification of market potentials of the organic product is important for the future development of the sector.

Although studies on seasoned organic markets in Europe and North America have shown that consumers are concerned with the environment when making consumption decisions (e.g., Carlsson, Frykblom and Lagerkvist 2007), the degree of concern differs among individuals. On one hand, most consumers choose organic products because of a perception that the products have unique (and in some cases superior) attributes compared to the conventional alternatives (Vindigni, Janssen and Jager 2002). For example, some consumers prefer organic products for self-interest motives such as health risk avoidance, while others select organic due to ethical and altruistic concerns about biodiversity, climate, or animal welfare. Similarly, many individuals with external orientation tend to respond to the social benefits of organic farming, and choose to reward local farmers for using environment-friendly production methods (e.g., Davis 1994).

On the other hand, a major reason for not selecting organic products by some consumers is linked to a perception that conventionally produced alternatives are better, especially given that organic quality attributes are intrinsic (i.e., credence good) and may be difficult to identify by visual inspection alone (e.g., Jolly *et al.*

1989; Barlagne *et al.* 2015). Likewise, it is argued that modern OA appears to be showing more signs of increasing intensification and specialization, similar to trends in conventional agriculture (e.g. Guthman 2004). Generally, these findings lend support to the idea of heterogeneity in preferences for organic products within the population. It is reasonable to hypothesize that preferences are not unique to the individual, but rather a group of individuals (e.g., Hu *et al.* 2004), thus in the present study we employ a hybrid latent class (HLC) approach (e.g., Hess, Shires and Jopson 2013; Mariel, Meyerhoff and Hess 2015), that controls for heterogeneous class-specific preferences.

A number of studies have researched preferences for attributes of organic products among urban consumers in SSA and have used hypothetical stated preference (SP) approaches (e.g., Philip and Dipeolu 2010; Probst *et al.* 2012). Using contingent valuation method, Philip and Dipeolu (2010) investigated consumers' preferences for organic vegetable in Nigeria, whereas Probst *et al.* (2012) employed mixed multinomial logit model (MMNL) to explore the existence of heterogeneity in preferences for organic products among urban consumers in Ghana, Benin and Burkina Faso. However, none of these studies employed a joint latent class specification that identify different market segments (classes) based on consumers' socioeconomic and attitudinal data, as well as on observed choice behavior and product characteristics, potentially making the classes more directly relevant to management decision-making.[49]

[49] According to Swait (1994), preferences are indirectly affected by attitudes through the latent class to which the consumer belongs, and as such attitudinal data are quite important in explaining choice behavior.

The integration of choice data with attitudinal data to shed light on taste differences go back to McFadden (1986), Swait (1994), and Ben-Akiva *et al.* (1999). It is worth noting that several studies making use of answers to attitudinal statements often directly incorporate the individual's responses as explanatory variables in the utility specification (e.g., Bechtold and Abdulai 2014).[50] However, proponents of HLC approach (e.g., Ben-Akiva *et al.* 1999) query whether responses to attitudinal statements should be included directly as error free explanatory variables in a model. The authors argue that respondents' answers are mainly indicators of true underlying latent attitudes, hence incorporating these responses directly to a model could potentially lead to measurement error and endogeneity bias problems.[51]

In this study, we examine heterogeneous preferences for organic products attributes among consumers' in Nigeria using household survey data from a discrete choice experiment (CE). Specifically, we use HLC model to investigate the sources of heterogeneity in preferences across classes of consumers and to estimate class-specific WTP values for the identified organic attributes.[52] This model framework

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[50] The authors used principal component analysis to identify a limited set of dimensions, and subsequently plugged them as direct measure of respondent's attitudes in choice model.

[51] They point out that these responses are indicators of underlying attitudes rather than a direct measure of attitudes. As such, are likely to suffer from measurement error, which is amplified by the use of categorical formats such as Likert scale. Additionally, these responses may be correlated with other unobserved factors that influence individual's choices, causing correlation between the modeled and random components of utility, potentially leading to endogeneity bias.

[52] Our approach in this study is suited to explaining the sources of heterogeneity (Boxall and Adamowicz 2002) and closely capture consumers' choice processes, by

allows us to jointly examine the response to the stated choice component as well as the response to the attitudinal questions, without risk of exposure to measurement error and endogeneity bias problems. Given that organic products are quasi-public goods, we account for both environment (public) and health-related (private) attitudes of respondents. Thus, we incorporate all sources of heterogeneity, including socioeconomic and attitudinal data. To the extent that the markets for organic products have shown potentials for growth, our study is formulated to provide more insight into heterogeneous consumers' preferences for organic products in Nigeria as well as to draw implications for future development of the sector.

The rest of the paper is organized as follows. The next section presents the econometric specification of the general CE framework, followed by a description of the design of our survey and the data in the third section. The empirical specification and results from the analysis are then reported in sections four and five, respectively. The final section provides concluding remarks and implications.

## 4.2 Econometric Framework

We employ the hybrid latent class (HLC) approach presented by Hess, Shires and Jopson (2013), in which a latent class model (LC) is used within the hybrid choice modeling framework. The framework explains the effect of respondent's attitudes on observed sequence of choices through the class allocation probabilities, such that responses to attitudinal questions are specified as functions of the underlying latent attitudes to avoid the risk of endogeneity bias (e.g., Ben-Akiva *et al.* 1999). The HCL is composed of two parts. The structural equation component

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explaining both the answers to attitudinal questions as well as the likelihood of being allocated to a given consumer segment.

explains both the latent variable and utility function in terms of observable exogenous variables and attributes, respectively. The measurement component links the latent variable to responses to the attitudinal questions (i.e., the indicators). In addition, the HLC model also has a class allocation model which itself has structural equations highlighting utility of the various classes.

The main structural equations component is based on the random utility theory (McFadden 1974), thus utility of respondent $n$ for alternative $i$ in choice situation $t$ is presented as:

$$U_{int} = V(z_{int}, m_n , \beta) + \varepsilon_{int} \tag{1}$$

where $V(z_{int}, m_n , \beta)$ is the deterministic part of utility function, with $z_{int}$ as the vector of attributes of alternative $i$ (including the conventional alternative dummy), $m_n$ a vector of socio-demographic characteristics and $\beta$ a vector of parameters. The term $\varepsilon_{int}$ is a random component assuming an i.i.d. EV (0, 1) and it accounts for unobserved attributes and characteristics.

Latent class models assume that discrete segments $C$ (classes) of the population have different choice behaviors and each class, $c$ is characterized by a unique class-specific utility parameter ( $\beta_c$). Given membership to a class $c$, the conditional probability that respondent $n$ chooses alternative $i$ in choice situation $t$ is expressed as:

$$P_n = \Pr(y_{nt}|c, z_n) = \prod_{t=1}^{T_n} \frac{e^{(\beta_c z_{int})}}{\sum_{j=1}^{J} e^{(\beta_c z_{jnt})}}, \tag{2}$$

where $y_{nt}$ denotes the sequence of choices for respondent $n$ over $T_n$ choice tasks. Equation (2) is a product of MNL probabilities and for identification reasons we fix the scale parameter to 1. The LC approach also hypothesizes that respondent's actual class assignment is probabilistic, since the classes are unobservable. Thus, let the class allocation probability ($\theta_{n,c}$) for respondent $n$ be modeled using a logit structure, which is given as:

$$\theta_{n,c} = \frac{e^{(\delta_{0,c}+\gamma_c m_n)}}{\sum_{c=1}^{C} e^{(\delta_{0,c}+\gamma_c m_n)}}, \qquad (3)$$

where utility of a class is a function of socio-demographics ($m_n$), with $\gamma_c$ and $\delta_{0,c}$ denoting the vectors of parameters and constant for class $c$, respectively. For normalization reasons, we fixed the constant to zero for one of the classes.[53] Therefore, the unconditional probability over sequence of observed choices is derived by taking the expectation over all classes, $C$. This is specified as:

$$P_n = \Pr(y_{nt}|z_n) = \sum_{c=1}^{C} \theta_{n,c} \prod_{t=1}^{T_n} \frac{e^{(\beta_c z_{int})}}{\sum_{j=1}^{J} e^{(\beta_c z_{jnt})}}, \qquad (4)$$

For the measurement equations component, studies have shown that the deterministic inclusion of responses to attitudinal statements (as direct measures of respondent's underlying attitudes) in a model may result in measurement error and endogeneity bias problems. In line with Hess, Shires and Jopson (2013), we account for these issues in the specifications. First, we consider respondent's attitude as a latent variable, which is defined as:

$$\alpha_n = f(M_n, \lambda) + \eta_n, \qquad (5)$$

where $f(M_n, \lambda)$ is the deterministic part of $\alpha_n$, with $f(.)$ specified as linear. The vectors $M_n$ and $\lambda$ denotes the socio-demographic variables of respondent $n$ and the estimated parameters, respectively. The random term ($\eta_n$) is assumed to be normally distributed with a zero mean and standard deviation, $\sigma_\eta$. Next, we use the

[53] Besides, if the class allocation probabilities are generic across respondents, only the constants ($\delta_{0,c}$) are computed (Mariel, Meyerhoff and Hess 2015).

values of the attitudinal indicators as dependent variables. Specifically, the value of the $kth$ indicator for respondent $n$ is specified as:

$$I_{kn} = h(\alpha_n, \zeta) + \omega_n, \tag{6}$$

where the indicator $I_{kn}$ is a function of latent variable $(\alpha_n)$ and vector of parameters $(\zeta)$. The random term, $\omega_n$ is normally distributed with a mean 0 and standard deviation, $\sigma_{I_k}$. To avoid the estimation of unnecessary parameters, we centered the indicators on zero. The indicators are responses to attitudinal questions, with a finite number of possible values (i.e., scale 1-5). As such, we use ordered logit structure for the five indicators ($I_1$-$I_5$). The measurement equation component consists of threshold functions, such that for a discrete indicator $(I_{kn})$ with strictly increasing $R$ levels $(i_1, i_1 \ldots . i_R)$, we compute the threshold parameters, $\tau_1, \tau_2 \ldots .. \tau_{R-1}$.

The likelihood of specific observed value of $I_{kn}(k = 1,2, \ldots .5)$ is expressed as:

$$L_{I_{kn}} = \; I_{(I_{kn}=i_1)}\left[\frac{e^{\left(\tau_{k,i_1}-\zeta_k\alpha_n\right)}}{1+e^{\left(\tau_{k,i_1}-\zeta_k\alpha_n\right)}}\right] + \sum_{r=2}^{R-1} I_{(I_{kn}=i_r)}\left[\frac{e^{\left(\tau_{k,r}-\zeta_k\alpha_n\right)}}{1+e^{\left(\tau_{k,r}-\zeta_k\alpha_n\right)}} - \frac{e^{\left(\tau_{k,(r-1)}-\zeta_k\alpha_n\right)}}{1+e^{\left(\tau_{k,(r-1)}-\zeta_k\alpha_n\right)}}\right] \; +$$

$$I_{(I_{kn}=i_R)}\left[1 - \frac{e^{\left(\tau_{k,(R-1)}-\zeta_k\alpha_n\right)}}{1+e^{\left(\tau_{k,(R-1)}-\zeta_k\alpha_n\right)}}\right], \tag{7}$$

where $\zeta_k$ measures the impact of the latent variable $(\alpha_n)$ on indicator $I_{kn}$ and $\tau_{k,1}, \tau_{k,2} \ldots .. \tau_{k,R-1}$ are a set of estimated threshold parameters. In application, the threshold parameters are estimated using a set of auxiliary parameters, $(\mu_{k,1}, \mu_{k,2} \ldots .. \mu_{k,(R-2)})$, in the threshold functions, such that $\tau_{k,r} = \tau_{k,r} + \mu_{k,r}$; where $\mu_{k,r} \geq 0, \forall\, r$. The auxiliary parameters are specified to guarantee that threshold parameters are strictly increasing; $\tau_{k,1} < \tau_{k,2} \ldots < \tau_{k,(R-1)}$. For identification, we constrained one of the threshold to 0 and the scale parameter to 1.

The latent variable $(\alpha_n)$ is linked to the remaining part of the model through the class allocation probabilities specified in Equation (3). In our test for the class allocation specification, we were unable to retrieve any significant socio-demographic interactions other than those captured through the latent variable specified in Equation (5). Thus, following Mariel, Meyerhoff and Hess (2015) we re-write Equation (3) as:

$$\theta_{n,c} = \frac{e^{(\delta_{0,c}+\delta_{1,c}\alpha_n)}}{\sum_{c=1}^{C} e^{(\delta_{0,c}+\delta_{1,c}\alpha_n)}}, \tag{8}$$

where $\delta_{0,c}$ and $\delta_{1,c}$ are parameters to be estimated. The sign of $\delta_{1,c}$ describes the effect of the latent variable $(\alpha_n)$ in determining the probability of belonging to a specific taste class.

The log-likelihood $(LL)$ function for the HLC model integrates the choice models with the measurement models (attitudinal variables) over $\eta_n$, conditional on a specific realization of the latent variable $(\alpha_n)$. Hence, the joint model is specified as:

$$LL(\beta,\delta,\lambda,\zeta,\tau) = \sum_{n=1}^{N} ln \int_{\eta} \left( P_n \prod_{k=1}^{8} L_{I_{kn}} \right) \mathrm{g}(\eta) d\eta, \tag{9}$$

where $P_n$ is defined in Equation (4), but with class allocation probabilities $\theta_{n,c}$ as in Equation (8) and $L_{I_{kn}}$ as expressed in Equation (7) for $k = 1,2,\dots,5$. For identification reasons, the standard deviation $(\sigma_\eta)$ of the random component $(\eta)$ is set to1.

### 4.3 Survey Design and Data Description

We elicit primary data on consumer preferences using hypothetical CE, given that market data for sales of organic products are unavailable in Nigeria. The data were drawn from a recent household survey undertaken in Kano State, North-Western Nigeria. This location is characterized by socio-demographic heterogeneity and ethnic mix that allowed for high representation in the dataset.

Interviews were conducted with questionnaire, and to ensure that subjects were generally representative, we targeted primary food buyers in the households. A total of 600 respondents were sampled using a multistage sampling approach. Following Hess Shires and Jopson (2013), our questionnaire focused on few areas of variation including: choice experiment, respondent's socio-demographic and attitudinal data. Respondents were initially probed on their level of awareness of OA, and based on their understanding of organic production, we proceeded with the CE. Also, given concern about hypothetical bias in CE, we attempted as best as possible to reduce its influence by exposing respondents to *ex-ante* mitigation treatments; cheap talk script (Cumming and Taylor 1999) and honesty priming (de-Magistris *et al.* 2013). We used between-subject approach, whereby each respondent was randomly assigned to participate in one of the two hypothetical CE treatments, which were described to participants before responding to the CE questions (e.g., Lusk and Shroeder 2004).

The choice sets, contained two experimentally-designed organic profiles and a 'status-quo' option. We generate the organic profile using a three stage Bayesian sequential approach (Scarpa, Campbell and Hutchinson 2007). Our final design involved 36 choice tasks orthogonally arranged in four blocks of nine choice scenarios each to minimize the chance of respondent fatigue.[54] An equal number of respondents were randomly assigned to each of these groups. As presented in Table 1, we describe each organic alternative by four quality attributes and a price. The price attribute in the choice sets were the prices for 1kg basket of tomatoes, with

[54] The final design was generated using the Ngene software (version 1.0) and we accounted for uncertainty of priors by employing normally distributed Bayesian priors. The final design with the lowest Bayesian D-error (0.2534) was attribute-level balanced.

Table 1: Attributes and attribute levels in the choice experiments

| Attributes | Description | Attribute Levels |
|---|---|---|
| Pesticide | Reduction in the level of pesticide residues content | 5%, 25% ,100% lower |
| Certification | Organic certification scenarios | Foreign, Foreign plus indigenous, Indigenous labels |
| Vitamin | Increase in vitamin A content | 5%, 25%, 100% higher |
| Price | Purchase price (in Naira) | ₦ 60, ₦ 80, ₦100 |
| Erosion | Reduction in the level of soil erosion | 5%, 25%, 100% lower |

three different price levels. The lowest price level represents the base price, which reflects the average retail market price; collected from the local marketplaces immediately prior to the experiment (Asche *et al.* 2015). We derive the pricing from local market experts' opinion and focus group discussions. The outstanding price levels reflect possible premium prices associated with the organic tomato products.

Attribute relating to the origin of the certifier of the organic product is also identified. Voluntary certification of organic products has been shown to be an important feature of the OA initiative in developing countries (e.g., Kleemann and Abdulai 2013).[55] Therefore, in this study we recognize three organic certification scenarios. The first level (base) is associated with the scenario in which the organic tomato is certified by foreign certifiers only. While, second (medium) and third (high) levels correspond to the scenarios with both foreign and indigenous third party certifiers, and indigenous certifiers only, respectively. The remaining three quality-attributes of the organic choice options concern: higher vitamin A content;

[55] In principle, eco-certification can improve producers' environmental performance, even in countries where state regulation is weak.

lower soil erosion and lower pesticide residues, and each were described by high, medium and low attribute levels.

Several studies have indicated that organic farming leads to lower foodborne residues relative to conventional farming (e.g., Dangour *et al.* 2009). Thus, high level (100% reduction) is related to the absence of residues, the medium level (25% reduction) implies traces of residues from one component (<0.01mg/kg), and the base level (5% reduction) comprises residues (>0.01mg/kg) from more than one component. A number of studies have found higher amounts of carotenoid content in organic vegetables, which is a precursor and good source of vitamin A. Vitamin A can strengthen eye vision and the immune system (Chowdhury *et al.* 2011). Hence, the vitamin A content could be 5% (base level), 25 % (medium), or 100% (high) higher in organic tomato than in the conventional counterpart. Similarly, OA ameliorates soil degradation by improving soil organic matter content. Studies show that water retention capacity on organic farming plots are higher than on conventional plots (e.g., Azadi *et al.* 2011). Thus, soil erosion could be 5% (high), 25% (medium), or 100% (low) lower on organic plots relative to conventional farms.

Furthermore, our questionnaire elicit basic information on socio-demographics characteristics and some attitudinal statements - such as questions about the respondent's household buying habits, their attitudes and beliefs. Table 2 presents the attitudinal statements used in the HLC model specification. These statements covered a wide range of aspects that are of both health and environmental concerns. These questions were scored on a five-point Likert scales ranging from *completely disagree* (1) to *completely agree* (5) (Likert 1932). From an a priori perspective, the third column shows the signs describing the expected tendency of responses from proponents of OA. For example, a positive sign for the fair payment statement implies that proponents would more probably choose higher values on the response scale for the specified indicator on incentivizing environment-friendly food production.

Table 2: Attitudinal statements and tendency of response

| Indicators | Definition | Hypothesis |
|---|---|---|
| $I_1$ | It is fair to pay farmers more for producing environment-friendly food | + |
| $I_2$ | Environmental problems are highly exaggerated | - |
| $I_3$ | My actions are too small to affect any environmental quality | - |
| $I_4$ | Government is doing enough to control environmental pollution | - |
| $I_5$ | Scientists are going too far with cloning | + |

Note: response scale ranges from ''completely disagree (1)'' to ''completely agree (5)''

We use a chi-square test to ensure our randomization was effective in matching the characteristics of subjects across the two *ex-ante* treatments. The test results show that the null hypothesis of equality between the socio-demographic characteristics across treatment samples cannot be rejected at the 5 percent significance level (see Table A1). We present information on the socioeconomic characteristics of the sample households used in the econometric modeling in Table 3. Each respondent was randomly assigned to participate in only one of two hypothetical CE treatments. The results indicate that most (82 percent) of the households are male-headed, with an average household size of about 10 persons. Household's average monthly income was estimated at around ₦ 47,000. On the average, respondents have less than 8 years of formal education. Likewise, awareness of organic products is also low among the sampled respondents; only 25 percent reported previous knowledge of certified organic farming. Moreover, environmental conservation practices, such as the recycle of food waste, are undertaken by 46 percent of the respondents.

Table 3: Sample Socio-demographics

| Variables | Definition | Mean | S.D. | Min | Max |
|---|---|---|---|---|---|
| Age | Age of household head in years | 43.34 | 11.7 | 17 | 75 |
| Gender | Dummy(1=if household head is male, 0 otherwise) | 0.82 | 0.39 | 0 | 1 |
| Education | Years of formal education of the household head | 7.29 | 4.13 | 0 | 26 |
| Income | Average monthly income in Naira (₦ '000) | 47.73 | 75.42 | 9 | 800 |
| Household Size | Number of members of the household | 9.88 | 2.66 | 4 | 15 |
| Awareness | Dummy(1=if previously aware of organic products, 0 otherwise) | 0.24 | 0.42 | 0 | 1 |
| Disease | Dummy(1=if incidence of food disease in 24months, 0 otherwise) | 0.17 | 0.38 | 0 | 1 |
| Region | Dummy(1=if urban dweller, 0= if rural dweller) | 0.52 | 0.50 | 0 | 1 |
| Recycling | Dummy(1=if food waste is often recycled, 0 otherwise) | 0.46 | 0.49 | 0 | 1 |

**4.4 Empirical Specification**

Each respondent was faced with up to nine choice tasks, and for the analysis, we made use of a sample of 5,400 observations from the 600 respondents.[56] Two different models were estimated on the data, a standard latent class model (LC) and the hybrid latent class model (HLC) as shown in Equation (4) and (9), respectively. The LC model is primarily included for illustrative purposes, given their past use in the previous studies (e.g., Bechtold and Abdulai 2014). The two models were coded in Biogeme (Bierlaire 2003), and for the HLC model, we simultaneously estimate the structural and measurement model components (e.g., Ben-Akiva *et al.* 1999).

[56] A sample of 2,700 observations from 300 respondents, each in the HP and CT treatments were used for the analysis.

As indicated previously, the LC structure assume that discrete segment of the population have different choice behavior and taste, and that the heterogeneity can be linked to individual's attitudes and perceptions. In discrete choice analysis, this translates into class-specific choice model and class-membership model specifications. To allow for some comparisons, the class-specific choice and class-membership components were treated consistently across the two models, ensuring that the base structure of the LC model equate to reduce form version of the hybrid structure (HLC) (e.g., Mariel, Meyerhoff and Hess 2015). For the class-specific choice model, in both the LC and HCL models, we consider the four quality attributes and price, and allow their effects to vary across classes. The quality attributes were all dummy coded, with the base levels set to zero.[57] Next, for the class-membership probabilities, we consider the constant $(\delta_{0,c})$ and parameter of the latent variable $(\delta_{1,c})$ in the logit structure. The sign of $\delta_{1,c}$ determines whether increases in the value of the latent variable $(\alpha_n)$ lead to an increased or decreased probability for a specific taste class. Generally, the specification at this stage corresponds to a standard LC structure which forms the basis of the developments in this paper.

The final component of the hybrid model is given by the measurement equations for the attitudinal indicators. To make use of the answers to the five attitudinal statements reported in Table 2, we hypothesize that the responses together with respondents' actual choices are driven by the underlying latent attitudes. The latent variable $(\alpha_n)$ is linked to the remaining part of the hybrid structure through the class allocation probabilities as specified in Equation (8). It is

[57] However, in estimating the models, we observe that the medium level of the attributes were not statistically significant from zero, thus for the reason of parsimony, the medium and base levels were effectively collapsed to form a single base level (e.g., Collins, Rose and Hess 2012).

important to note that we mainly consider respondents' answers to the four environment-related attitudinal statements ($I_1 - I_4$) and a health-related statement ($I_5$). In other words, the answers to these statements are assumed to be likely dependent on the underlying health and environmental attitudes of the respondents.

We employ an ordered logit specification (in Equation 7) to estimate the thresholds for each of the five ordered indicators (e.g., Daly *et al.* 2012), although the specific distribution of the responses led to our merging of the first three and last two levels for all indicators. We also simplify the model further by constraining the estimates of the indicators in Equation (7) to 1. As such, any differential impact of the latent variable on the indicators was plugged into the estimates for the thresholds.

As highlighted in section 2, the combine $LL$ function for the HLC model is composed of two components. The first component is $P_n$ as specified in Equation (4) which gives the likelihood of observed choices; this is obtained by taking the expectation over all $C$ classes (i.e., the product of the logit probabilities). Whereas the second component, $L_{I_{kn}}$ denoting the probability of responses to the attitudinal questions, is a product of five ordered logit terms (for $I_1$–$I_5$) as defined in Equation (7). We use a simultaneous estimation with integration over $\eta$ (as shown in Equation (9)), and also reflect the repeated choice nature of our data (Revelt and Train 1998). The distribution of the random latent variable, g($\eta$), is univariate normal, with zero mean and a standard deviation of one. Likewise, we estimate the LC model simultaneously, although without the $L_{I_{kn}}$ component and the integration over $\eta$ (Hess, Shires and Jopson 2013).

## 4.5 Empirical Results

In this section, we first discuss the results of the identification of the number of latent classes, before we proceed to present the maximum likelihood estimates for the best-fitting LC and HLC models. Finally, we present the class-specific WTP values for the identified attributes.

Models with two through five classes were estimated using Biogeme software (Bierlaire 2003). For each model, we determine the optimal number of latent classes (Boxall and Adamowicz 2002) using the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). We present the estimates for these models in Table 4. The log-likelihood values at convergence ($LL$) reveal improvement in the model fit as classes are added to the procedure up to the three class model. Inspection of the AIC and BIC values suggests that the three class model is the optimal solution,

Table 4: Criteria for number of classes

| Number of latent classes (C) | Observations (N) | Number of Parameters (P) | Log-likelihood (LL) | AIC[a] | BIC[b] |
|---|---|---|---|---|---|
| 2 | 5,400 | 38 | -7,741.1 | 15,558.1 | 7,904.39 |
| 3 | 5,400 | 44 | -7,659.4 | **15,406.9** | **7,848.47** |
| 4 | 5,400 | 50 | -7665.8 | 15,431.6 | 7,874.25 |

Note: Bold figures indicate that the optimum number of latent classes is three under both AIC and BIC.

[a]AIC (Akaike Information Criterion) is calculated using -2(LL _ P).

[b]BIC (Bayesian Information Criterion) is calculated using -LL + [(P/2) * ln(N)].

given that the minimum BIC and AIC statistics are clearly associated with three classes. We therefore estimate a three-class model for both LC and HLC specifications.

The maximum likelihood estimates for the LC and HLC models are reported in Tables that follows, and then the respective welfare measures. Foremost, we focus on the estimates derived from standard LC model on Tables 5 and 7, and then discuss results from the HLC model on Tables 5, 6 and 9. Generally, our results indicate existence of considerable heterogeneity in preferences across latent classes, as revealed by the differences in magnitude and significance of the utility function estimates. We observe that the class membership probabilities are significantly related to the consumers' attitudes. Similarly, as expected, we note that across models the price coefficient is negative and statistically significant in all classes, suggesting that respondents' utility decreases with increase in price. Furthermore, the results show that a decrease in pesticide residue increases respondents' preferences for organic tomatoes, as the attribute is positive and statistically significant in all the classes, across models.

From the LC model in Table 5, we observe that although members of class 1 exhibit lower utility for the conventional alternatives as shown by the negative and significant conventional alternative variable, they are more likely to be termed as *indifferent* to certified organic food. This is because the coefficient estimates for three of the four organic quality attributes identified are not statistically significant from zero, implying that the reduction of pesticide residues is the only relevant quality attribute for members of this class. For class 2, we find that all the organic quality attributes are positive and significant, suggesting that members of this class are likely to be associated with being *advocates* of organic products. In particular, our results show that members derive significantly higher utilities from the certification

Table 5: Maximum likelihood estimates from LC and HLC models - choice component

| | LC model | | | | | | HLC model | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Respondents | 600 | | | | | | 600 | | | | | |
| Observations | 5,400 | | | | | | 5,400 | | | | | |
| LL | -3,181.648 | | | | | | -7,659.443 | | | | | |
| Parameters | 20 | | | | | | 44 | | | | | |
| | Class 1 | | Class 2 | | Class 3 | | Class 1 | | Class 2 | | Class 3 | |
| *Class Prob.* | 0.218 | | 0.452 | | 0.330 | | | | | | | |
| Variable | Est. | $t$-Ratio | Est. | $t$-Ratio | Est. | $t$-Ratio | Est. | $t$-Ratio | Est. | $t$-Ratio | Est. | $t$-Ratio |
| *Utility function* | | | | | | | | | | | | |
| $\beta_{price}$ | -2.185 | -5.56 | -0.204 | -3.82 | -0.491 | -5.47 | -1.460 | -18.79 | -0.169 | -6.23 | -0.504 | -7.58 |
| $\beta_{pesticide}$ | 1.232 | 4.14 | 0.690 | 5.35 | 0.773 | 10.21 | 1.108 | 6.58 | 0.694 | 5.12 | 0.797 | 11.91 |
| $\beta_{certification}$ | -0.490 | -0.74 | 0.730 | 6.75 | -0.109 | -5.57 | -0.523 | -1.53 | 0.762 | 6.91 | -0.113 | -6.23 |
| $\beta_{vitamin}$ | 0.206 | 0.53 | 0.491 | 4.90 | 0.247 | 6.85 | 0.374 | 1.57 | 0.531 | 4.89 | 0.258 | 8.27 |
| $\beta_{erosion}$ | -0.162 | -0.60 | 0.688 | 6.28 | 0.227 | 9.26 | 0.067 | 0.37 | 0.748 | 6.75 | 0.230 | 10.31 |
| $\beta_{conventional}$ | -1.577 | -6.92 | -3.733 | -8.05 | -0.549 | -7.96 | -1.250 | -4.00 | -3.399 | -9.37 | -0.568 | -9.90 |
| *Class allocation function* | | | | | | | | | | | | |
| $\delta_{0,2}$ | 0.479 | 1.80 | | | | | -0.133 | -4.04 | | | | |
| $\delta_{1,2}$ | | | | | | | 0.412 | 5.44 | | | | |
| $\delta_{0,3}$ | -0.547 | -3.08 | | | | | -0.275 | -0.38 | | | | |
| $\delta_{1,3}$ | | | | | | | -0.899 | -1.92 | | | | |

Table 6: Maximum likelihood estimates from HLC model- structural and measurement components

| Variable | Est. | $t$-Ratio |
|---|---|---|
| *Structural Equation (LV specification)* | | |
| $\lambda_{Age}$ | 0.401 | 9.89 |
| $\lambda_{Recycling}$ | 2.515 | 6.24 |
| $\lambda_{Educ}$ | 0.186 | 8.47 |
| $\lambda_{H/hsize}$ | -0.021 | -0.08 |
| $\lambda_{Disease}$ | -1.358 | -3.00 |
| $\lambda_{Aware}$ | 4.461 | 12.50 |
| $\lambda_{Region}$ | 0.525 | 2.40 |
| *Measurement Equation (effects of LV)* | | |
| $\zeta_{I_1}$ | 0.737 | 18.39 |
| $\zeta_{I_2}$ | -0.536 | -11.57 |
| $\zeta_{I_3}$ | -0.495 | -19.54 |
| $\zeta_{I_4}$ | -0.050 | -2.37 |
| $\zeta_{I_5}$ | 0.344 | 7.54 |
| *Measurement Equation (thresholds)* | | |
| $\mu_{I_1,1,2\&3}$ | -1.115 | -6.72 |
| $\mu_{I_1,4\&5}$ | 0.022 | 1.16 |
| $\mu_{I_2,1,2\&3}$ | -1.214 | -5.46 |
| $\mu_{I_2,4\&5}$ | 0.027 | 2.14 |
| $\mu_{I_3,1,2\&3}$ | -0.912 | -6.87 |
| $\mu_{I_3,4\&5}$ | 0.055 | 2.02 |
| $\mu_{I_4,1,2\&3}$ | -0.290 | -7.69 |
| $\mu_{I_4,4\&5}$ | -0.015 | -2.55 |
| $\mu_{I_5,1,2\&3}$ | -0.055 | -2.98 |
| $\mu_{I_5,4\&5}$ | -0.033 | -3.86 |

program, increase in vitamin A contents, reduction in pesticide residues and lower soil erosion, and also obtain distinct disutility from the conventional alternative.

On the other hand, consumers who are likely to be members of class 3 prefer to maintain the status quo, as shown by the positive and statistically significant conventional alternative dummy. Members of this class also express significant disutility for the certification program attribute. However, based on available evidence, a product can only be correctly qualified as 'organic' when it is grown under a well-defined and unique set of certification procedures (IFOAM 2012)[58]. Therefore, members of class 3 are more likely to be labeled as *conservatives*. In general, our results reveal that of the respondents participating in the CE about 33% have a fitted probability to belong to class 3, while 22% and 45% will likely belong to classes 1 and 2, respectively. This finding suggests that organic products have considerable potential for growth in Nigeria, since the bulk of respondents (about 67 %) are more likely to belong to either class 1 (indifferent segment) or class 2 (advocates).

Table 7 presents WTP measures corresponding to significant attributes in the three classes of the LC model. The WTP measures are computed from the LC model estimates giving the implied monetary valuation of different changes in attribute levels. A positive WTP value in our results show how much the respondents would be willing to pay for a change of the given attribute from its base level, whereas a negative WTP suggests the amount they are willing to pay to prevent this change. For example, in the class 2, members are willing to pay a premium of ₦ 11.03, ₦ 8.97

[58] Available evidence shows that the certification programs gives consumers quality assurance and guarantee the products' integrity on the market (e.g., IFOAM 2012).

and ₦ 8.46 for lower pesticide residues, reduction in soil erosion, and certification attributes, respectively.

Table 7: Implied trade-offs and monetary valuation from the LC model

| | Class 1 | Class 2 | Class 3 |
|---|---|---|---|
| Lower Pesticide residues | 4.49 | 11.03 | 6.46 |
| | (3.52, 5.58) | (9.69, 11.36) | (4.47, 8.54) |
| Certification | NS | 8.46 | -7.94 |
| | | (7.43, 9.53) | (-8.88, -7.04) |
| Higher Vitamin A | NS | 5.90 | 3.76 |
| | | (4.54, 7.44) | (3.32, 4.22) |
| Lower Soil Erosion | NS | 8.97 | 4.04 |
| | | (7.04, 11.15) | (3.38, 4.72) |
| Conventional alternative | -6.42 | -7.13 | 7.69 |
| | (-7.42, -5.45) | (-8.05, -6.22) | (3.58, 8.60) |

Note: 95% confidence intervals calculated using the Krinsky and Robb (1986) method in parentheses. The CIs are based on 10, 000 replications.

NS: means attribute is not statistically significant.

Next, we focus on the results on the HLC model in Table 5. Foremost, it is worth noting that although the log-likelihood of HLC structure cannot be directly compared to the LC model fit[59], the estimated coefficients from both models are very similar. Also, given that we incorporate supplementary behavioral information in HLC choice specification, the accuracy of most of the coefficients increase, as expected (e.g., Mariel, Meyerhoff and Hess 2015). This finding confirms our hypothesis that the identified underlying health and environmental attitudes

[59] The HLC model structure allows for the joint estimation of the choice model and the measurement model.

influence respondents' class allocation probabilities, as all relevant coefficients are statistically significant at the 10% level.

Moreover, from the measurement components presented in Table 6, our results show that the latent variable actually inform assignment to latent classes in the HLC model. The latent variable has a significant impact on all five attitudinal indicators (ζ) identified. Similarly, the signs of the indicators suggest that proponents of organic products are more likely to be associated with higher latent variable. Thus, consistent with *a priori* expectation, we observe that the *advocates* of organic products assign higher values (positive signs) to both attitudinal statements relating to fair payment of environment-conscious farmers and the objections to cloning, while the remaining three indicators attract lower values (negative signs). Furthermore, from the estimates of the class allocation model, we observe that respondents with a lower latent variable are more likely to be in class 3, and least likely to fall into class 2, given that the signs of $\delta_{1,3}$ and $\delta_{1,2}$ are positive and negative, respectively. These findings conform to our earlier identification of class 3 as being characterized by strong opposition to organic products, while members of class 2 are identified as *advocates* of organic products.

To further describe the consumer segments (i.e., *advocates* and *conservatives*), we employ the socio- demographic variables ($\lambda$). The signs of the characteristics indicate that the latent variable is higher among older and more educated respondents, who are environment-conscious (recycle food waste) and have previous awareness of the concept of organic agriculture. Similarly, these segments of consumers are more likely to be resident in the urban areas and have modest household sizes. [60]

As specified in Equation (8), the class allocation probability is respondent-specific, and a function of the random latent variable ($\alpha$), which implies that the allocation probabilities also follow a random distribution. Thus, we simulate the class allocation probabilities using 10,000 Halton draws for the random latent variable and for each respondent, as in Equations (5) and (8). Here, we integrate the parameter estimates ($\lambda$) with the associated values of socio-demographic variables and the random errors, $\eta$ (e.g., Mariel, Meyerhoff and Hess 2015). The class allocation probabilities are shown in Figure 1, where the estimated distributions suggest that there is a higher likelihood of respondents belonging to classes 2 and 3 relative to class 1. Moreover, given that the latent variable ($\alpha$) is a function of socio-demographic variables, in Table 8, we report the simulated allocation probabilities for two opposing groups, *advocates* and *conservatives*. These results are also depicted in Figure 2. In this case, unlike the LC model, the subgroups are characterized by socio-demographic variables, the values in the first column define *conservatives* as being below the 25th percentiles of the corresponding variables; age, years of education, household size, and being unaware of organic concept and located in rural centers. The second column uses the 75th percentiles of these variables to define *advocates* that present diametrically opposing values of the different characteristics.

Clearly, the relative advantage of using the HLC is that it enables us to consistently examine the role played by respondents' underlying attitudes in

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[60] Our efforts to incorporate an income effect in the final model specification were unsuccessful.

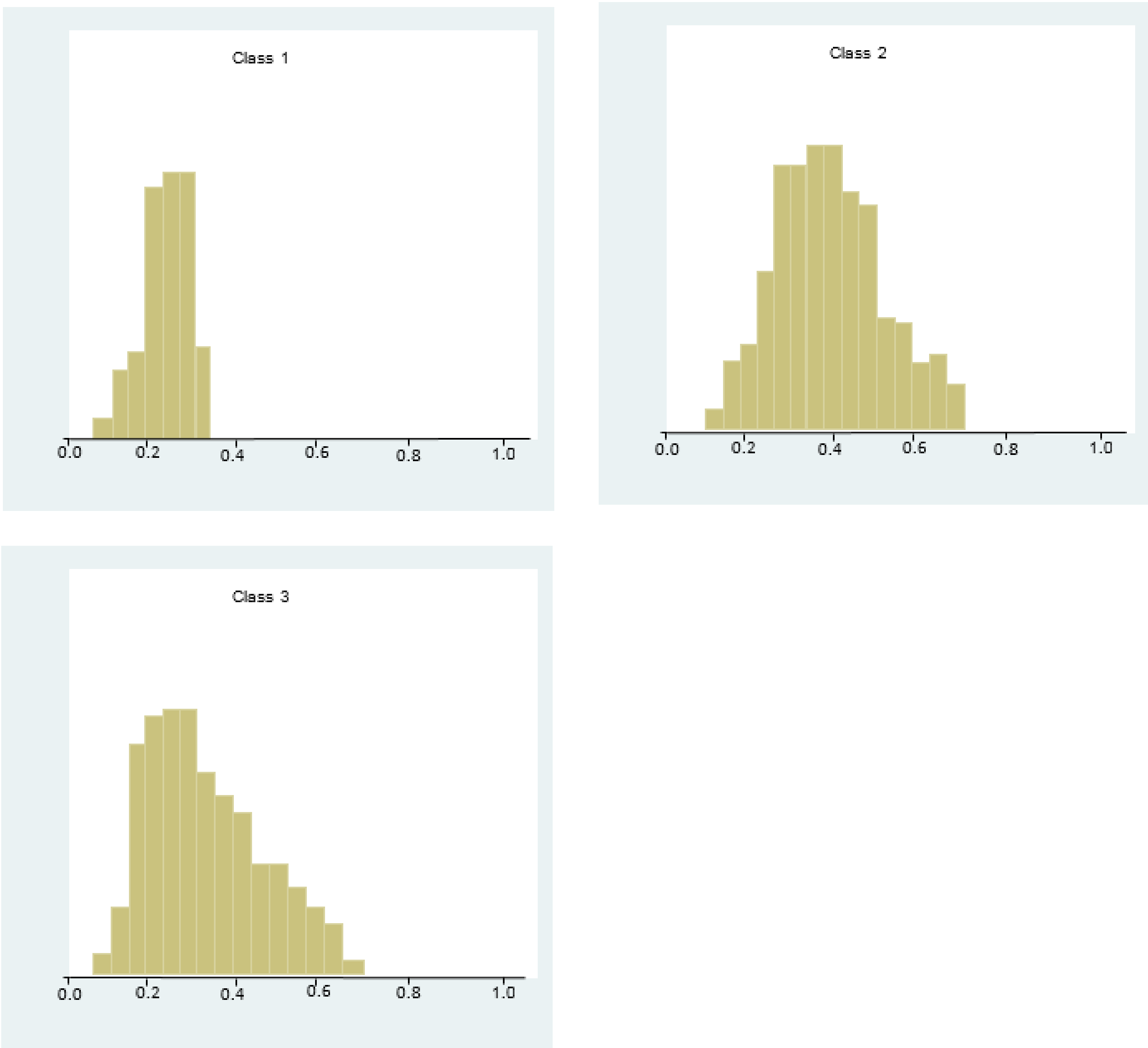


Figure 1: Simulated class allocation probabilities

explaining preferences for organic attributes. While the LC model has structural equation that explains preference function in terms of observable attributes, the HLC model has in addition to the structural aspect a measurement component for the endogenous (latent) variables that provide more behavioral insight. In other words, for the LC model, we identify consumer segments based on the choices of observable quality attributes, whereas in the HCL model, latent classes are consistently determined based on both the preferences for observable quality attributes as well as the underlying attitudes that explain respondents' preferences.

Table 8: Description of the opposing latent segments, from the HLC model

| | Conservatives | Advocates |
|---|---|---|
| Age (in years) | < 26 | >38 |
| Education ( in years) | <14 | >20 |
| Household size | >6 | <5 |
| Recycling | No | Yes |
| Disease | No | Yes |
| Region | Rural | Urban |
| Aware | Unaware | Aware |

Note: The simulated allocation of probabilities presented is for the 25 and 75 percentiles.

Turning next to the implied trade-off for the organic attributes derived from HLC model. In Table 9, we report the welfare measures and confidence intervals for the two subgroups. We calculate 95% confidence intervals using the Krinsky–Robb parametric bootstrapping method. Also, we simulate the WTP values for the sample population by computing weighted means of the WTP values in each class (e.g., Mariel, Meyerhoff and Hess 2015). We merged the values across respondents to obtain sample level distributions (pooled). A comparison of the WTP estimates for the attributes across the latent classes reveal notable differences in preference structure. Based on the WTP measures, our findings confirm the interpretation of the segments as mentioned above (i.e., *advocates* and *conservatives*). Although statistically significant differences exist between the premiums for the attributes across subgroup, the simulated welfare values show that the reduction in pesticide residues attribute attracts highest premium followed by lower soil erosion, and then higher vitamin A content and certification attributes. Similarly, corresponding simulated distribution of the pooled implied trade-off for each attribute is also represented in Figure 3, illustrating the reported respondents' preference ordering.

Table 9: Implied trade-offs and monetary valuation from the HLC model

| | Pooled | Advocates | Conservatives |
|---|---|---|---|
| Lower Pesticide residues | 4.91 [a, g] | 6.74 | 2.41 |
| | (3.52, 5.58) | (4.31, 7.21) | (1.98, 3.72) |
| Certification | 1.83 [b, f] | 6.56 | -2.97 |
| | (1.48, 3.19) | (6.09, 7.25) | (-1.88, -4.04) |
| Higher Vitamin A | 2.83 [c, f] | 3.55 | 2.01 |
| | (1.96, 3.17) | (3.09, 4.21) | (1.79, 2.25) |
| Lower Soil Erosion | 4.46 [d, g] | 5.53 | 3.00 |
| | (3.03, 5.17) | (4.58, 6.89) | (1.96, 4.70) |
| Conventional alternative | -1.29 [e] | -5.77 | 3.40 |
| | (-2.33, -1.04) | (-7.10, -4.38) | (2.52, 4.58) |

Note: 95% confidence intervals calculated using the Krinsky and Robb (1986) method in parentheses. The CIs are based on 10, 000 replications.
NS: means attribute is not statistically significant.
[a,b,c,d,e] This value is statistically distinct from all other WTP. [f, g] This value is not statistically different from others with the same superscript. The statistical tests on the differences in empirical distribution and is based on the complete combinatorial approach (Poe et al. 2005).

Respondents that are identified as *conservatives* appear to show preference for food products with reduced pesticide residues, although relative to *advocates*, the price premiums for this subgroup tends to be lower. This implies that members of the conservative subgroup are price sensitive and more likely to partly base their purchasing decision on price as well. Meanwhile, individuals that *advocate* for organic food have been shown to express significant preferences for all the organic quality attributes identified with the highest value placed on lower pesticide residues, Advocates Conservatives

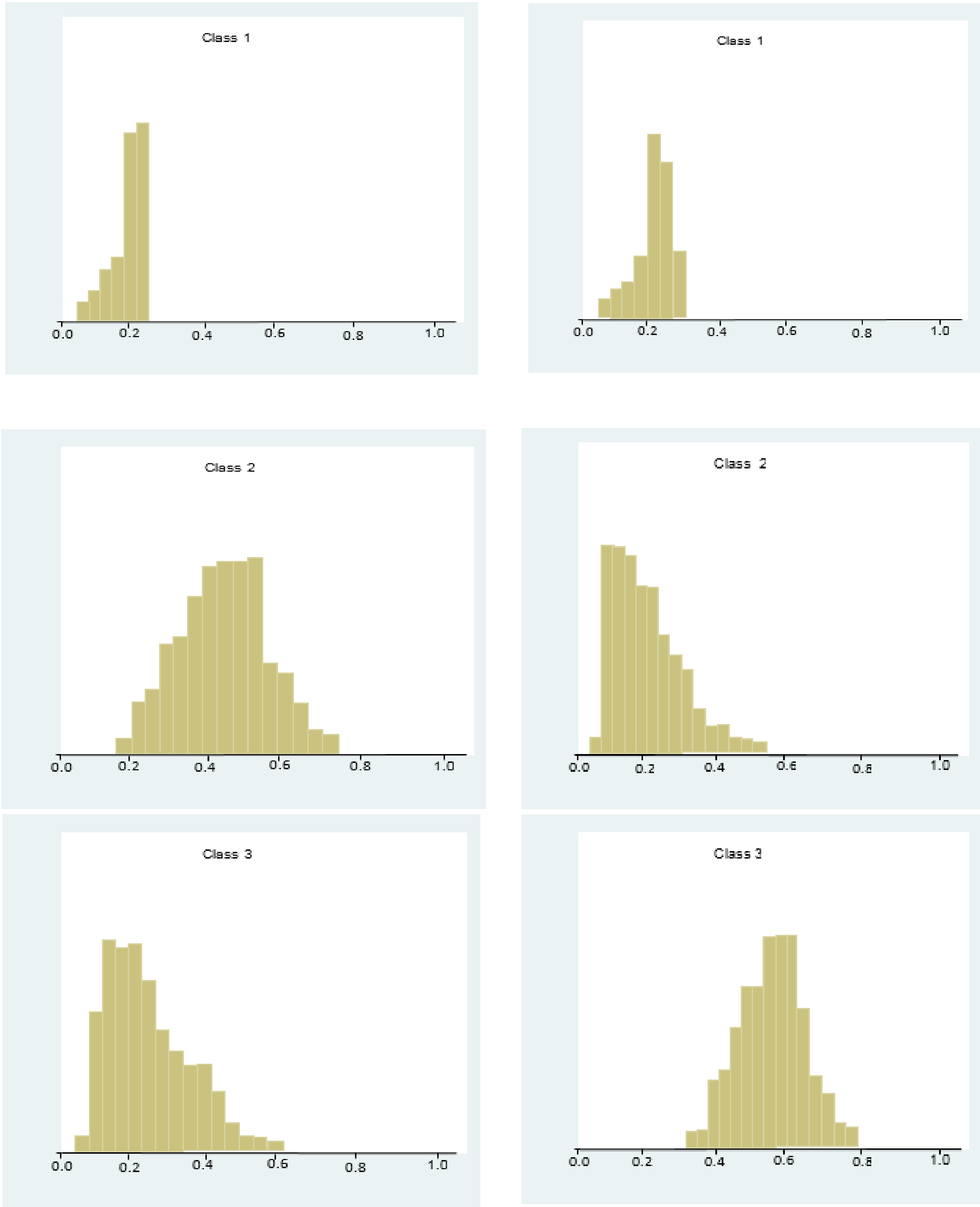


Figure 2: Simulated allocation probabilities for the opposing consumer segments

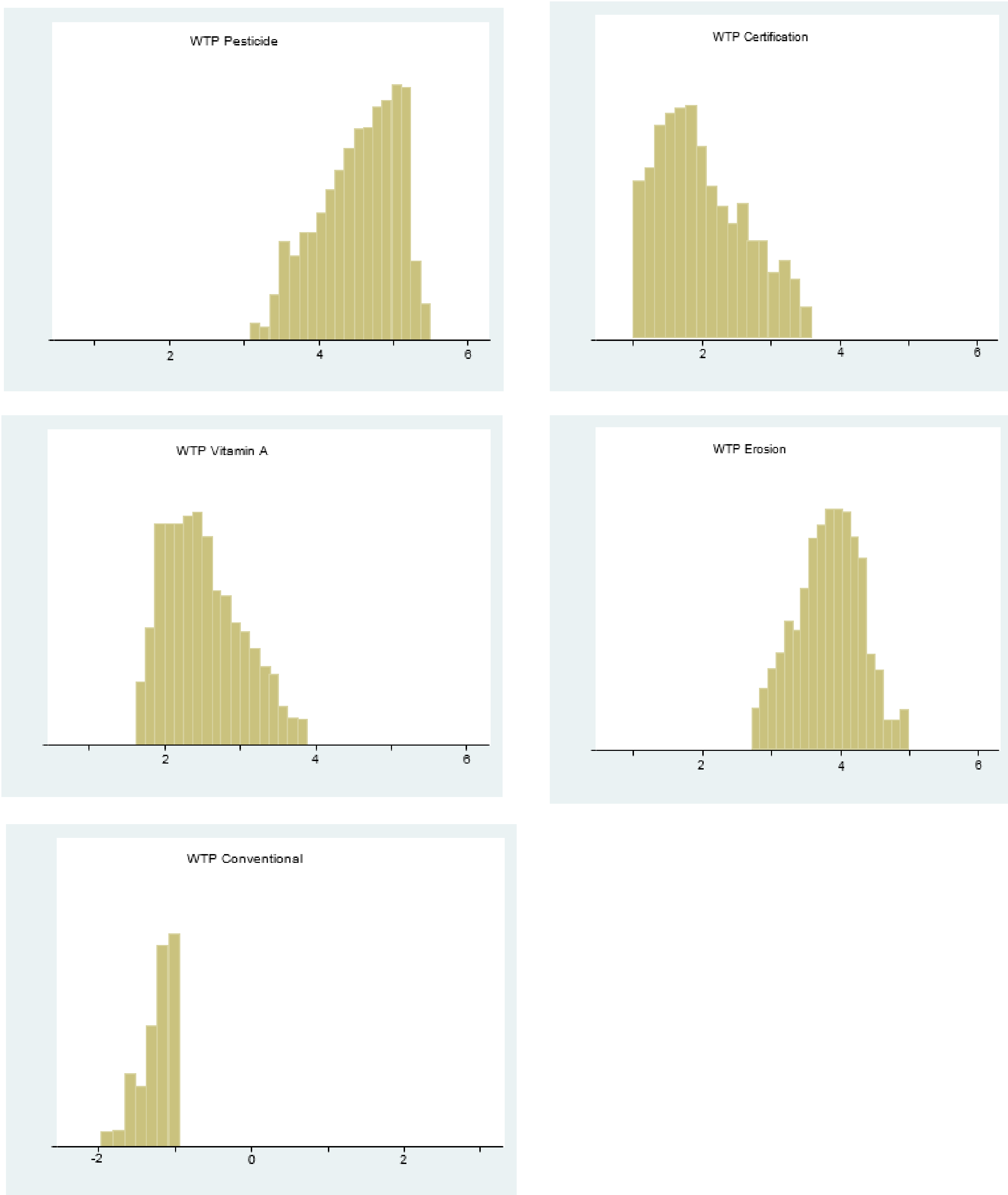


Figure 3: Simulated implied trade-off and monetary valuation

followed by certification, and then lower soil erosion and increased vitamin A content. For example, respondents in this segment are willing to pay ₦ 5.53 more for reduced soil erosion and even more for lower pesticide residues (₦ 6.74) and certification program (₦ 6.53). However, they obviously derive disutility from conventionally-produced tomatoes and would be willing to accept up to ₦ 5.77 as compensation.

On the other hand, in the *conservative* subgroup, the conventional alternative is more highly valued relative to the identified organic quality attributes. The high valuations of conventional tomatoes, may be attributed to the fact that members of this class perceive organic food products with skepticism. Moreover, the certification attribute is negative and statistically significant, suggesting that the quality of organic traceability network is not important for members of this class.

Generally, we observe that respondents (*advocates*) are willing to pay an additional ₦ 20 for organic tomatoes over the base retail price (₦ 60) for one kilogram basket of conventional tomatoes. This value corresponds to more than 30% premium when compared to the typical market prices results for conventional tomatoes during the peak seasons in Nigeria.[61] The simulated WTP values reveal that respondents are in favor of reducing the pesticide residues in food products,

[61] The WTP for organic certification found in this research is clearly within the range of price premiums identified by other studies. Although evidence from developing countries is limited, the review by Yiridoe, Bonti-Ankomah and Martin (2005) suggests an average WTP premium for organic certification of about 30%. While Coulibaly et al. (2011) on their study of private households in urban Ghana and Benin, calculate a premium for organic certification of 57–66% for cabbage and 50–56% for tomatoes.

regardless of whether they are categorized as indifferent, advocates or opponents of organic products. However, the valuation of certification attribute differs strongly between the two opposing groups, as the proponents would prefer tomatoes produced in accordance with the specifications of organic third-party certifiers that guarantee compliance with the production standards, as well as adequate inspection of the processes within the supply chain.

## 4.6 Conclusion

In this study, we examine the existence of preference heterogeneity for organic products, as well as the sources of heterogeneity for consumers in Nigeria. We use a hybrid model framework to jointly analyze the response to the stated choice component as well as the response to the attitudinal questions, without exposure to risks of endogeneity bias and measurement error.

Our results reveal that market for organic products exists in Nigeria, as consumers are willing to pay a premium for both health and environmental gains realized through organic production systems, although their quantitative valuation is higher for the health concerns. This finding reflects public opinion in Nigeria toward food safety and health concerns. Given that organic foods are recognized as products capable of generating health benefits, and considering the fact that older people are more concerned with health than younger people, this finding is in line with expectations. Likewise, our result is consistent with earlier research demonstrating that age seems to increase health-related concerns and also attractiveness of products with health claims (e.g., Bechtold and Abdulai 2014).

Furthermore, we note that individuals with stronger preferences for organic products tend to attach a global value to the certification program, whereas the valuation tends to be more restrictive among respondents that prioritize the status quo option (conventional alternative). Another interesting issue that emerges from our study, is the issue of regional heterogeneity. We observe that difference in geographic location has significant impact on consumers' choice of organic products. Similarly, while across market segments willingness to pay for health improvement increases significantly, we found that advocates of organic products are more likely to be resident in the urban areas. These result suggest that to sustain organic production on the demand for healthier food, it is important to improve the frame conditions (that is, the distribution and sale systems) for the marketing of organic foods as part of a policy strategy.

In addition, we find that respondents' level of awareness of organic food production characteristics (prior to the survey) is a relevant and significant factor in increasing their WTP for the organic quality attributes, predominantly, better-informed respondents demonstrate higher WTP. Thus, the idea that environment-conscious consumers tend to seek information, and the notion that information may shift preferences for environmental conservation appear to be supported by our results.

Overall, our findings contribute to the debate on the potential of organic certification to correct environmental externalities in agricultural production. We find that respondents display a range of different preferences and that the behavioral asymmetry may be reflecting differences in underlying attitudes. More so, we observe that in order to drive the market for organic produce, a key element in the strategy to reach consumers would be to facilitate access to the products (via urban sale outlets). Moreover, actions to better inform the public in general is cardinal to promote concern for the health and environment as well as a shift in preferences while also driving the demand for organic products. Furthermore, despite the fact that WTP is higher for the private attributes of organic production systems relative to the public attributes, environmental preferences also provide a feasible foundation for the development of the organic market in Nigeria.

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## Appendix

TABLE A1: Sample Characteristics, Percentages

| Variable Definition | Honesty priming | Cheap talk |
|---|---|---|
| **Gender** | | |
| Female | 18.67 | 17.67 |
| Male | 81.33 | 82.33 |
| Chi-Square (1) = 2.1576 | | |
| *p-value* = 0.142 | | |
| **Age** | | |
| Between 18-40 years | 24.0 | 23.33 |
| Between 41-60 years | 59.67 | 59.67 |
| More than 60 years | 16.33 | 17.0 |
| Chi-Square (2) =1.8402 | | |
| *p-value* = 0.398 | | |
| **Level of Education** | | |
| None | 12.0 | 12.0 |
| Primary | 18.33 | 18.33 |
| Secondary | 66.0 | 66.33 |
| Tertiary | 3.67 | 3.33 |
| Chi-Square (3) = 1.1553 | | |
| *p-value* = 0.764 | | |
| **Ave. Monthly Income (₦)** | | |
| Low income (≤ 30,000) | 13.67 | 14.56 |
| Medium income (30,001 – 150,000) | 58.0 | 57.67 |
| High income (> 150,000) | 27.33 | 27.78 |
| Chi-Square (2) = 2.6755 | | |
| *p-value* = 0.262 | | |
| **Awareness of organic** | | |
| Aware | 22.33 | 22.33 |
| Unaware | 77.76 | 77.76 |

| | | |
|---|---|---|
| Chi-Square (1) = 0.3403 | | |
| *p-value* = 0.560 | | |
| **Food-related Disease** | | |
| Incidence | 13.67 | 13.33 |
| No-incidence | 86.33 | 86.67 |
| Chi-Square (1) = 1.1696 | | |
| *p-value* = 0.279 | | |
| **Household size** | | |
| Less than 4 persons | 29.33 | 28.67 |
| Between 4 – 10 persons | 54.33 | 54.0 |
| More than 10 persons | 16.33 | 17.33 |
| Chi-Square (2) = 1.9810 | | |
| *p-value* = 0.371 | | |

# Chapter 5

# General Conclusions

This research has made three broad contributions. First, it has deepened the understanding of the impact of *ex-ante* hypothetical bias mitigation methods in choice experiments, by linking observed differences in respondents' attribute processing strategies (ANA), and hence WTP, to variation in the hypothetical bias mitigation technique employed. Second, insight is provided into the nonmarket valuation of organic products (credence goods), by accounting for scale and preference heterogeneity. The third area in which contribution has been made is the empirical application of a more intuitive approach to identifying sources of heterogeneous preference for organic products, in the context of SSA. Detailed summary of these key findings are presented in the following subsections.

## 5.1 Impact of Ex-Ante Hypothetical Bias Mitigation Methods on Attribute Non-Attendance in Choice Experiments

In exploring the effects of the priming tasks (Cheap Talk and Honesty Priming) on respondents' ANA vis-à-vis their WTP values, a hybrid models that account for potential endogeneity and measurement errors is estimated, as well as the commonly used mixed multinomial logit (MMNL), endogenous attribute attendance (EAA) and mixed EAA models, as robustness checks. Results from this study show that the incidence of ANA varies across the treatments in general, with significant differences in ANA rates between respondents exposed to the mitigation strategies (HP and CT) and the baseline (N) group. It is observed that the use of *ex ante* hypothetical bias mitigation methods tend to elevate the congruence between inferred and stated ANA, as well as reduce nonattendance, irrespective of the ANA model employed. Furthermore, although the variation in model specifications impact on WTP values, ordering of the attributes for respondents in a given ex *ante* treatment remains relatively consistent. Evidence from the pattern of the results in this empirical application also suggest that WTP estimates derived from models when mainly controlling for hypothetical bias are lower relative to WTP values obtained when solely accounting for stated ANA. However, more substantial effect on WTP estimate is attained by jointly accounting for ANA as well as adopting measures to mitigate upward bias. In terms of relevance to practitioners, based on these findings, it can be inferred that incorporating indicators of stated ANA in models is likely to provide more reliable WTP values in instances when hypothetical bias mitigation methods are incorporated in CE.

## 5.2 Measuring Heterogeneity, Survey Engagement and Response Quality in Preferences for Organic Products in Nigeria

In this chapter, consumers' preferences and WTP for attributes of organic products is evaluated, while accounting for both scale and preference heterogeneity. Data on survey engagement is modeled jointly with respondent's answers to the stated choice questions, thus allowing the linking of part of the heterogeneity to differences in scale without the risks endogeneity bias and measurement error. Similarly, differences in survey engagement and the resulting scale heterogeneity is linked to the *ex ante* mitigation strategies employed, as well as measured characteristics of the respondents. The empirical results show that market for organic products exists in Nigeria, with respondents being more inclined towards health concerns and could serve as an important entry point for marketing. Furthermore, increases in the latent engagement variable tend to raise respondents' probability of agreement with statements relating to survey understanding and realism, as well as the likelihood of longer survey duration, and higher model scale. Moreover, the level of survey engagement appear to be higher among respondents that were exposed to the HP treatment, with a higher value for younger and more educated respondents, that are aware of OA concept prior to the survey. These results lend support to the idea of the importance of *ex-ante* hypothetical bias mitigation methods, particularly HP, in triggering proper behavior and candor from respondents in a hypothetical CE setting. In terms of policy relevance, the findings generally show that institutionalizing third-party certification for organic food products would be an appropriate policy strategy in promoting organic products. Also, the adoption of effective sensitization programs would be essential for the successful development of a sustainable organic sector in Nigeria.

### 5.3 Identification of Consumer Segments and Market Potentials for Organic Products in Nigeria: A Hybrid Latent Class Approach

In this chapter, market potentials for organic products attributes in Nigeria is identified. Although few studies on SSA have attempted to investigate the existence of heterogeneity in preferences for organic products, none of these studies have examined the sources of preference heterogeneity among consumers. Using a hybrid model framework, the response to the stated choice component as well as the response to the attitudinal questions are jointly analyzed, without the risks that arise from traditional methods. Findings from this study show that market for organic products exists in Nigeria, as consumers are willing to pay a premium for both health and environmental gains realized through organic production systems, although their quantitative valuation is higher for the health concerns. This finding reflects public opinion in Nigeria toward food safety and health concerns, and it is consistent with results from studies on matured organic markets in Europe and North America. Furthermore, based on the attitudinal indicators used, segments of consumers are identified. In fact, it is noted that individuals with stronger preferences for organic products tend to attach a global value to the certification program, whereas the valuation tends to be more restrictive among respondents that prioritize the status quo option (conventional alternative). Similarly, findings in this study contribute to the debate on the potential of organic certification to correct environmental externalities in agricultural production. Respondents are observed to display a range of different preferences and this behavioural asymmetry tends to reflect differences in underlying attitudes. More so, it is observed that in order to drive the market for organic produce, a key element in the strategy to reach consumers would be to facilitate access to the products (via urban sale outlets), Moreover, actions to better inform the public in general is noted to be cardinal in promoting concern for the health and environment as well as a shift in preferences while also driving the demand for organic products. Finally, despite the fact that willingness to pay is higher for the private attributes of organic production systems relative to the public attributes, environmental preferences also seem to provide a feasible foundation for the development of the organic market in Nigeria.

# Appendices

## Appendix 1: Questionnaire Sample

TREATMENT 1: *Cheap Talk*

Studies show that people tend to act differently when they face hypothetical decisions. In other words, they say one thing and do something different. For example, some people state a price they would pay for an item, but they will not pay the price for the item even when they see this product in a grocery store.

There can be several reasons for this different behavior. It might be that it is too difficult to measure how the buying of an item affect the household budget. Another possibility is that it might be difficult to visualize themselves getting the product from a grocery store shelf and paying for it. Do you understand what I am talking about?

We want you to behave in the same way that you would if you really had to pay for the product and take it home. Please take into account how much you really want the product, as opposed to other alternatives that you like or any other constraints that might make you change your behavior, such as taste or your grocery budget. Please try to really put yourself in a realistic situation.

TREATMENT 2: *Honesty Priming*

Before participating in the Choice experiment task, for each set of words below, please develop a grammatically correct sentence (or write it down in the space provided, if possible). You do not have to take into account all the words in each sentence.

| **S/No.** | Task | Response |
|---|---|---|
| **1.** | person **honest** this red is | |
| **2.** | is round the earth | |
| **3.** | must always tell you **truth** the | |
| **4** | tomatoes are the up red | |
| **5** | whales live in oceans the | |
| **6** | she interest **genuine** learning in has a | |
| **7** | Summer table hot is in | |
| **8** | met I person week **fair** a | |
| **9** | explanation is **honest** this an | |
| **0** | within seem your to be opinions **genuine** | |
| **11** | **sincerity** is your reflected in behavior your from | |
| **12** | makes baker bread drink | |
| **13** | man is this **fair** market | |
| **14** | the table **honesty** is human a quality | |
| **15** | words his are **sincere** are | |
| **16** | like basketball he I | |

| | | |
|---|---|---|
| **17** | **honestly** talk usually I round | |
| **18** | opinions are your **fair** from | |
| **19** | milk give cows the | |
| **20** | person over **sincere** a met I | |
| **21** | thirst the water removed he the | |
| **22** | says she always lunch **truth** the | |
| **23** | **true** this is a story earth | |
| **24** | wallet the is of **genuine** leather this | |

**Note**: Subjects did not see the words in bold but in normal font

**Section A:** *Food Purchasing and Consumption Practices*

| The first sets of questions are about your actual food purchasing and consumption practices. Please remember that your answers are completely confidential and we are interested in what you really do and not what you think you should do. | | |
|---|---|---|
| A/1. | Do you do the shopping for your household? | 1. Yes ☐ 2. No ☐ |
| A/2. | Where do you normally purchase most of your food? | 1. Open market ☐<br>2. Supermarket ☐<br>3. Directly from the farmer ☐<br>4. Home delivery ☐<br>5. Restaurant ☐<br>6. Specialist store ☐ |
| A/3. | Which of the following best describes your dietary requirements? | 1. Vegetarian ☐<br>2. Weight reduction diet ☐<br>3. Diabetic diet ☐<br>4 Others (specify)……………………………<br>……………………………………………… |
| A/4. | Do you read product labels before purchase? | 1. Yes ☐ 2. No ☐ |

**Section B (1)**: *Lifestyle*

| | | |
|---|---|---|
| ***The next few questions are not directly about food, but about some of the other issues that sometimes affect the way we think about food.*** | | |
| ***B/1***. | Do you participate in any sport? | 1. Yes ☐ 2. No ☐ |
| ***B/2.*** | If yes, how often do you play? | 1. Less than once a week ☐<br>2. Once a week ☐<br>3. Twice a week ☐<br>4. More than twice a week ☐ |
| ***B/3.*** | How often do you go for medical check-up? | 1 Always ☐<br>2. Most of the time ☐<br>3. Occasionally ☐<br>4. Never ☐ |
| ***B/4.*** | How often do you recycle paper, glass and other household waste products (e.g. compost your food scraps at home)? | 1 Always ☐<br>2. Most of the time ☐<br>3. Occasionally ☐<br>4. Never ☐ |

**The next sets of questions are about the sorts of things that influence your decisions about food. We would like you to give each item a score out of five (5) depending on how important it is to you when you make decisions about what you are going to eat. A score of 1 = *"item is not at all important"* and 5 = *"item is extremely important".***

**Please when answering it is important that you let us know which item really does influence your decisions about what you eat and not how much you think they should influence your decisions.**

***B/5.*** How important is it to you that the food you eat on a typical day is:

| | It is completely not important | It is not important | Neutral | It is moderately important | It is extremely important |
|---|---|---|---|---|---|
| **Nutritious** | ☐ | ☐ | ☐ | ☐ | ☐ |
| **Not forbidden by your religion** | ☐ | ☐ | ☐ | ☐ | ☐ |
| **Has no blemishes/ visible defect** | ☐ | ☐ | ☐ | ☐ | ☐ |
| **Is quick(easy) to prepare and is convenient in consumption** | ☐ | ☐ | ☐ | ☐ | ☐ |
| **Easily available in shops and supermarkets** | ☐ | ☐ | ☐ | ☐ | ☐ |

| | It is completely not important | It is not important | Neutral | It is moderately important | It is extremely important |
|---|---|---|---|---|---|
| **Tested and certified as free of chemical residues** | ☐ | ☐ | ☐ | ☐ | ☐ |
| **Is familiar/ Is what you usually eat** | ☐ | ☐ | ☐ | ☐ | ☐ |
| **It conforms to what is encouraged in the community** | ☐ | ☐ | ☐ | ☐ | ☐ |
| **It is recommended by Experts** | ☐ | ☐ | ☐ | ☐ | ☐ |
| **Is not expensive(cheap)** | ☐ | ☐ | ☐ | ☐ | ☐ |
| **Comes from a country that you approve of politically** | ☐ | ☐ | ☐ | ☐ | ☐ |
| **Is grown locally/manufactured in Nigeria** | ☐ | ☐ | ☐ | ☐ | ☐ |
| **Has been produced in a way that conserve the environment** | ☐ | ☐ | ☐ | ☐ | ☐ |

**Section B (2):** *Lifestyle*

| ***B/6.*** How strongly do you **agree** or **disagree** with each of the following statements? | | | | | |
|---|---|---|---|---|---|
| | Completely agree | Agree | Neutral | Disagree | Completely disagree |
| I think it is fair to pay farmers more for producing food in an environmental-friendly way | ☐ | ☐ | ☐ | ☐ | ☐ |
| Scientists are going too far with cloning | ☐ | ☐ | ☐ | ☐ | ☐ |
| Environmental problems are highly exaggerated | ☐ | ☐ | ☐ | ☐ | ☐ |
| My actions are too small to affect any environmental quality | ☐ | ☐ | ☐ | ☐ | ☐ |
| Government are doing enough to control environmental pollution | ☐ | ☐ | ☐ | ☐ | ☐ |

**Section C (1)**: *Awareness and Preference for Organic Products*

| | | |
|---|---|---|
| *C/1*. | **If you were to receive more information on nutritional (food) health, which medium would be the best for you?** | **1.Neighbours☐ 2. Relatives☐ 3.Friends ☐ 4. Extension agents ☐ 5.Religious/traditional☐ leaders 6. Radio ☐ 7. Televesion☐ 8. Public meetings ☐ 9.Agricultural shows☐ 10. Others ……………………………. …………………………….** |
| ***C/2.*** | Are you aware of organic products? | 1. Yes☐ 2. No☐ |
| ***C/3.*** | If yes, when did you know or become aware of organic products? (Years) | …………………… |
| ***C/4.*** | How would you best describe an organic products? …………………………………………………………………………….. ……………………………………………………………………………………………………………………………… | |

**In questions C/5-C/13, there are different combinations of organic products profile for Tomato. The alternatives A and B are from organic farming, while alternative C is a conventional product.**

**Note: Please, decide on selection set for a product that you would buy with the given attributes. If you do not prefer any of products or do not buy them for yourself, then just imagine that you buy the food for your family or good friends.**

C/5. Which **one** of these products would you choose? Please *tick* either **A**, **B** or **C**

| **Products** | **Organic Tomato A** | **Organic Tomato B** | **Conventional Tomato C** |
|---|---|---|---|
| **Pesticide Residues** | Chemical usage is reduced by **25%**<br> | Chemical usage is reduced by **5%**<br> | |
| **Nutritive Content** | Vitamin A in Tomato is increased by **5%**<br> | Vitamin A in Tomato is increased by **5%**<br> | |
| **Environmental Conservation** | Soil erosion is reduced by **100%**<br> | Soil erosion is reduced by **25%**<br> | |
| **Origin of Certifier(s)** | Foreign label | Foreign & indigenous labels | |
| **Price** | Purchase price of Tomato 1Kg<br> | Purchase price of Tomato 1Kg<br> | Purchase price of Tomato 1Kg<br> |
| ***I will buy…*** | ☐ | ☐ | ☐ |

C/6. Which **one** of these products would you choose? Please *tick* either **A**, **B** or **C**

| **Products** | **Organic Tomato A** | **Organic Tomato B** | **Conventional Tomato C** |
|---|---|---|---|
| **Pesticide Residues** | Chemical usage is reduced by **5%**<br> | Chemical usage is reduced by **100%**<br> | |
| **Nutritive Content** | Vitamin A in Tomato is increased by **5%**<br> | Vitamin A in Tomato is increased by **25%**<br> | |
| **Environmental Conservation** | Soil erosion is reduced by **25%**<br> | Soil erosion is reduced by **25%**<br> | |
| **Origin of Certifier(s)** | Indigenous label | Foreign & indigenous labels | |
| **Price** | Purchase price of Tomato 1Kg<br> | Purchase price of Tomato 1Kg<br> | Purchase price of Tomato 1Kg<br> |
| ***I will buy…*** | ☐ | ☐ | ☐ |

C/7. Which **one** of these products would you choose? Please *tick* either **A**, **B** or **C**

| **Products** | **Organic Tomato A** | **Organic Tomato B** | **Conventional Tomato C** |
|---|---|---|---|
| **Pesticide Residues** | Chemical usage is reduced by **100%**  | Chemical usage is reduced by **25%**  | |
| **Nutritive Content** | Vitamin A in Tomato is increased by **25%**   | Vitamin A in Tomato is increased by **5%**   | |
| **Environmental Conservation** | Soil erosion is reduced by **25%**  | Soil erosion is reduced by **5%**  | |
| **Origin of Certifier(s)** | Indigenous label | Foreign & indigenous labels | |
| **Price** | Purchase price of Tomato 1Kg   | Purchase price of Tomato 1Kg   | Purchase price of Tomato 1Kg   |
| ***I will buy…*** | ☐ | ☐ | ☐ |

C/8. Which **one** of these products would you choose? Please *tick* either **A**, **B** or **C**

| **Products** | **Organic Tomato A** | **Organic Tomato B** | **Conventional Tomato C** |
|---|---|---|---|
| **Pesticide Residues** | Chemical usage is reduced by **100%**  | Chemical usage is reduced by **25%**  | |
| **Nutritive Content** | Vitamin A in Tomato is increased by **5%**   | Vitamin A in Tomato is increased by **100%**   | |
| **Environmental Conservation** | Soil erosion is reduced by **5%**  | Soil erosion is reduced by **25%**  | |
| **Origin of Certifier(s)** | Foreign & indigenous labels | Foreign & indigenous labels | |
| **Price** | Purchase price of Tomato 1Kg   | Purchase price of Tomato 1Kg   | Purchase price of Tomato 1Kg   |
| ***I will buy…*** | ☐ | ☐ | ☐ |

C/9. Which **<u>one</u>** of these products would you choose? Please *<u>tick</u>* either **A**, **B** or **C**

| **Products** | **Organic Tomato A** | **Organic Tomato B** | **Conventional Tomato C** |
|---|---|---|---|
| **Pesticide Residues** | Chemical usage is reduced by **5%**  | Chemical usage is reduced by **100%**  | |
| **Nutritive Content** | Vitamin A in Tomato is increased by **25%**   | Vitamin A in Tomato is increased by **100%**   | |
| **Environmental Conservation** | Soil erosion is reduced by **100%**  | Soil erosion is reduced by **5%**  | |
| **Origin of Certifier(s)** | Foreign label | Foreign & indigenous labels | |
| **Price** | Purchase price of Tomato 1Kg   | Purchase price of Tomato 1Kg   | Purchase price of Tomato 1Kg   |
| ***I will buy…*** | ☐ | ☐ | ☐ |

C/10. Which **<u>one</u>** of these products would you choose? Please *<u>tick</u>* either **A**, **B** or **C**

| **Products** | **Organic Tomato A** | **Organic Tomato B** | **Conventional Tomato C** |
|---|---|---|---|
| **Pesticide Residues** | Chemical usage is reduced by **100%**  | Chemical usage is reduced by **25%**  | |
| **Nutritive Content** | Vitamin A in Tomato is increased by **100%**   | Vitamin A in Tomato is increased by **25%**   | |
| **Environmental Conservation** | Soil erosion is reduced by **100%**  | Soil erosion is reduced by **100%**  | |
| **Origin of Certifier(s)** | Foreign label | Foreign & indigenous labels | |
| **Price** | Purchase price of Tomato 1Kg   | Purchase price of Tomato 1Kg   | Purchase price of Tomato 1Kg   |
| ***I will buy…*** | ☐ | ☐ | ☐ |

C/11. Which **one** of these products would you choose? Please *tick* either **A**, **B** or **C**

| **Products** | **Organic Tomato A** | **Organic Tomato B** | **Conventional Tomato C** |
|---|---|---|---|
| **Pesticide Residues** | Chemical usage is reduced by **5%**<br> | Chemical usage is reduced by **100%**<br> | |
| **Nutritive Content** | Vitamin A in Tomato is increased by **100%**<br> | Vitamin A in Tomato is increased by **5%**<br> | |
| **Environmental Conservation** | Soil erosion is reduced by **5%**<br> | Soil erosion is reduced by **100%**<br> | |
| **Origin of Certifier(s)** | Foreign & indigenous labels | Foreign & indigenous labels | |
| **Price** | Purchase price of Tomato 1Kg<br> | Purchase price of Tomato 1Kg<br> | Purchase price of Tomato 1Kg<br> |
| ***I will buy…*** | ☐ | ☐ | ☐ |

C/12. Which **one** of these products would you choose? Please *tick* either **A**, **B** or **C**

| **Products** | **Organic Tomato A** | **Organic Tomato B** | **Conventional Tomato C** |
|---|---|---|---|
| **Pesticide Residues** | Chemical usage is reduced by **25%**<br> | Chemical usage is reduced by **5%**<br> | |
| **Nutritive Content** | Vitamin A in Tomato is increased by **100%**<br> | Vitamin A in Tomato is increased by **100%**<br> | |
| **Environmental Conservation** | Soil erosion is reduced by **25%**<br> | Soil erosion is reduced by **100%**<br> | |
| **Origin of Certifier(s)** | Indigenous label | Foreign & indigenous labels | |
| **Price** | Purchase price of Tomato 1Kg<br> | Purchase price of Tomato 1Kg<br> | Purchase price of Tomato 1Kg<br> |
| ***I will buy…*** | ☐ | ☐ | ☐ |

C/13. Which **one** of these products would you choose? Please *tick* either **A**, **B** or **C**

| **Products** | **Organic Tomato A** | **Organic Tomato B** | **Conventional Tomato C** |
|---|---|---|---|
| **Pesticide Residues** | Chemical usage is reduced by **25%**  | Chemical usage is reduced by **5%**  | |
| **Nutritive Content** | Vitamin A in Tomato is increased by **25%**  | Vitamin A in Tomato is increased by **25%**  | |
| **Environmental Conservation** | Soil erosion is reduced by **5%**  | Soil erosion is reduced by **5%**  | |
| **Origin of Certifier(s)** | Foreign & indigenous labels | Foreign & indigenous labels | |
| **Price** | Purchase price of Tomato 1Kg  | Purchase price of Tomato 1Kg  | Purchase price of Tomato 1Kg  |
| ***I will buy…*** | ☐ | ☐ | ☐ |

**Section D:** *Attribute Processing statements*

| *D/1.* | **How much do you feel you assess (attended to) the following attributes of the alternatives in the sequence of Choice tasks before finally making your choice?** | | | | |
|---|---|---|---|---|---|
| | | | | | |
| Attributes | **Never** | **Rarely** | **Sometimes** | **Often** | **Always** |
| **Purchase Price** | ☐ | ☐ | ☐ | ☐ | ☐ |
| **Pesticide Residue** | ☐ | ☐ | ☐ | ☐ | ☐ |
| **Soil Erosion** | ☐ | ☐ | ☐ | ☐ | ☐ |
| **Vitamin A Nutrient** | ☐ | ☐ | ☐ | ☐ | ☐ |
| **Certification** | ☐ | ☐ | ☐ | ☐ | ☐ |

| *D/2.* | **Please** rank **your level of involvement and understanding of the Choice tasks presented to you. (1=** ***Do not agree*****, 5=** ***Fully agree*****)** |
|---|---|
| | |
| **''All the attributes of the choice alternatives were important in my choice decisions''** | ☐ |
| **"I was able to fully understand the tasks I was faced with"** | ☐ |
| **"I was able to make choices as in a real world scenario"** | ☐ |

| *D/3.* | **Please** rank **level of importance of the attributes in making the choices you made in the task. (1=** ***Most important*****, 5=** ***Least important*****)** |
|---|---|
| Attributes | |
| **Purchase Price** | ☐ |
| **Pesticide Residue** | ☐ |
| **Soil Erosion** | ☐ |
| **Vitamin A Nutrient** | ☐ |
| **Certification** | ☐ |

**Section E:** *Socio-demographic Characteristics*

<table>
<tr><td colspan="9">The next few questions will give us a better picture of the people who gave us their opinions as part of this study. Please let me remind you again that all responses are confidential.</td></tr>
<tr><td>E/1.</td><td colspan="8">LGA: ……………………..</td></tr>
<tr><td>E/2.</td><td colspan="8">Name of village: ……………………..</td></tr>
<tr><td>E/3.</td><td colspan="5">Gender of respondent</td><td colspan="3">1. Male ☐ 2. Female ☐</td></tr>
<tr><td>E/4.</td><td colspan="5">Marital Status of respondent</td><td colspan="3">1.Single ☐ 2.Married☐<br>3.Divorced ☐ 4.Widow ☐</td></tr>
<tr><td>E/5.</td><td colspan="8">Age of respondent …………………… (Years)</td></tr>
<tr><td>E/6.</td><td colspan="8">Respondent’s years of education …………………… (Years)</td></tr>
<tr><td>E/7.</td><td colspan="5">What is your highest level of education?</td><td colspan="3">0.Islamic Education ☐<br>1.Primary ☐<br>2.Secondary ☐<br>3.Tertiary ☐</td></tr>
<tr><td>E/8.</td><td colspan="8">Please provide information about your household composition</td></tr>
<tr><td></td><td colspan="4">Male members</td><td colspan="4">Female members</td></tr>
<tr><td></td><td>Below 5 years (< 5)</td><td>Between 5 and 18 years (5 – 18)</td><td>Between 18-60 years (18 - 60)</td><td>Aged above (> 60 )</td><td>Below 5 years (< 5)</td><td>Between 5 and 18 years (5 – 18)</td><td>Between18-60 years (18 - 60)</td><td>Aged above 60 (> 60 )</td></tr>
<tr><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td colspan="8">Total (Household Size) =</td></tr>
<tr><td>E/9.</td><td colspan="5">Does any member of the household experienced food-related sickness within the last 24 months?</td><td colspan="3">1. Yes☐ 2. No ☐</td></tr>
<tr><td>E/10.</td><td colspan="5">If E/9 is yes, then what was the food-related disease?</td><td colspan="3">Please specify……………………………<br>…………………………………………</td></tr>
<tr><td>E/11.</td><td colspan="5">How long ago was this incidence/ when does this happen?</td><td colspan="3">Please specify……………………………<br>…………………………………………</td></tr>
<tr><td>E12.</td><td colspan="5">What is your <u>main</u> occupation?</td><td colspan="3">1.Civil servant ☐ 2. Vocational ☐</td></tr>
</table>

☐

| | | |
|---|---|---|
| | | 3. Farming 4.Trading ☐<br>5. Others (specify) ……………………<br>……………………………………... |
| E/13. | Do you own any of the following? (please *tick* all that apply) | 1. Radio ☐ 2. TV☐<br>3. Bicycle ☐ 4. Car ☐<br>5. Motorcycle ☐ 6. Land ☐<br>7. House ☐<br>8. Others …………………………….. |
| E/14. | What is your average monthly income? ………………………… (Naira) | |

**FEEDBACK SHEET (CHEAP TALK)**

Please indicate any general question or comment you may have on this study …………………………

…………………………………………………………………………………………………………

…………………………………………………………………………………………………………

**FEEDBACK SHEET (HONESTY PRIMING)**

Ia. Do you know (or can you guess) the purpose of this study? Yes ☐ No ☐

Ib. If yes, can you please explain? ……………………………………………………………………………..

..…………………………………………….. ……………………………………………………

…………………………………………………………………………………………………………

II. Please indicate any other general question or comment you may have on this study ………………..

…………………………………………………………………………………………………………

…………………………………………………………………………………………………………

**Note**: *Question* (I) *is included as an additional debriefing measure in the honesty priming treatment only.*

Appendix 2: Curriculum Vitae

**Muhammad Baba Bello**, born on 10th October, 1980 in Kano, Nigeria

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**Education**

| | |
|---|---|
| 11/2011 – 1/2016 | PhD fellow, University of Kiel, Germany<br>Thesis title: Three Essays on Modeling Consumer Preferences in the Presence of Hypothetical Bias and Attribute Non-Attendance in Food Choice Experiments. |
| 2008-2010 | M.Sc. in Agricultural Economics, Bayero University Kano, Nigeria<br>Thesis title: Economics of Small Scale Rice Farming in Kano River Irrigation Project Phase I Area. |
| 2006 | Certificate in Data Processing, Online Computer Academy Kano, Nigeria |
| 2000-2005 | B. Agric. Tech (Agricultural Economics & Extension), Abubakar Tafawa Balewa University Bauchi, Nigeria<br>Thesis title: Economics of Small Scale Fertilizer Marketing in Kano Metropolis. |
| 1998 | Secondary school certificate, Federal College of Education Staff Sec. Sch., Kano |
| 1985-1992 | Primary school certificate, Aliyu Ibn Abitalib Primary School Kano, Nigeria |

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**Professional Experience**

| | |
|---|---|
| 11/2011 – 1/2016 | PhD fellow, Department of Food Economics and Consumption Studies, University of Kiel, Germany |
| 2008 - Present | Academic Staff, Department of Agricultural Economics and Extension, Bayero University Kano, Nigeria |
| 2007 - 2008 | Part – Time Academic Staff, Department of Cooperative Economics and Management, Kano State Polytechnic, Nigeria |
| 2003 - 2004 | Internship at Kano State Agricultural Supply Company, Nigeria |

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