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A Query Approach to Modeling Attendance to Attributes in Discrete Choice Experiments

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Overlooking respondents' attribute attendance in choice experiments affects coefficient estimates, model fit, performance measures, and welfare estimates. How best to identify and account for individual attribute processing strategies is still unclear. Query theory suggests that preferences are subject to the processes and dynamics associated with retrieval from memory. We apply Query theory to the study of attendance to attributes to approximate the thoughts generated by individuals while they make choices in a choice experiment. Our results demonstrate that the stated and query approaches improve model fit and performance. The query approach has distinct advantages but also important limitations.

Key words: attribute nonattendance, discrete choice experiments, genetically modified organisms, query theory

Introduction

In the last decade, discrete choice experiments (DCEs) have become one of the most widely used methods of consumer valuation. In a DCE, participants are asked to consider a product that is defined by several attributes (Hensher, Rose, and Greene, 2015); often, they are given a no-choice alternative. Conventionally, each attribute and attribute level are treated as relevant to the estimation of individual-level utility (Hess and Hensher, 2010). More recently, research has focused on how people process attributes presented to them in choice experiments. Respondents may attend to some attributes and ignore others during each choice task (Hess and Hensher, 2010; Scarpa et al., 2013) and thereby may not make trade-offs between all the attributes as assumed. Consequently, overlooking respondents' attendance to attributes (AA) in choice models can affect coefficient estimates, model fit, performance measures, and welfare estimates (Campbell, Hutchinson, and Scarpa, 2008; Hensher and Rose, 2009; Scarpa et al., 2009; Carlsson, Kataria, and Lampi, 2010; Scarpa et al., 2013; Hensher, 2014; Caputo et al., 2018). Hence, accounting for the patterns of AA is essential for estimating reliable results.

Previous studies have examined the strategies used by respondents in choice experiments (Ahi and Kipperberg, 2020; Balcombe, Fraser, and McSorley, 2015; Bello and Abdulai, 2016; Erdem, Campbell, and Hole, 2015; Hess and Hensher, 2010; Lew and Whitehead, 2020; Scarpa et al., 2009,

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2013); however, while much research has been devoted to various methods of identifying patterns of attribute attendance, it is still unclear how best to account for individual attribute processing strategies in DCEs. In light of this, our study explores the potential of query theory (Johnson, Häubl, and Keinan, 2007) to examine the thought processes of individuals in a DCE. We suggest that respondents go through a series of mental queries when confronted with choice tasks and that the content of these queries influences choice behavior. By asking respondents to use a reporting method called *aspect listing*, useful information is produced that can help us better understand the information processing strategies of individuals in a DCE. Principally used to infer how thoughts influence valuation by examining the order and valence (value increasing or decreasing) of thoughts (Kemper, Popp, and Nayga, 2020; Dsouza et al., 2023), query theory data offer a robust pool of artifacts representing the thoughts given attention by individuals during each choice task. Our study explores whether such data could be useful in the accounting for patterns of AA.

Several approaches have been explored to account for AA, including the inferred approach and the stated approach. In the inferred approach, AA is inferred through the estimation of analytical models, which are often based on latent class or mixed logit models (Hess and Hensher, 2010; Caputo, Nayga, and Scarpa, 2013; Scarpa et al., 2013; Collins and Hensher, 2015). One of the most common inferred approaches (Scarpa et al., 2009, 2013; Hensher and Greene, 2010; Caputo, Nayga, and Scarpa, 2013) is the equality-constrained latent class method, which imposes specific restrictions on the utility functions for each class of respondent by constraining some coefficients to 0 for selected attribute classes determined to be ignoring attributes. Hess and Hensher (2010) suggested inferring AA through the use of mixed (random parameters) logit models (MXLs). The MXLs are first used to derive individual-level estimates of coefficients and variance, which are then used to examine respondent-specific coefficients of variation to identify large “signal-to-noise” ratios and thereby infer attribute nonattendance.

In the stated approach, self-reported statements of AA have been included in surveys in order to condition models based on self-stated intentions of AA (Bello and Abdulai, 2016; Hensher, 2006; Hensher and Rose, 2009; Hess and Hensher, 2010; Islam, Louviere, and Burke, 2007). Stated approach data are used in practice in two principal ways: these data can be used directly within utility functions or incorporated using a latent variable approach (Hess et al., 2013). The latent variable structure approach was developed to avoid endogeneity issues with the direct approach; however, if the latent variable structure is suggested and then the latent variables are merely replaced with observable data (stated attendance to attributes) this would imply misspecification (Chalak, Abiad, and Balcombe, 2016). The direct use of stated attendance data can be thought of as a reduced form arising from an unobserved latent structure (Chalak, Abiad, and Balcombe, 2016). In our study, we adopt this view and use the stated attendance data by directly incorporating these data into our utility functions.

While asking respondents direct questions seems to indicate that some respondents consistently ignore certain attributes, it is not clear whether researchers should rely on this information during model estimation (Hess and Hensher, 2010). To illustrate, endogeneity problems could occur by conditioning the modeled choice process on the stated processing strategies (Hensher, 2008); the same concerns about the quality of responses in the choice data extend to direct questions about decision-making heuristics. If stated measures of attendance are affected by respondent inaccuracies from accidental or intentional misrepresentation, such measures would be uninformative and invalid. Scarpa et al. (2013) compared the stated methods to both the latent class and MXL methods of inferring AA, concluding that it is not possible to identify which approach best accounts for these patterns and that overlooking the issue in choice experiments can have significant consequences for welfare estimates.

As the literature demonstrates, stated AA data can be used in many ways. A common approach is to use an MXL model in which attributes reported as ignored by respondents are eliminated from the model. Such “attribute elimination” models assign a zero-utility weight to attributes ignored. However, such an assumption is problematic because reporting that an attribute does not factor into a decision does not necessarily indicate that the attribute was ignored; it may be the case that the attribute was indeed considered but did not factor into the decision. In other words, the attribute may have some weight in the decision-making process and could even be associated with negative utility. Hess and Hensher (2010) proposed a validation method using self-reported AA data to specify an indirect utility function that estimates two coefficients for each attribute. This eases the assumption of "all or nothing" AA and acknowledges that ignoring an attribute does not necessarily indicate that it has 0 utility weight.

As an alternative approach, we posit that attribute processing strategies can be examined using psychological theories of choice. Specifically, we suggest that query theory offers a psychological explanation for the decision heuristics used by individuals in DCEs. Query theory suggests that decision makers construct their preferences by asking internal queries about the available options (Johnson, Häubl, and Keinan, 2007; Weber et al., 2007). Preference construction and choice are an automatic and unconscious process of arguing with oneself (Weber and Johnson, 2011). People sequentially generate arguments for selecting each of the various choice options, with the first option considered to have a major advantage because arguments for the default choice option are generated first (Johnson, Häubl, and Keinan, 2007). Using an aspect-listing task in which respondents list the thoughts they experienced while making each choice, our study explores the use of query theory to examine AA and how utilizing these query data affects model structure, fit, patterns of heterogeneity, and welfare estimates.

The main goal of this study is to evaluate, for the first time in the literature, the usefulness of the query approach in accounting for individuals' information processing strategies in a DCE. Query theory offers an unexplored avenue by which one can account for AA. Our study contributes to the literature by comparing the stated approach to the query approach, both at the choice task level, wherein we use the principles of query theory to account for the information processing strategies of individuals. Following the literature from social psychology (Johnson, Häubl, and Keinan, 2007; Weber et al., 2007) and applied economics (Kemper, Popp, and Nayga, 2020), we use a verbal report method called "aspect listing" to obtain an approximation of the aspects (thoughts) considered during each choice task of the experiment. We then use the self-reported aspects listed by respondents to determine which attributes individuals attended during each choice task. Specifically, our study employs a between-subjects design in which respondents are randomly assigned to one of two groups: the stated approach group or the query approach group. Our study differs from previous research by being the first study to use query theory in an attempt to account for patterns of AA in a DCE. Second, our study offers new insights into the effectiveness of the stated approach.

Query Theory

The four key principles of how preferences are formed according to query theory (QT) (Weber and Johnson, 2011) are (i) people query past experience for evidence supporting different choice options; (ii) these queries are executed sequentially and automatically; (iii) the first query is weighed more heavily because of output interference (as evidence for the first considered option is generated, evidence supporting the alternative options is temporarily unavailable) and—due to output interference—the first thought is more heavily weighted in the overall decision; and (iv) choice is based on the resulting balance of evidence. Hence, the content of considered options is important because it influences the balance of evidence. QT suggests that if respondents in a DCE attend only to certain attributes, then the balance of evidence changes, and models of choice should be adjusted for such behavior.

Johnson, Häubl, and Keinan (2007) used QT to examine the endowment effect and suggested that people construct values by posing a series of queries whose order differs for sellers and choosers. Their results suggest that the variations in valuations between buyers and sellers were caused by the different aspects retrieved by buyers and sellers resulting from output interference. Importantly, they demonstrated that the content of the recalled aspects differs for selling and choosing and that

Table 1. Choice Experiment Attributes and Levels with Effects Coding

Attributes	Coding	Levels
Price	\$2.99	\$2.99 price level
	\$6.99	\$6.99 price level
	\$10.99	\$10.99 price level
	\$14.99	\$14.99 price level
	0	No-buy option[a]
GM content	−1, −1	No information provided on GM content
	1, 0	The Non-GMO Project Verified label and statement
	0, 1	This product contains genetically modified ingredients
	0, 0	No-buy option[a]
Carbon footprint	−1, −1, −1	No information provided on Carbon Footprint
	1, 0, 0	79 oz CO2e/lb, representing the low carbon emissions level
	0, 1, 0	90 oz CO2e/lb, representing the medium carbon emissions level
	0, 0, 1	112 oz CO2e/lb, representing the high carbon emissions level
	0, 0, 0	No-buy option[a]
Local	−1	No information about where birds raised and food grown
	1	Birds raised and food grown in your state (local)
	0	No-buy option[a]

Notes: [a]The no-buy option is a fixed comparator presented during all choice tasks. It is not an attribute level.

the aspects predict valuations. Further, Weber et al. (2007) provided empirical support for the QT premise that the order of thoughts matters by using QT to explain asymmetric discounting. They successfully reduced people's discounting of future rewards by setting up an experiment in which the decision was reframed in a way that directed attention to the delayed outcome.

QT documents the cognitive mechanisms used by individuals to form preferences; like all knowledge, preferences are subject to the processes associated with retrieval from memory, which can help explain a range of phenomena in valuation research (Johnson, Häubl, and Keinan, 2007; Weber and Johnson, 2006). Our study extends this logic to explain AA in DCEs by examining the queries, albeit indirectly, generated by people in our experiment. QT should help document improvements to models based on the queries of individuals. If the content of aspects listed by respondents accurately documents AA, then individual, specific coefficient estimates for attributes that have been attended to should be larger (in absolute terms) than those not attended to, as observed by Scarpa et al. (2013).

Materials and Methods

Choice Set Design

The product evaluated in this study was boneless, skinless chicken breast. Table 1 summarizes the choice experiment attributes and describes each level. Effects coding was chosen over dummy coding since it allows the attribute coefficients to be uncorrelated with the constants, avoiding confounding effects (Bech and Gyrd-Hansen, 2005; Hensher, Rose, and Greene, 2005; De Marchi et al., 2016). The prices used in our study represented a sample of 2015 prices found in supermarkets (both physical locations and online) and in USDA price reports for chicken (US Department of Agriculture, 2015). For the genetically modified (GM) content attributes, a non-GMO Project Verified label was included, and the mandatory labeling style statement "this product contains

Table 2. Distribution of Attendance to Attributes across Two Approaches

Attributes		Stated Approach Choice Task (SAT) (N = 4,040)	Query Approach Choice Task (QAT) (N = 3,784)
Price	No. of obs.	3,411	2,543
	Percentage (%)	84.4	67.2
GM content	No. of obs.	2,753	976
	Percentage (%)	68.1	25.8
Carbon footprint	No. of obs.	2,197	347
	Percentage (%)	54.4	9.2
Local	No. of obs.	2,503	571
	Percentage (%)	62.0	15.1

genetically engineered ingredients" was used.[1] The "this product contains GM" language was chosen to measure how consumers respond if such language appears on products due to new federal regulations. Two additional sustainability-related labels were included: carbon footprint and local production.[2] All attribute levels are described in Table 1.

Respondents completed eight choice tasks in this experiment, with each task consisting of two experimentally designed products and a no-buy option. The allocation of attribute levels to alternatives was designed using a D-efficient design obtained in two stages (Bliemer and Rose, 2010). The first stage was an orthogonal design for the pilot, in which 250 respondents were used (Addelman, 1962). Next, a multinomial logit model (MNL) was estimated using data from the pilot to obtain coefficient estimates for use as priors for the data from the second wave. The orthogonal design defined the first alternative in each choice set, and a shifting strategy was used to define the second alternative in each set as described in Bunch, Louviere, and Anderson (1994) and Street and Burgess (2007). Designs involved 32 choice tasks in four blocks of eight tasks each.

Experimental Treatments

Stated Approach

Using the stated approach, there are two opportunities to ask respondents about AA in an experiment: at the end of all choice tasks or after each individual choice task (Bello and Abdulai, 2016; Puckett and Hensher, 2008; Scarpa et al., 2013; Scarpa, Thiene, and Hensher, 2010). After completion of each of the eight respective choice tasks, respondents were presented with the following question: "Which of the following attributes did you IGNORE or CONSIDER when making your choice?" The response options were binary for each attribute with the options "ignored" and "considered." Our stated approach model estimated at the choice task level (SAT), and attendance was allowed to vary across the eight tasks. Table 2 reports the distribution of AA using the stated approach.

Query Approach

To obtain information on the thoughts considered during each choice task of the experiment, a verbal report method called an aspect listing was used, following Johnson, Häubl, and Keinan (2007), Weber et al. (2007), and Kemper, Popp, and Nayga (2020). Respondents were asked, "What were

[1] Permission was granted by the Non-GMO Project to use their logo, statement, and label in our DCE (www.nongmoproject.org).

[2] The CO_2 levels followed those used by Van Loo et al. (2018).

you thinking of as you made this decision. We would like you to list your reasons below one at a time and to consider both positive and negative reasons. You can list up to three reasons." Subsequently, the content of the responses was recorded to approximate the thought processes of respondents in each treatment. Each respondent completed eight choice tasks with three text fields for the aspect listing available at each task.[3] This process provided 24 total opportunities for each respondent to list their thoughts during the experiment and respondents could list more than one aspect per text field, each of which had a 100-character limit.[4] Notably, the aspects listed approximate the thoughts that actually occurred as respondents made decisions, particularly given that the queries themselves may be automatic and difficult to observe directly (Johnson, Häubl, and Keinan, 2007). Specifically, aspect listing is designed to capture the effect of these unobservable queries by documenting what they produce; this method is easy to implement, particularly in large sample market settings like the one used in this study. Participants in the query approach treatment (473 people) listed a total of 4,437 aspects that were usable. This means that on average, respondents listed 9.38 aspects during the experiment, which consisted of 8 paired comparisons or 1.17 aspects per choice task. This low response rate could indicate fatigue and that respondents were not attending to all the attributes in our study. Alternately, respondents could be fatigued and not listing all attributes to which they actually attended in the experiment.

Other QT studies (Johnson, Häubl, and Keinan, 2007; Weber et al., 2007) have asked participants to self-code aspects they had listed during the experiment; comparatively, this method was avoided in our study to minimize respondent fatigue. Accordingly, our team coded individual responses (see Appendix 1).[5] Additionally, the aspect-listing task was left more open and allowed for comments about individuals' decisions to be entered.[6] Completion time increased by 9 minutes on average (from 10 to 19 minutes) when the aspect-listing task was requested. Additional time was associated with the task of manually coding responses from the 473 respondents who provided text in three text fields per task across eight choice tasks. Aspect responses were coded by the attributes used in the study (price, GM content, carbon footprint, location) or by "other" in cases where the responses listed aspects not related to the attributes of our study (i.e., "I don't like white meat" or "prefer all-natural"). Appendix Table A1 lists examples of value-decreasing, -increasing, and -neutral aspects listed by respondents for each attribute. Table 2 summarizes the distribution of AA in the query approach treatment. Using the query approach, we estimate that respondents ignore price 33% of the time. Notably, price was the most mentioned attribute, representing over half of all aspects listed by respondents.

An attribute mentioned by an individual was considered to be a signal that the individual attended to that attribute. In this regard, how we implement the query approach is similar to the stated approach, with the main difference being that the stated approach asks the question directly and the query approach is open ended.

Using the query approach, if a respondent mentions an attribute, we assume that the person derives utility (either positive or negative) from the attribute mentioned. If a respondent does not attend an attribute (i.e., the respondent does not mention that attribute), the coefficient was restricted to 0, removing it from the utility function. This is the "attribute elimination" method mentioned previously. Due to the concerns of relying on such a strict "all or nothing" assumption about utility, this restriction was relaxed in subsequent analyses, in which these coefficients are not forced to be 0. Using Hess and Hensher's (2010) validation approach, we also estimated models with dual coefficients for each attribute using the query approach and the stated approach.

[3] Prior research by Johnson, Häubl, and Keinan (2007) indicated that on average, participants listed fewer than three responses during the aspects listing task in their experiment.

[4] We acknowledge that limiting the amount of text that individuals could report in the aspect-listing exercise could have limited some respondents from listing all of their thoughts and we could therefore be underreporting the number of aspects considered by some respondents.

[5] Johnson, Häubl, and Keinan (2007) note that aspects coded by novice raters produce similar results in their experiments.

[6] Another reason for our choice to manually code the aspects data (which required a great deal of time) was the unique nature of individual responses.

In contrast with the stated approach, in which respondents were asked to indicate both considered and ignored attributes, in the query approach, respondents were asked to report their thoughts; thus, the data on ignored attributes were collected indirectly. We note this difference because of the potential issue of reliability regarding the stated approach, which forces respondents to ponder the attributes they are ignoring. The question remains of whether requiring a person to report on the attributes they ignore also requires them to attend to the attribute in order to respond to the question. At the choice task level, as respondents progress through a series of choices, asking respondents to report on what they are not considering could influence their thought processes as they progress to each subsequent task. Our query approach addresses this by requesting that respondents list their thoughts while making decisions. While not requiring respondents to provide their thoughts about all attributes could lead to underreporting of AA, the smaller amount of data gained from our query approach could be viewed as more reliable due to the exertion of less direct influence over attributes considered by respondents.

Econometric Methodology

To examine respondents' preferences, we employed a discrete choice framework consistent with random utility theory (McFadden, 1974) and Lancaster consumer theory (Lancaster, 1966). The DCE literature emphasizes that individuals have heterogeneous preferences. Accordingly, the MXL approach with error components was used to evaluate attendance to attributes in the context of models to address random taste variation (Train, 2009). The utility function is specified as follows:

$$
\begin{aligned}
U_{ijt} = NONE &+ \beta_{1i}PRICE_{ijt} + \beta_{2i}NGE_{ijt} + \beta_{3i}GME_{ijt} + \beta_{4i}LOE_{ijt} \\
&+ \beta_{5i}MDE_{ijt} + \beta_{6i}HIE_{ijt} + \beta_{7i}LCE_{ijt} + \eta_{ijt} + \varepsilon_{ijt},
\end{aligned} \tag{1}
$$

where i is the respondent, j refers to three options available in the choice set, and t refers to the number of choice situations. The alternative-specific constant (*NONE*) takes a value of 1 if selected and a value of 0 when either of the two designed alternatives available is selected. We expect NONE to be negative and significant, signifying that consumers obtain higher utility by selecting one of our designed alternatives than the no-buy option. *PRICE* is a continuous variable represented by the four experimentally designed price levels ($2.99, $6.99, $10.99, $14.99). The nonprice attributes—non-GMO (*NGE*), contains genetically engineered ingredients (*GME*), low carbon footprint (*LOE*), medium carbon footprint (*MDE*), high carbon footprint (*HIE*), and local production (*LCE*)—are effects-coded variables taking a value 1 if the product carries the corresponding labels, a value of −1 in the absence of the label (no label information presented), and a value of 0 when the no-buy (*NONE*) option is selected. The utilities of the two products are more likely to be correlated with each other than with the no-purchase option (Scarpa, Ferrini, and Willis, 2005) because the no-buy option is always present across choice tasks and is actually experienced by the consumer, while the two product options are hypothetical and change across choice tasks. To capture this correlation across utilities, we include an error component, η_{ijt}, which is normally distributed and has a mean of 0, inflating the variance of utility for choice options apart from the no-buy option. Further, ε_{ijt} is an unobserved random term that is distributed following an extreme value type-I (Gumbel) distribution independently and identically distributed (*i.i.d.*) over alternatives.

Modeling Attendance to Attributes

We first employ the most conservative approach by assuming that when a respondent ignores an attribute in a choice task, the coefficient for that attribute is restricted to 0 in utility parameters, βs, in equation (1). Hensher, Rose, and Greene (2005) argued that if a respondent ignores an attribute in a choice task, then the coefficient for the attribute should be 0 in the utility function. However, Hess and Hensher (2010) documented the limitations of such an approach. Therefore, we next employed the validation approach, in which utility parameters were not set to 0 and dual coefficients for each attribute were estimated. Although a person may report that they have ignored an attribute, they may still have a marginal utility for that attribute that differs from 0 (Carlsson, Kataria, and Lampi, 2010). Similarly, with the query data, if a respondent does not mention an attribute, this may indicate low attendance to the attribute, rather than necessarily indicating that the attribute was ignored. For each attribute level in the utility function, two coefficients were estimated: one for the observations where individuals were considered to attend to the attribute (AA) and one for the observations where it is assumed that individuals only minimally attended to or did not attend to attributes (NA).

Scarpa, Thiene, and Hensher (2010) noted that respondents' individual processing strategies may change as they progress through a series of choice tasks. This finding implies that an individual's tendency to consider or ignore attributes may not be constant throughout the entire set of choice tasks. Therefore, it is important to allow an individual's patterns of AA and attribute nonattendance (ANA) to vary from one choice task to another. We adopted the choice task-level approach when estimating our models.

Data

The data were collected through a national web-based DCE survey built with the Sawtooth Software, Inc. (2016) package and collected by (Survey Sampling International (SSI), 2016) using their nationally representative consumer panel. The panel consisted of 978 participants who were the primary grocery shoppers for their households; hence, our subject pool is nonstandard (Harrison and List, 2004).

A between-subjects design was used in which respondents were randomly assigned to only one of two treatments. The first treatment was the stated approach treatment, and 505 participants were assigned to this group. In this treatment, respondents were asked after each choice task to state their consideration or disregard of each attribute. The second treatment was the query approach treatment, and 473 participants were assigned to this group. In this treatment, respondents were asked to list their thoughts during each choice task.

The sample from SSI is balanced by sociodemographic characteristics and by four main US Census regions for regional balance across the United States. Our experiment consisted of two tasks. In the first, respondents in both treatments participated in a DCE in which they made choices between poultry products differentiated by the various genetically modified (GM) content labels, production location, and carbon footprint. Once the DCE was finished, all respondents in both treatments were asked a series of survey questions related to food preferences and demographic data.

Results

This study included 978 respondents in the two treatments, with each respondent completing eight choice tasks with three choices or alternatives per task. We also tested whether there were differences in sociodemographic profiles across treatments using a chi-square test. The results show no significant differences in observable characteristics across treatments, which suggests that our randomization provided a balanced sample across the treatments. The demographic characteristics of our samples can be found in the appendix. We estimated equation (1) using an MXL with correlated errors and variance-enhancing error components where price and all effects-coded attribute-level variables are considered random, following a normal distribution.[7] Estimations were conducted

[7] Numerous versions of the MXL models were estimated, using normal, lognormal, and constrained triangular parameter distributions. Models were also estimated with independently distributed as well as correlated coefficients and both dummy coded and effects coded models were estimated. In the interest of brevity, we limit the results to the model using independent normal distributions for all random coefficients. Results from other models are available on request.

using NLOGIT 5 using 1,000 Halton draws to provide more accurate simulation for the random parameters (Train, 2009).[8]

In our results, we compared the performance of the stated approach in identifying patterns of AA with that of the query approach. Following Hess et al. (2013), we compared the two approaches based on (i) the rates of AA between the various models, (ii) differences in model fit between models, and (iii) the heterogeneity patterns for individual coefficients. Welfare estimates from such models are often important; therefore, we also estimated willingness to pay and compared these values across the models using the combinatorial approach suggested by Poe, Giraud, and Loomis (2005). Finally, to test whether the query and stated approaches yielded the same underlying preferences, we estimated a pooled model (see Table 3). This model was abbreviated as the pooled baseline (PAB).

Comparison of Model Fit and Heterogeneity Patterns

We abbreviated the respective models using the following notation: SAB (stated approach baseline) refers to the baseline stated approach model, and SAT (stated approach choice task) is the stated approach model at the choice task level. Table 2 presents the attendance data from the stated approach treatment. The percentage of respondents attending the price attribute was 84%, 68% for the GM content attribute, 54% for the carbon footprint attribute, and 62% for local production.

Next, we compared the model fit of the SAB with that of the SAT; Table 3 presents these results. Comparing models using measures of estimation criteria with respect to the baseline model offers some clues as to whether our models improved. We focused on the Bayes information criterion (BIC) and the Akaike information criterion (AIC) divided by the number of observations, as shown in Table 3. The SAT model offers improvements in fit over the baseline, with a BIC/N of 1.45 and AIC/N of 1.39. These results are in line with previous studies in which accounting for AA improved model fit (Hensher, Rose, and Greene, 2005; Campbell, Hutchinson, and Scarpa, 2008). A comparison of the SAB and the SAT models indicated that all the coefficients for our random parameters increased in magnitude, with the most substantial increases occurring in the three carbon footprint attribute levels. Additionally, all the random parameter coefficients in our SAT model are significant and have the expected signs.

We next compared the two stated approach models in terms of patterns of heterogeneity. We observed a decrease in heterogeneity, measured by the coefficient of variation (CV) when moving from the base (SAB) to the SAT model for all the coefficients for our random parameters in the model except price, which remained approximately the same. This finding indicates that what was previously captured as heterogeneity is now accommodated by our model conditioned for AA using the stated approach.

Using the query approach, AA is based on the direct observation of attributes attended to, as these represent the aspects listed by respondents. This approach differs from the stated approach, where respondents indicate both considered and ignored attributes. The query approach, therefore, should be viewed as a more conservative approach to the detection of AA. As with the stated approach results, we present the results of two query treatments (Table 3). The respective models were abbreviated using the following notation: QAB (query approach baseline) refers to the baseline model and QAT (query approach choice task) is the query approach model employed at the choice task level.

Table 2 presents the distributions of attendance to attributes across the two models using data from the query approach treatment. The percentage of respondents attending the price attribute was 67%, 26% for the GM content attribute, only 9% for the carbon footprint attribute, and 15% for local production.

[8] Following Hensher and Greene (2003), all MXL models were estimated using 25, 50, 150, 250, 500, 1,000, 2,000, 2,500, and 5,000 draws to identify the number of draws required to produce stable results. Shuffled Markov-chain draws and Halton draws were compared for use in simulations and returned similar results. Stable results were obtained at 1,000 Halton draws, so we adopted this for all of the models presented here.

Table 3. Pooled Baseline, Stated, and Query Data Models using the Choice Task Approach for Modeling Attributes Attended

Variables	Coeff.	Stated Base (SAB) Baseline Estimate	Stated Choice Task (SAT) Stated Data Estimate	Query Base (QAB) Baseline Estimate	Query Choice Task (QAT) Query Data Estimate	Pooled Base (PAB) Pooled Baseline Estimate
PRICE	μ	−0.40***	−0.44***	−0.53***	−0.46***	−0.45***
		(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
	σ	0.40***	0.43***	0.35***	0.26***	0.35***
		(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
NON-GM	μ	1.27***	2.06***	1.44***	3.25***	1.35***
		(0.15)	(0.15)	(0.21)	(0.19)	(0.12)
	σ	1.72***	1.98***	2.67***	3.58***	1.82***
		(0.14)	(0.16)	(0.18)	(0.3)	(0.16)
GM	μ	−0.74***	−1.06***	−1.02***	−2.08***	−0.87***
		(0.1)	(0.1)	(0.13)	(0.19)	(0.08)
	σ	1.02***	1.16***	1.49***	2.50***	1.23***
		(0.1)	(0.11)	(0.13)	(0.29)	(0.13)
LOWCO2	μ	0.22**	0.55***	0.31***	2.21***	0.25***
		(0.09)	(0.11)	(0.12)	(0.31)	(0.07)
	σ	0.29*	0.48***	0.74***	0.83*	0.70**
		(0.15)	(0.18)	(0.15)	(0.49)	(0.32)
MEDIUMCO2	μ	0.06	0.22*	−0.05	0.62*	0.01
		(0.09)	(0.12)	(0.1)	(0.36)	(0.06)
	σ	0.22	0.48***	0.14	1.32***	0.46
		(0.16)	(0.17)	(0.21)	(0.49)	(0.34)
HIGHCO2	μ	−0.03	−0.26**	−0.10	−2.06***	−0.06
		(0.08)	(0.12)	(0.08)	(0.4)	(0.06)
	σ	0.43***	0.73**	0.52***	2.28***	1.18***
		(0.17)	(0.31)	(0.17)	(0.57)	(0.4)
LOCAL	μ	0.27***	0.54***	0.26***	2.23***	0.26***
		(0.05)	(0.07)	(0.06)	(0.18)	(0.04)
	σ	0.37	0.60***	0.54***	1.70***	0.32
		(0.25)	(0.21)	(0.09)	(0.21)	(0.42)
No-buy	μ	−5.76***	−6.00***	−4.98***	−3.83***	−5.27***
		(0.35)	(0.32)	(0.27)	(0.23)	(0.2)
Error Component	σ	3.64***	4.06***	2.60***	3.23***	3.03***
		(0.32)	(0.3)	(0.24)	(0.16)	(0.26)
Model fit measures						
No. of obs.		4,040	4,040	3,784	3,784	7,824
Log likelihood		−2923.68	−2766.67	−2684.23	−2490.66	−5645.06
BIC		6, 154.60	5, 840.59	5, 673.28	5, 286.15	11, 621.83
BIC/N		1.52	1.45	1.50	1.40	1.49
AIC		5, 921.36	5, 607.34	5, 442.46	5, 055.32	11, 364.13
AIC/N		1.47	1.39	1.47	1.34	1.45
AIC3		5, 958.36	5, 644.34	5, 479.46	5, 092.32	11, 401.13
AIC3/N		1.47	1.40	1.45	1.35	1.46
Patterns of heterogeneity						
PRICE	*cv*	−0.98	−0.99	−0.67	−0.56	−0.77
NON-GM (NGE)	*cv*	1.36	0.96	1.85	1.10	1.35
GM (GME)	*cv*	−1.37	−1.09	−1.46	−1.20	−1.41
LOWCO2 (LOE)	*cv*	1.34	0.87	2.40	0.38	2.85
MEDIUMCO2 (MDE)	*cv*	3.68	2.23	−2.77	2.15	50.09
HIGHCO2 (HIE)	*cv*	−12.95	−2.77	−5.05	−1.11	−18.68
LOCAL (LCE)	*cv*	0.63	0.75	0.51	0.98	0.22

Notes: Values in parentheses are standard errors. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% levels, respectively.

Next, we compared the model fit of the two query models presented in Table 3 using the measures of estimation criteria BIC/N and AIC/N. The QAT models experienced model improvements with respect to the baseline similar to those experienced by the SAT. In terms of coefficient estimates, we observed that all the coefficients for our random parameters increase in magnitude when moving from the baseline model (QAB) to the choice-task-level model using the query approach (QAT), with substantial increases observed in the medium and high carbon footprints and local production.

Compared the query approach models in terms of patterns of heterogeneity, we observed a decrease in heterogeneity (*CV*) when moving from the base to the QAT model, which suggests that the query approach at the choice task level (QAT) addresses AA in our data.

Differences in Willingness to Pay

Table 4 shows the results of six hypothesis tests that compare willingness-to-pay (WTP) values from each respective model, including the pooled baseline (PAB). Hypothesis 1 compares WTP values for each attribute from the SAB and SAT models. The results indicate that WTP values for the non-GMO, GM, low carbon footprint, and local attributes are all significantly different between the SAB and SAT models. The WTP values for each of these attributes in the SAT model were larger in magnitude than those in the baseline model (SAB). Hypothesis 2 compares the WTP values for each attribute from the query approach models, QAB and QAT. The results demonstrate that the WTP values for all attributes are significantly different between the QAB and QAT models, with increases in magnitude larger than those in the stated approach models.

Hypothesis 3 compares the two baseline models, SAB and QAB; no significant differences in WTP were found for any attribute. Hypothesis 4 compares the two choice task approach models, SAT and QAT. The WTP values from the QAT model were larger in magnitude for all attributes, and these differences were significant for the non-GMO, GM, low carbon footprint, and local attributes. Finally, hypotheses 5 and 6 compare the two approach baselines, SAB and QAB, to the pooled baseline, PAB; no significant differences in WTP values were found in either respective comparison.

Validation Method Using Dual Coefficients for Attributes

Next, we estimated equation (1) without restricting the coefficients (β) of the "ignored" attributes to 0. This estimation provided two coefficients for each attribute: one for the observations where individuals are considered to be attending to attributes (AA) and one for the observations where we are less certain about AA. We estimated models using the stated and query approaches at the choice task level. A comparison of these models provided a further understanding of how both approaches identify patterns of AA. Table 5 presents the results of these models. The columns headed "AA" refer to coefficients where respondents are considered to be attending to attributes, while the "NA" columns refer to coefficients where AA is uncertain. The model fit criteria of BIC/N and AIC/N indicate that the QAT dual-coefficient model has slightly lower values than the SAT model, with BIC/N values of 1.43 and 1.57 and AIC/N values of 1.23 versus 1.38, respectively. The patterns of heterogeneity (CV) associated with the two models offer further evidence regarding the effectiveness of each approach in identifying patterns of AA. As shown in Table 5, the choice-task-level stated approach (SAT) appears effective at identifying patterns of AA based on the patterns of heterogeneity. If the model has properly identified patterns of AA, we would expect the CV associated with each AA attribute to be relatively lower than the CV associated with each NA attribute. This is the case for all but one attribute level, the medium carbon footprint. For all other attributes, the magnitude of the CV is larger for the NA attribute than for to the AA equivalent attribute.

As for the query approach models with dual coefficients, the results reveal that the heterogeneity patterns for all AA attributes are smaller in magnitude than the CV associated with each NA attribute. In fact, each CV for the AA attributes is at 1.30 or below.

Table 4. Willingness to Pay ($ /lb for boneless, skinless chicken breast) across Five Models and Hypothesis Tests

Hypotheses Tests	*NON-GM*	*GM*	*LOWCO2*	*MEDIUMCO2*	*HIGHCO2*	*LOCAL*
$H0_1(WTP^{SAB} - WTP^{SAT}) = 0$						
[b]WTP^{SAB}	3.16	−1.84	0.54	0.14	−0.08	0.68
[c]WTP^{SAT}	4.71	−2.43	1.27	0.49	−0.60	1.24
Mean difference	−1.55	0.58	−0.72	−0.35	0.52	−0.56
p-value[a]	0.001	0.034	0.019	0.151	0.071	0.002
$H0_2\ (WTP^{QAB} - WTP^{QAT}) = 0$						
[d]WTP^{QAB}	2.75	−1.94	0.58	−0.10	−0.18	0.50
[e]WTP^{QAT}	8.05	−5.29	4.60	1.74	−4.51	6.11
Mean difference	−5.29	3.34	−4.02	−1.83	4.32	−5.61
p-value[a]	0.000	0.000	0.000	0.012	0.000	0.000
$H0_3\ (WTP^{SAB} - WTP^{QAB}) = 0$						
[b]WTP^{SAB}	3.16	−1.84	0.54	0.14	−0.08	0.68
[d]WTP^{QAB}	2.75	−1.94	0.58	−0.10	−0.18	0.50
Mean difference	0.40	0.10	−0.04	0.23	0.11	0.18
p-value[a]	0.214	0.376	0.452	0.207	0.338	0.149
$H0_4\ (WTP^{SAT} - WTP^{QAT}) = 0$						
[c]WTP^{SAT}	4.71	−2.43	1.27	0.49	−0.60	1.24
[e]WTP^{QAT}	8.05	−5.29	4.60	1.74	−4.51	6.11
Mean difference	−3.34	2.86	−3.33	−1.25	3.91	−4.87
p-value[a]	0.000	0.000	0.000	0.065	0.002	0.000
$H0_5\ (WTP^{SAB} - WTP^{PAB}) = 0$						
[b]WTP^{SAB}	3.16	−1.84	0.54	0.14	−0.08	0.68
[f]WTP^{PAB}	2.96	−1.90	0.54	0.02	−0.14	0.57
Mean difference	0.20	0.06	0.00	0.11	0.06	0.11
p-value[a]	0.325	0.416	0.496	0.334	0.402	0.238
$H0_6\ (WTP^{QAB} - WTP^{PAB}) = 0$						
[d]WTP^{QAB}	2.75	−1.94	0.58	−0.10	−0.18	0.50
[f]WTP^{PAB}	2.96	−1.90	0.54	0.02	−0.14	0.57
Mean difference	−0.20	−0.04	0.04	−0.12	−0.05	−0.07
p-value[a]	0.325	0.416	0.496	0.334	0.402	0.238

Notes: [a]*p*-values were estimated using the combinational method of Poe, Giraud, and Loomis (2005) with 1,000 Krinsky and Robb (1986) bootstrapped WTP estimates. The *p*-value reports results of the one-sided test for our hypotheses for each corresponding pair of attributes.
[b]WTPSAB indicates mean WTP estimates from the Stated Approach Baseline.
[c]WTPSAT indicates mean WTP estimates from the Stated Approach Choice Task Attendance to Attributes.
[d]WTPQAB indicates mean WTP estimates from the Query Approach Baseline.
[e]WTPQAT indicates mean WTP estimates from the Query Approach Choice Task Attendance to Attributes.
[f]WTPPAB indicates mean WTP estimates from the Stated and Query Pooled Baseline.

Table 6 presents the results of two hypothesis tests comparing the WTP values from the dual-coefficient models SAT and QAT. WTP values were estimated for both sets of coefficients—AA attributes and NA attributes—and compared across treatments. Hypothesis 7 compared the WTP of the AA attributes from the SAT and QAT models. The QAT dual-coefficient model was found to produce WTP values of significantly greater magnitude than the SAT dual model did. This result could signal that the conservative query approach does a better job of identifying true AA, leading to larger coefficient estimates and WTP values. However, these results could also be interpreted as the query approach simply identifying those with the strongest preferences and, therefore, the easiest to identify AA, which would also lead to higher WTP values where AA is determined by this approach.

Table 5. Stated and Query Approach Models with Dual Coefficients for Attributes Attended and Not Attended

		Choice Task Stated (SAT)		Choice Task Query (QAT)	
		Attending (AA)	Not Attended (NA)	Attending (AA)	Not Attended (NA)
Variables	Coeff.	Estimate	Estimate	Estimate	Estimate
PRICE	μ	−0.52***	−0.18***	−1.11***	−0.44***
		(0.04)	(0.06)	(0.1)	(0.08)
	σ	0.46***	0.39***	0.41***	0.76***
		(0.04)	(0.11)	(0.06)	(0.1)
NON-GM	μ	2.47***	−0.72**	7.41***	1.38***
		(0.23)	(0.31)	(0.95)	(0.36)
	σ	2.43***	1.01*	8.74***	3.48***
		(0.22)	(0.58)	(1.13)	(0.48)
GM	μ	−1.34***	0.11	−5.06***	−0.92***
		(0.15)	(0.21)	(0.76)	(0.23)
	σ	1.53***	0.44	6.59***	2.06***
		(0.14)	(0.5)	(0.97)	(0.37)
LOWCO2	μ	0.77***	−0.18	4.02***	0.29
		(0.15)	(0.23)	(1.1)	(0.25)
	σ	0.76***	0.50	3.94***	1.43***
		(0.26)	(0.69)	(1.45)	(0.51)
MEDIUMCO2	μ	0.25*	−0.14	1.65**	−0.09
		(0.15)	(0.2)	(0.74)	(0.21)
	σ	0.70***	0.46	1.77*	0.68
		(0.22)	(0.62)	(1.01)	(0.57)
HIGHCO2	μ	−0.42***	0.33*	−4.61***	0.01
		(0.16)	(0.2)	(1.31)	(0.21)
	σ	1.02***	0.51	5.57***	1.34**
		(0.37)	(0.58)	(2.05)	(0.55)
LOCAL	μ	0.69***	−0.22*	6.58***	0.04
		(0.1)	(0.13)	(0.99)	(0.14)
	σ	0.79***	0.37	5.20***	1.03***
		(0.11)	(0.32)	(1.1)	(0.26)
No-buy	μ	−6.50***		−7.40***	
		(0.45)		(0.7)	
Error Component	σ	3.71***		4.83***	
		(0.39)		(0.5)	
Model fit measures					
No. of obs.		4,040		3,784	
Log likelihood		-2674.80		-2,206.90	
BIC		6,354.38		5,410.66	
BIC/N		1.57		1.43	
AIC		5,591.60		4,655.79	
AIC/N		1.38		1.23	
AIC3		5,712.60		4,776.79	
AIC3/N		1.41		1.26	
Patterns of heterogeneity					
PRICE	*cv*	−0.90	−2.23	−0.37	−1.73
NON-GM (NGE)	*cv*	0.99	−1.40	1.18	2.51
GM (GME)	*cv*	−1.14	3.86	−1.30	−2.23
LOWCO2 (LOE)	*cv*	0.99	−2.71	0.98	4.98
MEDIUMCO2 (MDE)	*cv*	2.81	−3.27	1.07	−7.74
HIGHCO2 (HIE)	*cv*	−2.44	1.55	−1.21	108.58
LOCAL (LCE)	*cv*	1.14	−1.68	0.79	24.85

Notes: Values in parentheses are standard errors. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 6. Willingness to Pay ($ /lb for chicken breast) across Two Dual-Coefficient Models and Hypothesis Tests

Hypotheses Tests	*NON-GM*	*GM*	*LOWCO2*	*MEDIUMCO2*	*HIGHCO2*	*LOCAL*
$H0_7$ ($WTP^{SATAA} - WTP^{QATAA}$) = 0						
[b]WTP^{SATAA}	4.78	−2.60	1.49	0.48	−0.81	1.34
[c]WTP^{QATAA}	6.69	−4.56	3.63	1.49	−4.17	5.94
Mean difference	−1.91	1.96	−2.14	−1.00	3.37	−4.60
p-value[a]	0.000	0.000	0.000	0.000	0.000	0.000
$H0_8$ ($WTP^{SATNA} - WTP^{QATNA}$) = 0						
[d]WTP^{SATNA}	−4.38	0.67	−1.14	−0.84	2.00	−1.36
[e]WTP^{QATNA}	3.19	−2.12	0.66	−0.21	0.03	0.09
Mean difference	−7.57	2.79	−1.79	−0.63	1.96	−1.45
p-value[a]	0.000	0.001	0.002	0.138	0.000	0.000

Notes: [a]*p*-values were estimated using the combinational method of Poe, Giraud, and Loomis (2005) with 1,000 Krinsky and Robb (1986) bootstrapped WTP estimates. The *p*-value reports results of the one-sided test for our hypotheses for each corresponding pair of attributes.
[b]WTP^{SABAA} indicates mean WTP estimates from the Stated Approach Choice Task Dual Coefficients Model, Attributes Attended.
[c]WTP^{QATAA} indicates mean WTP estimates from the Query Approach Choice Task Dual Coefficients Model, Attributes Attended.
[d]WTP^{SABNA} indicates mean WTP estimates from the Stated Approach Choice Task Dual Coefficients Model, Attributes Not Attended.
[e]WTP^{QATNA} indicates mean WTP estimates from the Query Approach Choice Task Dual Coefficients Model, Attributes Not Attended.

Hypothesis 8 compared the WTP for the NA attributes, with significant differences found for five of the six attributes but with mixed results regarding the differences in magnitude.

The results of the validation method with dual coefficients demonstrate the pitfalls associated with models in which an ignored attribute is assumed to have 0 utility. When comparing the results shown in Tables 3 and 5, the validation method using both the stated and query approach leads to improved model fit. Comparing the welfare estimates from Tables 4 and 6 also highlights the impact that using the validation method can have on WTP values. While the differences in WTP values from the SAT "all or nothing" and dual-coefficient models reveal only minor differences in WTP values from AA, with WTP differences ranging from $0 to $0.22. The disparity between these models using the query approach is greater, with WTP differences ranging from $0.17 to $1.36. The ability of the validation method to relax the assumption of 0 utility for attributes determined to be ignored is an advantage of this method.

Summary and Conclusions

Failure to account for patterns of AA in choice models can affect coefficient estimates, model fit, performance measures, and welfare estimates; therefore, accounting for patterns of AA is essential in estimating reliable results. While various methods for identifying patterns of AA have been proposed, it is still unclear how best to account for individual attribute processing strategies in DCEs. We use query theory, for the first time in the DCE literature, to account for attribute attendance by examining the thought processes of individuals in a DCE. We asked respondents to use a reporting method called aspect listing, which allows individuals to report any thoughts that were relevant to their decision making during each choice task. We observed that the majority of all aspects listed relate to the attributes in our DCE. This observation provides a high level of certainty that the aspects listed can be considered as predictors of attribute attendance. In this regard, the query approach is conservative compared to the other common approaches, including the stated approach. We acknowledge that the mention of an attribute during the aspect listing exercise could also represent some other phenomenon rather than attendance to an attribute. Failing to mention an attribute does not necessarily indicate that the attribute was ignored. Nevertheless, our results appear to support the conclusion that the aspects listing task indeed yielded data useful for identifying patterns of attribute attendance.

Our comparison of the stated and query approaches highlights the challenges in identifying AA and the difficulties that arise in properly modeling AA. The results of our validation models using dual coefficients indicate that the patterns of AA reported by respondents using the stated approach may suffer from a lack of certainty. The heterogeneity patterns from the stated approach model indicate that some individuals who stated that they were ignoring attributes may not actually be ignoring those attributes. This observation reveals a problem in relying on these data to accurately identify patterns of AA. The query approach, on the other hand, has the benefit of identifying attendance to attributes using a more general method in which respondents are free to list all thoughts that were important as they made each choice. If we view the mention of an attribute as attendance, this could represent a high level of certainty of attendance to that attribute. Importantly, negative or value-decreasing thoughts listed about attributes are also considered attendance to attributes, allowing not only for nonzero values in the utility function but also for negative values. The query approach represents a conservative approach for identifying patterns of AA, and more work is needed to better explore its usefulness compared to the stated approach.

Our results show that the stated and query approaches all improve model fit statistics; however, in terms of improvement to model coefficients, the query approach outperforms the inferred stated approach by returning coefficients for attributes with patterns of heterogeneity (CV) that indicate the query approach has effectively identified patterns of AA. The heterogeneity estimates from our dual-coefficient models offer perhaps the strongest support for the use of the query approach. When we relax the assumption that AA is "all or nothing," we see more clearly how reliable the methods are in identifying patterns of AA. Our query approach outperformed the stated approach.

The stated approach has a strong advantage: Its questions are easy to implement in an online setting such as ours. In contrast, the query approach is time consuming, requiring additional steps to collect and synthesize text responses to open-ended questions, thereby potentially introducing new sources of error due to researcher bias and data entry errors. There are also several possible advantages to the open-ended nature of the query, which allows for greater expression of thoughts and heterogeneity in responses. Individuals have different experiences and consider a range of information and memories when making a decision. Therefore, while not all aspects relate to attributes of a designed experience, the query approach has the advantage that it may allow for a more accurate representation of the thoughts considered in a decision. We have also experimented with training subjects to self-categorize the aspects listed during an experiment, which saves a great deal of research time. Results between self-coded aspects and researcher-coded aspects were not significantly different.

Perhaps the most important limitation is how we conducted our aspect-listing task. We did not force respondents in our experiment to list aspects for each attribute or to provide more than one response per choice task. This could have led to underreporting, despite the results that indicate that our query approach generally produced better models. However, much remains to be learned about how to gather aspect data and how to classify aspects in an experiment such as ours. In future experiments, it would be interesting to observe whether the combination of the query approach with other indicators of attribute attendance and attention, such as ranking data (Chalak, Abiad, and Balcombe, 2016) and eye tracking (Lewis, Grebitus, and Nayga Jr, 2016; Van Loo et al., 2018) can better capture respondents' attention to various attributes in the choice tasks. Our study begins the conversation about the potential of using query theory in addressing attendance to attribute issues in DCEs.

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Online Supplement: A Query Approach to Modeling Attendance to Attributes in Discrete Choice Experiments

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Coding of Aspects for the Query Method

Pilot Survey

We implemented a pilot survey utilizing 250 respondents. The data from the pilot were used to estimate a model whose coefficient estimates were then used as priors in our final experimental design. Both the pilot and final experiment involved 32 choice tasks arranged in four blocks of eight tasks each. The query data collected during the pilot were used to ensure the survey's reliability and validity in terms of providing the usable information during the aspect listing task. The results of the pilot survey indicated that respondents were listing thoughts that indicated the processes leading to their decisions in each choice task, including, importantly, references to the attributes of the experiment. The data from the pilot were similar to those from the full experiment, which found that approximately 95 % of all thoughts listed made reference to the specific attributes of the experiment.

Coding of Aspects

Subjects in our experiment made eight paired comparisons between two hypothetical poultry products. We asked subjects to list aspects regarding each decision. However, because we were examining paired comparisons, we had to put great thought into how we coded responses. For instance, if product A has a lower price than product B, the subject may list "product A is cheaper" and "I would never spend that much on chicken." When coding aspects, we take into account the positive or negative framing of the aspects listed by subjects. Continuing with the previous example, in the context of our experiment, we posit that considering the negative and positive framing of aspects is necessary for our purposes of classification because, in our experiment, the choices made in each paired comparison depend on multiple attributes, including three nonprice attributes. In a choice experiment, the trade-offs between attributes are critical to the estimation of utility and willingness to pay. When considering only the aspects concerning price, the distinction may seem minor; however, subjects also listed aspects referencing the nonprice attributes of the products. For example, consider a paired comparison where product A is boneless, skinless chicken breast priced at $2.99/lb with no information about GM content and product B is the same product but with a price of $6.99/lb and labeled as non-GMO. The subject lists the aspects of "too expensive" and "I prefer to buy non-GMO" and the subject chooses product A. In our study, we would code this as a value-increasing aspect for the GM-content attribute and a value-decreasing aspect for price. This means that in regards to attendance to attributes, we would code these responses as the participant attending to the price and GM attributes.

Because we are interested in the attributes truly being considered in the valuation exercise in each choice task, we also had to make decisions while coding the data as to how to handle

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responses that mentioned attributes but could have indicated nonattendance or other types of unhelpful information, such as protest responses. Given the topic of GM elicits, at times, strong responses from respondents, we had many responses that were classified as protest responses for the purpose of attribute attendance. For example, we had respondents who chose the "none" option regardless of whether a product was listed as non-GMO or GM, and the aspects listed were statements such as "I hate GMOs" or "I will not eat frankenfoods". If these aspects had been listed in the context of the respondent choosing the non-GMO product, they would be categorized as attending to the GM content attribute; however, when the respondent chose "none" over all 8 choice tasks, including those tasks that had an option to avoid GM content, we classified these as unusable.

Finally, we used a blind process to code aspects. Two researchers (one professor and one student) discussed the coding process, then coded each response in isolation, first coding each comment based on the attribute mentioned (or "other" if no attribute was mentioned) then coded based on whether the thought was value increasing, decreasing, or neutral. The two datasets were compared and discrepancies were compared and addressed by our full team (two coders and two additional professors). The blind coding process and reconciliation were used in an effort to reduce research bias and increase reliability of the measures. Examples of aspects listed by respondents and how they were coded are shown in table A1.

Table A1. Examples of Aspects Listed by Respondents

Attributes	**Value-Decreasing Aspects**	**Value-Increasing Aspects**	**Value-Neutral Aspects**
price	I wouldn't pay $6.99/lb for chicken	product 1 is more affordable	price is of no concern
gm	don't want my chicken fed a genetically engineered diet	I do like that it's a verified non-GMO	I really don't care how its raised or fed
carbon	I don't like the high carbon footprint on the first chicken breasts	carbon footprint is acceptable	Carbon Footprint in regards to food production does not weigh on my decision at all
location	Would prefer origin listed	I like that the second choice is raised in my own state	It doesn't matter to me if the birds are raised in my state
other	I like to buy organic meats, I can't tell if the first is organic or not.	healthier option	no real difference

Table A2. Sample Characteristics, Counts and Percentages

	Query Approach		Stated Approach		Total	
	Count	Percent	Count	Percent	Total	Percent
Gender						
Male	175	34.3%	171	32.7%	346	33.5%
Female	335	65.7%	352	67.3%	687	66.5%
$\chi 2$ = 0.303						
p-value = 0.582						
Age group						
18–24 years	41	8.0%	47	9.0%	88	8.5%
25–34 years	110	21.6%	104	19.9%	214	20.7%
35–44 years	89	17.5%	116	22.2%	205	19.8%
45–54 years	84	16.5%	68	13.0%	152	14.7%
55–64 years	96	18.8%	88	16.8%	184	17.8%
65 years or older	90	17.6%	100	19.1%	190	18.4%
$\chi 2$ = 6.529						
p-value = 0.258						
Education level						
Some grade school	0	0.0%	1	0.2%	1	0.1%
Some high school	8	1.6%	6	1.1%	14	1.4%
High school diploma	169	33.1%	134	25.6%	303	29.3%
Associates degree (2-year degree)	106	20.8%	103	19.7%	209	20.2%
Bachelor's degree (4-year degree)	152	29.8%	175	33.5%	327	31.7%
Master's degree	62	12.2%	77	14.7%	139	13.5%
Doctoral degree	13	2.5%	27	5.2%	40	3.9%
$\chi 2$ = 13.347						
p-value = 0.038						
Income						
Under $20,000	68	13.3%	57	10.9%	125	12.1%
20,000-39,999	102	20.0%	106	20.3%	208	20.1%
40,000-59,999	111	21.8%	88	16.8%	199	19.3%
60,000-79,999	78	15.3%	79	15.1%	157	15.2%
80,000-99,999	62	12.2%	94	18.0%	156	15.1%
100,000-119,999	32	6.3%	36	6.9%	68	6.6%
120,000-139,999	18	3.5%	19	3.6%	37	3.6%
140,000-159,999	19	3.7%	19	3.6%	38	3.7%
160,000 and above	20	3.9%	25	4.8%	45	4.4%
$\chi 2$ = 10.930						
p-value = 0.206						
Race						
American Indian or Alaska Native	6	1.2%	8	1.5%	14	1.4%
Asian	26	5.1%	23	4.4%	49	4.7%
Black or African American	42	8.2%	39	7.5%	81	7.8%
Native Hawaiian or Other Pacific Islander	3	0.6%	6	1.1%	9	0.9%
White	417	81.8%	429	82.0%	846	81.9%
Mixed	10	2.0%	18	3.4%	28	2.7%
No response	6	1.2%	0	0.0%	6	0.6%
$\chi 2$ = 9.874						
p-value = 0.130						