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Query Theory Applications: Choice Experiments under Oath, Attendance to Attributes, and Genetically Modified Food Labeling Policy

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Abstract

In recent years, there has been an intensifying campaign by some stakeholders regarding concern over genetically modified (GM) foods in the U.S. As a result, the issue of labeling has entered into the federal agenda. This research uses Query Theory to provide a deeper understanding of the demand for GM foods and the preferences for GM policy. Query theory is first applied to the formation of hypothetical bias in the estimation of consumers' willingness-to-pay. To address this, the honesty oath is used as an ex-ante technique to reduce hypothetical bias.

Paper one using Query Theory in a discrete-choice experiment (DCE) setting to examine the mechanism behind the effectiveness of the honesty oath in reducing hypothetical bias in discrete choice experiments. Our results show that the honesty oath can change the content and order of queries, thereby reducing hypothetical bias in discrete choice experiments.

In the second paper, Query Theory is used to examine the thought processes of individuals in a DCE in order to deduce attendance to individual attributes. Respondents may attend some attributes of the good in question and ignore others during each choice task. As a result, respondents may not make the trade-offs between all the attributes as assumed. The results show that the query approach to modeling attendance to attributes outperforms two other common approaches: the stated and inferred approaches.

Finally, in paper three, Query Theory is applied to the study of the influence of cultural worldview on the demand for GM foods policy in the U.S. Our results demonstrate that an individual's cultural worldview influences their preferences for GM policy and consumer valuations. The results also support our Query Theory prediction that cultural worldview influences individual's affective reactions to choice options leading to significantly different valuations. Though important differences do exist between individuals with different CWVs,

there is common ground as well. Support for mandatory labeling is high with 82 percent of respondents indicating support for mandatory labeling which ranged from 71 percent to 88 percent, depending on CWV.

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Dedication

In memory of my grandmother, Ruth Rippee.

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List of Published Papers

Chapter 2 (under review)

Kemper, N.P., Popp, J.S., and Nayga, R.M. 2016. A Query Theory Account of a Discrete Choice Experiment under Oath. Under Review. Submitted to the *Journal of Environmental Economics and Management*.

Chapter 3 (pending submission)

Kemper, N.P., Popp, J.S., Nayga, R.M., and Bazzani, C. 2016. A Query Approach to Modeling Attendance to Attributes in Discrete Choice Experiments. For submission to the *American Journal of Agricultural Economics*.

Chapter 4 (pending submission)

Kemper, N.P., Popp, J.S., Nayga, R.M., and Kerr, J.B. 2016. Cultural Cognition, Query Theory and Preferences for Genetically Modified Food Policy. For submission to *Nature Biotechnology*.

Introduction

Historically, American consumers in general have not viewed genetically modified (GM) foods as risky relative to other risks such as nuclear power, gun violence, and climate change (Kahan et al., 2011). As a result, U.S. GM policy has remained largely unchanged since the 1990s and can be best described as a preventative approach which seeks to minimize harm once harm is scientifically demonstrated (Patterson and Josling, 2005). As a result, the U.S. system of GM food labeling has traditionally focused on voluntary labeling where companies label products based on the perceived demand for GM (or non-GM) attributes. However, recent changes to GM labeling policy in the U.S. will change the way in which GM foods are labeled.

GM labeling has reached the policy agenda at the state and national levels driven in part by two ballot initiatives in 2012 and 2013 in California and Washington; these initiatives helped sparked renewed concern over GM foods in the U.S. (Costanigro and Lusk, 2014). Both initiatives failed but were well covered in the national news. In 2014, Vermont successfully passed a mandatory food labeling law, the first of its kind in the U.S. On July 29, 2016 president Obama signed a bill requiring food containing GM ingredients to be labeled (Enoch, 2016); however, companies can comply with this requirement via the use of smartphone scanning codes as an alternative to written text on the package and the federal law supersedes all GM labeling laws at the state level. The legislation is viewed as a victory for farm advocacy groups, food companies and the biotechnology industry. Some opponents of the new law have encouraged food companies to continue to label the GM ingredients while the U.S. Department of Agriculture creates the new federal guidelines (Halloran, 2016).

In order to raise the state of concern over GM labeling, proponents of mandatory GM labeling successfully mobilized supporters by emphasizing the themes of: 1) food safety, 2) the

collusion of big business and government and 3) the “right to know” (Lendman, 2015). The organics movement took a similar path leading to the development of the National Organic Program (Ingram and Ingram, 2005). GM labeling for the consumers’ “right to know” has ties to the basic founding principles of democracy and encompasses issues such as the right to religious freedom, the right to information, the ethics of transparency and societal concerns (Klintman, 2002). The success of mandatory labeling advocates defies research findings that suggest that average American consumer tends to have positive attitudes towards GM foods (Frewer et al., 2013). The perceived risk of GM foods is an important factor in its acceptance (Rodriguez-Entrena et al., 2015) but the public’s beliefs about risk are often very different from the beliefs of experts (Curtis et al., 2004; Jenkins-Smith and Bassett, 1994; Kahan et al., 2011).

Mintz (2016) studied articles on genetically modified organisms (GMOs) published in major national newspapers from 2011 and 2013. The results show that some of the major arguments regarding GMOs focus on technical performance and the potential for environmental harm. The major players receiving media coverage are the biotechnology industry and the U.S. government. Importantly, there was a sharp increase in GM coverage in mid-2013 caused by two focusing events: 1) Proposition 37 in California and 2) the discovery of unapproved GM wheat being grown on a farm in Oregon. Media coverage can have a polarizing impact on the views of the public as seen in the polling numbers regarding mandatory GM labeling. However, a better understanding how different groups of individuals form preferences for GM foods and the policy that regulates the market for these products is important for informing consumers, agribusiness industry stakeholders and the policy making process. This research uses Query Theory (QT) to provide a deeper understanding of demand for GM products and preferences for GM labeling.

There are four key premises of QT (Johnson et al., 2007; Weber and Johnson, 2011). First, people break down valuation questions into a series of queries of past experiences for evidence supporting the choice options under being considered. Second, an individual's queries are executed sequentially. Third, a person's first query produces richer representations of thoughts than following queries and therefore the first query is a more heavily weighted in the decision. Fourth, the order of options presented to an individual is considered of critical importance as order strongly influences the balance of evidence. Query theory has been used to examine a range of behaviors including: 1) the endowment effect (Johnson *et al.,* 2007) where ownership changed the order of queries, 2) in studies of intertemporal choice (Weber *et al.*, 2007) where the default date of consumption determined the order of queries, and 3) in (Hardisty *et al.*, 2010) where attribute framing was shown to change the order of queries. In all three studies, thought listings provided by decision makers explained the observed behavioral effects. Preferences are subject to the processes and dynamics associated with retrieval from memory; therefore, these principles can help explain a range of phenomena in preference research (Johnson et al., 2007; Weber and Johnson, 2006). We extend this logic to the study of GM foods and GM policy preferences by examining the queries generated by people in three experiments. In all three experiments we follow Johnson *et al.* (2007) and Weber *et al.* (2007) and use the verbal report methods called aspect listing to proximate the queries generated by individuals while making choices in our experiments.

Query theory is first applied to the formation of hypothetical bias in the estimation of consumers' willingness-to-pay. In a discrete choice experiment (DCE) choice task, participants are typically asked to consider a product that is defined by multiple attributes and a no-choice or status quo alternative. DCEs allow for the identification of the tradeoffs that individuals make

between attributes and the estimation of marginal willingness-to-pay (WTP) values when the price is included (Hensher et al., 2015). Hypothetical bias is a frequently documented limitation of DCEs (Murphy et al., 2005); specifically, researchers have observed a discrepancy between what a person indicates they would pay in a survey (hypothetical) and what a person would actually pay (non-hypothetical) (Champ et al., 1997; Harrison, 2006; Loomis et al., 2014). Furthermore, hypothetical bias is demonstrated in a large body of empirical work in light of the popularity of stated-preference methods, specifically DCEs (Harrison, 2006). Notably, careful planning in survey design can maximize external validity by motivating respondents to seriously engage in hypothetical choice tasks and mimic incentives they face when making the same choices in the real world (Hainmueller et al., 2015). To address hypothetical bias, the honesty oath is used as an ex-ante technique to reduce hypothetical bias in this study. Deeper exploration into how choices are made and how values are constructed by people answering DCE questions is critical for determining the validity of monetary measures calculated from responses. Using Query Theory (Johnson et al., 2007), we suggest that respondents go through a series of mental queries when confronted with choice tasks in a DCE, noting that the order in which these queries are processed influences choice behavior. We explore the effectiveness of Query Theory in uncovering the thought processes and behaviors of individuals in a DCE, by using a simple aspect-listing task to gain information on the thought processes of individuals. We posit that Query Theory could offer a social psychological explanation for the valuation differences often observed in economic experiments.

Second, Query Theory is used to examine the thought processes of individuals in a DCE in order to deduce attendance to individual attributes. In a DCE, participants are asked to consider a product that is defined by several attributes and a no-choice alternative (Hensher et

al., 2015). Respondents may attend some attributes and ignore others during each choice task (Hess and Hensher 2010; Scarpa et al. 2013) and, therefore, respondents may not make the trade-offs between all the attributes as assumed. Overlooking respondents' attendance to attributes (AA) in choice models can affect coefficient estimates, model fit, performance measures and welfare estimates (Campbell et al. 2008; Carlsson et al. 2010; Hensher 2014; Hensher and Rose 2009; Scarpa et al. 2009; Scarpa et al. 2013). Hence, accounting for patterns of AA is essential for estimation of reliable results. While much research has been devoted to various methods for identifying patterns of attribute attendance, it is still unclear how best to account for individual attribute processing strategies in DCEs. Our study uses Query Theory (Johnson et al. 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. We again use the report method called *aspect-listing* to gain useful information that can help us understand the information processing strategies of individuals. Query theory offers an unexplored avenue by which to account for patterns of AA.

In the third experiment, Query Theory is applied to the study of the influence of cultural worldview on the demand for GM foods policy in the U.S. Because fundamental differences in cultural values exist between individuals, polarizing issues like GM foods are rarely solved through more scientific data (Kahan et al., 2011). The tendency for individuals to conform beliefs to values defined by cultural identities is known as cultural cognition and this plays a significant role in how people evaluate risk and interpret information from experts and the media (Kahan et al., 2011). In this experiment, we first use cultural cognition theory to explore how individuals' cultural worldviews result in divergent preferences for GM policy. Specifically, we examine the preferences for GM food labeling and GM discounts required by individuals to

consumer GM foods using cultural worldview as a key explanatory variable. We then use Query Theory (Johnson *et al.*, 2007; Weber *et al.*, 2007) to document how an individual's affective responses to GM food labels depends upon the person's CWV leading to significantly different product valuations.

Our three papers provide important insights for policy makers. DCEs are a popular method for estimating the welfare measures often sought by policy makers conducting cost-benefit analyses. Our first two papers offer suggestions for improving DCEs to provide more reliable welfare measures by use of the honesty oath in survey design and by accounting for patterns of attendance to attributes. Our third paper emphasizes the importance of CWV on GM policy preferences. As the USDA develops the new federal mandatory labeling program for GM foods, it is important to consider the preferences of individuals with different worldviews and search for common ground among groups. As the new rules for GM labeling are developed, a framework is needed that includes individuals with broad range of worldviews. Our results demonstrate that individuals less likely to support change in GM food labeling policy still, in fact, support mandatory GM labeling at a high level. This shows that although many differences do exist, there is common ground between individuals with differing CWVs.

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A Query Theory Account of a Discrete Choice Experiment under Oath

Abstract

Discrete choice experiments are now one of the most popular stated-preference methods used by researchers to elicit individuals' preferences for public and private goods. One highly documented limitation of stated-preference methods is the formation of hypothetical bias in the estimation of consumers' willingness-to-pay for a good or service. To address this, the honesty oath is used as an ex-ante technique to reduce hypothetical bias. Accordingly, our study provides a query account of the honesty oath in a discrete-choice experiment setting by using Query Theory to examine the mechanism behind the effectiveness of the honesty oath in reducing hypothetical bias in discrete choice experiments. Our results show that the honesty oath can change the content and order of queries; thereby reducing hypothetical bias in discrete choice experiments.

Keywords: Discrete choice experiments, Honesty oath, Hypothetical bias, Query theory, Willingness to pay

Introduction

Discrete choice experiments (DCE's) are now one of the most widely used stated-preference methods by researchers to obtain individuals' preferences for public and private goods. In a DCE choice task, participants are typically asked to consider a product that is defined by multiple attributes and a no-choice or status quo alternative. Furthermore, DCE's allow for the identification of the tradeoffs that individuals make between attributes and the estimation of marginal willingness-to-pay (WTP) values when the price is included (Hensher et al., 2015). While DCE's are effective predictors of actual behavior (Hainmueller et al., 2015), it has not yet been realized if a DCE can measure and convert behavior into the monetary measures often sought for cost-benefit analyses (Jacquemet et al., 2016). Notably, careful planning in survey design can maximize external validity by motivating respondents to seriously engage in hypothetical choice tasks and mimic incentives they face when making the same choices in the real world (Hainmueller et al., 2015). If respondents use cognitive shortcuts in DCE responses, such bounded rational behavior should be identified so it can be removed through survey design (*ex ante*), or post-survey calibration (*ex post*) (Jacquement et al., 2016; Loomis, 2014). To determine the validity of monetary measures calculated from responses, deeper exploration is critical into how choices are made and how values are constructed by people answering DCE questions. Using Query Theory (Johnson et al., 2007), we suggest that respondents go through a series of mental queries when confronted with choice tasks in a DCE, noting that the order in which these queries are processed influences choice behavior. We explore the effectiveness of Query Theory in uncovering the thought processes and behaviors of individuals in a DCE, by using a simple aspect-listing task to gain information on the thought processes of individuals.

Hypothetical bias is a frequently documented limitation of DCE's (Murphy et al., 2005); specifically, researchers have observed a discrepancy between what a person indicates they would pay in a survey (hypothetical) and what a person would actually pay (non-hypothetical) (Champ et al., 1997; Harrison, 2006; Loomis et al., 2014). Furthermore, hypothetical bias is demonstrated in a large body of empirical work in light of the popularity of stated-preference methods, specifically DCEs (Harrison, 2006). While no theoretical approach has fully explained the existence of hypothetical bias (Mitani and Flores, 2010), it is clear that values from hypothetical experiments differ from real values (List and Gallet, 2001; Murphy et al., 2005; de-Magistris et al., 2013). Accordingly, in this study, we use Query Theory to illuminate how values are constructed by individuals in a DCE. Understanding how approaches that mitigate hypothetical bias influence the content and order of thoughts may provide valuable clues into how these methods modify choice behavior in DCEs, particularly because queries are processed one after another. Particularly, Query Theory provides a deeper awareness of people's thought processes and the mechanisms behind the choice of alternatives in choice tasks.

There has been no consensus on which approach is best to correct for hypothetical bias, although several *ex ante* and *ex post* approaches to reduce hypothetical bias have emerged in the literature. To illustrate, one approach is the use of the honesty oath, which is based on the premise that hypothetical bias is a result of a lack of commitment to truth telling (Jacquemet et al., 2011). A growing body of evidence exists to support the ability of the honesty oath to reduce hypothetical bias in a number of settings. For example, Jacquemet *et al.* (2009, 2010, 2013) used an oath as a commitment device and found that when participants make a promise in a hypothetical setting, they are more inclined to provide unbiased and accurate answers. Jacquemet *et al.* (2013) also compared the oath to a cheap talk script and found that the solemn oath

improves the revelation of true preferences in both real and hypothetical contexts; the solemn oath also outperformed cheap talk in reducing or eliminating hypothetical bias. Additionally, they confirmed the ability of the oath to improve the reliability of elicited preferences in a series of Vickrey second-price auctions, discovering that the oath increased the willingness of subjects to tell the truth due to a strengthening of the intrinsic motivation to do so. Further, Jacquemet *et al.* (2016) used a lab experiment to examine truth telling within a DCE framework to elicit preferences for a World Wildlife Fund (WWF) Adopt-a-Dolphin program. Their results suggest that the reliability of elicited preferences can be significantly improved by asking subjects to sign a solemn oath; the results also show that the oath can reduce hypothetical bias.

Jacquemet *et al.* (2016) also collected self-reported data on: 1) level of agreement with WWF, 2) honesty, and 3) happiness, in order to better understand how the honesty oath affects individual behavior in their experiment. First, they found that respondents in the hypothetical treatment (no oath) more strongly agreed with WWF than in the real treatment; however, this effect was eliminated when respondents were under oath. Second, they also found that the self-reported measure of honesty increased under oath. Third, subjects under oath were found to spend less time completing the survey; this, combined with the happiness results, indicated that the oath decreased individuals' tendency to engage in self-serving assessments. Taken together, the results of the three questions suggest that truthfulness improves under oath. Individuals under oath were less prone to express positive general attitudes, seeing themselves as more honest in their answers. Furthermore, the oath appears to decrease happiness. These results offer new insights into how the honesty oath influences the behavior of individuals in experiments.

In this study, we posit that Query Theory (QT) could offer a psychological explanation for the valuation differences often observed in economic experiments. Specifically, QT suggests

that decision-makers construct their preferences by asking internal queries about the available options (Johnson et al., 2007; Weber et al., 2007). It also suggests that preference construction and choice are automatic and unconscious processes of arguing with oneself (Weber and Johnson, 2011). According to QT, people sequentially generate arguments for selecting each of the various choice options, with the first option having a major advantage because arguments for the default choice-option are generated first (Johnson et al., 2007). Furthermore, positive or negative affective reactions to choice options also impact which option is considered first, and the effect is stronger when no default action exists (Johnson et al., 2007; Weber et al., 2007). Given the conclusion by Jacquemet *et al.* (2016)—that individuals under oath are less prone to express positive general attitudes and have a reduced likelihood of engaging in self-serving behavior—we seek to use QT in this study to examine any differences in positive and negative affective reactions by respondents under oath, while compared to experimental controls.

The main goal of this study is to address the effectiveness of the honesty oath through QT to induce more honest behavior in a DCE. Particularly, Query Theory examines how the honesty oath affects changes in individual behavior in a DCE. In order to test for the presence of hypothetical bias, we first assessed two control groups: a baseline control, which is a group given no honesty oath, and another control group named "academic control," which is a group given no honesty oath, but that is also explicitly told their responses would be used for academic purposes only. This type of assessment allowed for the testing of the presence of bias in our baseline control and provided two treatments through which the effectiveness of the honesty oath in mitigating hypothetical bias could be assessed. Our third treatment was the experimental treatment where respondents were under the honesty oath. Notably, we had no non-hypothetical or "real" treatment due to the absence of products that represent product alternatives in our DCE;

therefore, we assumed that the observation of lower WTP in the honesty oath treatment, in comparison to the controls, was an indication of reduced hypothetical bias, given our use of a private good. Following Johnson *et al.* (2007) and Weber *et al.* (2007), we used a verbal report method called “aspect listing” in the two control groups and the treatment group to obtain some indication of the aspects, i.e., thoughts, in each choice task of the experiment. Next, we compared the aspect listing results to test for differences between the two controls and our experimental treatment when subjects were under honesty oath. Finally, we added three “non-query” groups where respondents were not asked to list thoughts, in order to assess any effects that the aspect-listing task itself might have on the results. Our study employs a between-subjects design where respondents were randomly assigned to one of the six groups.

Our study seeks to answer four main research questions: 1) does the honesty oath reduce hypothetical bias in our DCE; 2) does the honesty oath change the content of queries; 3) does the honesty oath change the order of queries; and 4) do queries predict people’s valuations? The results of our experiment provide evidence to answer these questions. Our study differs from previous research in three important ways. First, we test the effectiveness of the honesty oath to reduce hypothetical bias in a DCE to assess preferences for a private market good—chicken breast meat. Second, to our knowledge, this is the first study to use QT to explain how the honesty oath affects the behavior of individuals in reducing hypothetical bias. Third, most of the studies on the honesty oath were conducted using limited pools of subjects in France. Our study represents a relatively large-scale implementation of the oath in an experiment by using an English language oath in the United States.

Query Theory

There are four key premises of QT (Johnson et al., 2007; Weber and Johnson, 2011). First, it assumes that people break down valuation questions into a series of queries of past experiences for evidence supporting different choice options. Second, these queries are executed sequentially and may be done automatically without the awareness of the decision maker. Third, the first query produces richer representations of thoughts than subsequent queries, which occurs because of output interference, i.e., as evidence for the first considered option is generated, evidence supporting the alternative options is temporarily unavailable, and therefore the first query is a more heavily weighted representation than subsequent queries. Fourth, different response modes produce different query orders; hence, the order of options considered is of critical importance as it influences the balance of evidence.

A number of studies have used QT in different contexts, for example, Johnson *et al.* (2007) used QT to examine the endowment effect and provided a memory-based account suggesting that people construct values by posing a series of queries whose order differs for sellers and choosers. Their results suggest that the differences in valuations between buyers and sellers were caused by output interference; i.e., the queries of buyers and sellers retrieve different aspects of the object and the medium of exchange, thereby producing different valuations (Johnson et al., 2007). They then demonstrated that the content and structure (order) of the recalled aspects differed for selling and choosing, and the content and order of those aspects predicted valuations. Similarly, Weber *et al.* (2007) provided empirical support for the QT premise that order of thoughts matters. They used QT to explain asymmetric discounting (preference for smaller financial rewards now rather than larger rewards later) and succeeded in reducing people’s discounting of future rewards by setting up an experiment where the decision

was reframed to direct attention to the delayed outcome. This experiment provided clear evidence that the order of query matters and that by manipulating the order of thoughts, people make difference choices.

Johnson *et al.* (2007) categorized aspects considered by people into two categories: value-increasing and value-decreasing, given that QT suggests valuation is based on a series of sequential queries. Notably, value-increasing aspects tend to enhance the value of the object under consideration, while aspects that focus on negative properties are termed value-decreasing. The content of these queries, or the balance of value-increasing and decreasing aspects, is important, as is the order and which aspects are listed first. They found that the order of queries depends on the endowment state, reflecting that people tend to first assess the advantages of the status quo, then assess the advantages of the alternative state. However, the question remains whether the premises of QT can be useful in the account of the use of honesty oaths to mitigate hypothetical bias in DCEs.

Preferences are subject to the processes and dynamics associated with retrieval from memory; therefore, these principles can help explain a range of phenomena in valuation research (Johnson et al., 2007; Weber and Johnson, 2006). We extend this logic to the explanation of hypothetical bias in DCEs by examining the queries generated by people who have taken the honesty oath. Johnson *et al.* (2007) found that the content and order of queries depended on response mode; hence, it would be reasonable to expect that the aspects listed by people under oath should also differ from those not subjected to the oath. Given Jacquemet *et al.'s* (2016) finding that people under oath are less likely to express positive general attitudes and to engage in self-serving behavior, it should follow in our experiment that people under oath express fewer positive aspects and greater negative aspects than those not under oath. Furthermore, QT

documents the cognitive mechanisms used in constructing preferences (Weber and Johnson, 2006) and thereby should help document the shift in positive and negative queries under consideration during more truthful decision making. If the source of hypothetical bias is a result of less-than-truthful answers, we should see a change in the balance of aspects in both content and order when honesty oath respondents are compared to an experimental control. It is therefore important to understand how the oath changes query order because the order of options considered influences the balance of evidence.

Experimental Design and Methods

The data were collected through a national, web-based choice experiment survey built using the software package Sawtooth Software (Sawtooth Software, 2016) and collected by Survey Sampling International (SSI) (SSI, 2016), using their nationally representative consumer panel. The panel consisted of 3,049 participants who were the primary grocery shoppers for their households, randomly placed into one of six treatments with approximately 500 participants per treatment. Notably, the sample from SSI is balanced by socio-demographic characteristics, as well as the four main U.S. Census regions for regional balance across the US. Furthermore, respondents in the honesty oath treatments were presented with the oath they had to accept or decline[1], before they were allowed to move forward with the DCE and survey. Respondents who agreed to take the oath and continue with the survey spent, on average, approximately 10 seconds reading and agreeing to the oath, which was consistent across the query and non-query oath treatments (10.043 seconds and 10.151 seconds, respectively).

In the query honesty oath treatment, 44 respondents declined to take the oath and 504 agreed (92%); whereas in the non-query honesty treatment, 38 refused the oath and 508 agreed

[1] Respondents who declined to proceed with the survey under oath were exited from the survey.

(93%). The experiment consisted of two tasks, the first of which required respondents in all six groups to participate in a DCE where they made choices between poultry products differentiated by various GM labels, production location, and carbon footprint. For the three query groups, respondents were asked during each choice task to list the things they were considering as they made their decisions. The second task required respondents in all six groups to answer a series of survey questions related to food preferences and demographic data.

Choice Set Design

Boneless skinless chicken breast was chosen for use in the DCE for a number of reasons. First, boneless skinless chicken breast is a widely consumed product in the US. Second, only recently have meat and poultry products used non-GM label statements. Also, the product is sold in packages that could carry a non-GM label. Furthermore, two complementary labels were included in the study, one of which was local production of both birds and feed; the other was carbon footprint. Table 1 shows the choice experiment attributes and levels with corresponding effects coding. Effects coding was used because of the benefits provided when there are potential interactions between two categorical variables, such as local and carbon footprint. Additionally, effects-coded data provide reasonable estimates of both main effects and interaction effects; whereas dummy coded data provide only simple effects, i.e., the effects of one variable at one level of the other variable (Bech and Gyrd-Hansen, 2005). In this study, it is important to clearly examine and distinguish the main and interaction effects of all attribute levels.

Price has four levels that reflect 2015 nominal prices found across U.S. supermarkets. Prices were sampled from retail outlets of both brick and mortar stores and online retailers. Notably, USDA price reports for chicken were also consulted (USDA ERS, 2015). One objective of this study hinged on determining consumers' preferences for chicken breast carrying a Non-

GMO Project Verified label; therefore, the second chosen attribute was genetically modified (GM) content, which had three levels: 1) no information, 2) Non-GMO Project Verified[2], and 3) "this product contains genetically engineered ingredients." Particularly, the selected GM labels are currently valid labeling options under the U.S. system of voluntary labeling. With President Obama's recent signing of bill S.764, which put a federal standard for labeling GM foods into place (Blake, 2016), we included the "contains GM" language, in part, to gauge how consumers respond to such language in the event it appears on products in the future. Consumers' preferences were also examined for two additional sustainability labels: carbon footprint and local production. The third attribute was carbon footprint, which had four levels: no information, low, medium, and high carbon footprint (values of CO_2 in Table 1). Specifically, the CO_2 levels followed those used by Van Loo *et al.* (2014). The final attribute was local production, which was defined by the birds and feed being grown in the respondent's own state. Notably, the "local" attribute had two levels: no information and "birds and feed grown in your state."

Each respondent was presented with eight choice tasks where each task included two experimentally designed options and a no-buy option. The allocation of attribute levels to alternatives was designed using a sequential design and D-efficient criteria. Bliemer and Rose (2010) show that D-efficient multinomial logit (MNL) base designs perform well for mixed (random parameters) logit models (MXL). For simplicity, the first stage was an orthogonal design and was implemented for the pilot, utilizing 250 respondents. The data from the pilot were used to estimate a model whose coefficient estimates were then used as priors for the data collected in the first wave. All designs were obtained and evaluated using Sawtooth Software

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

(Sawtooth Software, 2016) and Ngene version 1.1.2 (Choice Metrics, 2012) and involved 32 choice tasks arranged in four blocks of eight tasks each[3].

Aspect-Listing and Ex-Post Classification

Following Johnson *et al.* (2007) and Weber *et al.* (2007), a verbal report method called, an aspect listing, was used to obtain information on the aspects considered during each choice task of the experiment. Respondents were asked, “please tell us what you were 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.” Next, the content and order of the responses were recorded to approximate the thought processes of respondents in each treatment[4]. The aspects listed are an approximation of the thoughts that actually occurred as the respondents made decisions, given that the queries themselves may be automatic and difficult to observe directly (Johnson et al., 2007). Accordingly, the aspect listing is designed to capture the effect of these unobservable queries by documenting what they produce. More sophisticated measures exist, but the aspect-listing method is easy to implement particularly in large sample market settings (Johnson et al., 2007) such as the one used in this study.

Unlike Johnson *et al.* (2007) who asked participants to self-code aspects they had listed during the experiment (both the focus and valence of each aspect), participants in our study were not asked to perform this task. Because each participant in our study was required to perform eight separate choice tasks, it was important to minimize respondent fatigue by not adding another task. Furthermore, the aspect listing task was left more open, thereby allowing for any

[3] Final design details available from the authors upon request.
[4] Each respondent completed eight choice tasks with three text fields for the aspect listing available at each task. This process provided 24 total opportunities for each respondent to list their thoughts during the experiment.

comments regarding the individual's decision to be entered. This wide range of comments was permitted in order to evade bias responses to the survey, which can occur when respondents asked to think about what the administrators view as important in their decisions. The overall goal here was to gain a clear picture of what respondents were thinking while making their decisions[5].

Our choice experiment without the aspect-listing task took respondents less than 10 minutes to complete on average; with aspect-listing average completion time increasing to just over 19 minutes. Because of the intensity of the process for respondents, we manually classified (coded) the aspects ex-post[6]. Notably, the task of manually coding responses from approximately 1,500 respondents who provided up to three responses per task across eight choice tasks (over 36,000 opportunities to enter text in total) required a great deal of time and effort. Additionally, each response was processed three times during coding in order to reduce errors in data entry. Our understanding of the responses improved as read the responses; this required multiple revisions and additional time.

Data were first coded by the attributes mentioned by respondents (price, gm content, carbon footprint, location, or other). Additionally, an "other" category was included because not all submitted comments were related to the attributes in our design, e.g., respondents could

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[5] 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. We tested multiple software programs including SPSS Text Analytics for Surveys, SAS Text Analytics, and LIWC2015 for instance and found that it took more time to learn the software and check for and correct errors than to manually hand code the data. We found SPSS Text Analytics to be useful in searching for attributes mentioned and we did use it to help verify and compare our data entry; however, analyzing the valence of aspects required that each statement be read and evaluated independently and complex statements containing multiple aspects and both positive and negative sentiments required careful consideration and were therefore manually coded.

[6] Johnson et al. (2007) note that aspects coded by novice raters produce similar results in their experiments.

comment that they "prefer organic products" or would rather "eat beef tonight." As seen in Table 2, between 75 and 79% of all aspects listed made mention of the attributes in the experiment, depending on treatment. The next step was to classify all aspects listed into one of three categories: 1) value-decreasing, 2) value-increasing, or 3) value-neutral, since the valence (the intrinsic attractiveness or aversiveness) of aspects listed in QT is significant. Furthermore, respondents' aspects were not forced into positive or negative categories[7] in that respondents were not asked to self-categorize aspects, but they were allowed to record any thoughts they wanted in response to our request, whether positive, negative, neutral, or unusable. Particularly, many people's neutral aspects simply reflected their indifference to one of the products or attribute levels in our experiment. As shown in Table 2, between 4.6% and 6.7% of the aspects listed were classified as value-neutral.

Treatment Descriptions

Our study employed a between-subject design where respondents participated in only one of the treatments of the experiment. Because our target population was consumers and not students, we had a non-standard subject pool (Harrison and List, 2004). Also, all treatments used a standard hypothetical choice experiment. As mentioned previously, the first two treatments represent the baseline control treatments, with the first treatment representing our baseline control with query task (QBC), and the second treatment representing our academic control with query task (QAC) where subjects were explicitly instructed that their responses would not be used in any way to make product or pricing decisions[8]. Importantly, respondents in these first

[7] Examples of aspects categorized as value-decreasing, increasing, and neutral can be found in Appendix Table A1.
[8] Similar to a point made by Carson, Groves, and List (2014), respondents in our survey were told at the beginning that the survey was being conducted by university researchers to help inform decisions and the identity of our sponsoring agent. This may limit the ability of producing

two baseline controls were not exposed to or required to take an oath. The third treatment (QHO) used an honesty oath[9] based on Jacquemet *et al.* (2009, 2010, and 2013) and read as follows:

> *"I undersigned swear upon my honor that, during the whole experiment, I will: Tell the truth and always provide honest answers."*

Treatments 4–6 are identical to treatments 1–3 with the exception that respondents in treatments 4–6 were not asked to list their thoughts while going through each choice task. The results of these treatments are presented briefly in the results as a test of robustness to our main research findings and are discussed minimally throughout to save space.

Econometric Methodology

Respondents' preferences and WTPs were analyzed using a discrete choice framework consistent with random utility theory (McFadden, 1974) and Lancaster consumer Theory (Lancaster, 1966). A Mixed (Random Parameters) Logit (MXL) model with correlated errors and error components was used to estimate preferences and WTP. The utility function is specified as follows:

$$U_{ijt} = \mathrm{NONE} + \beta_1 PRICE_{ijt} + \beta_2 \mathrm{NGE}_{ijt} + \beta_3 \mathrm{GME}_{ijt} + \beta_4 \mathrm{LOE}_{ijt} + \beta_5 \mathrm{MDE}_{ijt} + \beta_6 \mathrm{HIE}_{ijt} + \beta_7 \mathrm{LCE}_{ijt} + \eta_{ijt} + \varepsilon_{ijt} \tag{1}$$

where *i* is the individual respondent, *j* refers to three options available in the choice set (Product A, Product B, and None) and *t* refers to the number of choice situations. The alternative-specific constant (NONE) is dummy coded, taking the value 1 for the no-buy option and 0 otherwise. *PRICE* is a continuous variable represented by the four experimentally designed price levels ($2.99, $6.99, $10.99, $14.99). The non-price attributes Non-GMO (NGE), Contains Genetically

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a truly hypothetical group because respondents may be aware that the data will at least be used for academic research purposes.

[9] The appendix contains a screen capture of the honesty oath as seen by individuals in our experiment. Only respondents randomly assigned to the honesty oath treatment who responded "agree" to take the oath were allowed to proceed.

Engineered Ingredients (GME), Low Carbon Footprint (LOE), Medium Carbon Footprint (MDE), High Carbon Footprint (HIE), and Local Production (LCE) are effects coded variables taking the value 1 if the product carries the corresponding labels, taking the value of -1 if there is an absence of a label, and 0 for the no-buy option. η_{ijt} is an error component that is normally distributed, but with zero mean (inflating the variance of utility for options other than the no-buy option), while ε_{ijt} is an unobserved random term that is distributed following an extreme value type-I (Gumbel) distribution independent and identically distributed (iid) over alternatives.

The common approach to estimating equation (1) in preference space is to assume price has a fixed coefficient; this is a widely accepted and practiced specification (Layton and Brown, 2000; Lusk and Schroeder, 2004; Revelt and Train, 1998). Fixing the price coefficient ensures that the estimated WTP will be normally distributed and all respondents will have a negative price coefficient. This practice was followed in our study to estimate WTP for the purpose of testing our hypotheses. Additionally, Scarpa *et al.* (2008) found that estimating WTP directly using WTP space, reduced the incidence of large WTP values and allowed for greater control in specifying the distribution of WTP. As a test of the robustness of our results to the econometric specification, the assumption of a fixed price coefficient was relaxed and the utility was specified in WTP space in order to test our hypotheses. Our utility function is therefore re-written as:

$$U_{ijt} = \alpha[\theta_1 \mathrm{NONE} + PRICE_{ijt} + \theta_2 \mathrm{NGE}_{ijt} + \theta_3 \mathrm{GME}_{ijt} + \theta_4 \mathrm{LOE}_{ijt} + \theta_5 \mathrm{MDE}_{ijt} + \theta_6 \mathrm{HIE}_{ijt} + \theta_7 \mathrm{LCE}_{ijt}\,] + \varepsilon_{ijt} \qquad (2)$$

where $\theta_i = \beta_i / \alpha$ are the WTP estimates.

Following de-Magistris *et al.* (2013), data were pooled for the two treatments involved in the hypothesis; then an extended utility was specified with the appropriate set of treatment dummy variables dependent on the hypothesis, in order to test our hypotheses given this new utility specification. Our extended utility function appears as follows:

$$U_{ijt} = \alpha[\theta_1 NONE + PRICE_{ijt} + \theta_2 NGE_{ijt} + \theta_3 GME_{ijt} + \theta_4 LOE_{ijt} + \theta_5 MDE_{ijt} + \theta_6 HIE_{ijt} + \theta_7 LCE_{ijt}] + \delta_1 (NGE_{ijt} \text{ x } tr) + \delta_2 (GME_{ijt} \text{ x } tr) + \delta_3 (LOE_{ijt} \text{ x } tr) + \delta_4 (MDE_{ijt} \text{ x } tr) + \delta_5 (HIE_{ijt} \text{ x } tr) + \delta_6 (LCE_{ijt} \text{ x } tr) + \varepsilon_{jt} \quad (3)$$

where *tr* is coded 1 for the first treatment in the analyzed hypothesis and 0 otherwise. For each of our 3 hypotheses relating to WTP, one extended utility function was specified, and thus three *tr* dummy variables were used. The signs and significance of the estimated δ enabled us to test differences in marginal WTP between the two treatments in each analyzed hypothesis.

Sample Characteristics

Our study included 3,049 respondents in the six treatments[10]. Each respondent completed eight choice tasks with three choices or alternatives per set, for a total number of 73,176 observations (around 12,200 observations per treatment). Importantly, using a chi-square test, it was tested if there were differences in socio-demographic profiles across treatments. The results of this test suggest that the null hypothesis of equality between observable characteristics across treatments cannot be rejected, which partly suggests that our randomization was successful in providing a balanced sample across treatments. For the preference space models, equation (1) was estimated using an MXL with correlated errors and variance enhancing error components, where price was a fixed parameter and all effects-coded attribute level variables were considered random following a normal distribution[11]. Estimations were conducted with

[10] The three query treatments are given the majority of the space in the presentation of results and discussion. The three non-query treatments are presented in the appendix, and more detailed results are available from the authors upon request. The non-query treatments are included as a test of the robustness of our data on the effectiveness of the honesty oath. We found similar results on the effectiveness of the honesty oath with or without the query task.

[11] Numerous versions of the MXL models were estimated, using of normal, lognormal, and constrained triangular combinations of these distributions. Models were also estimated with independently distributed coefficients, as well as correlated coefficients; both dummy coded and effects-coded models were used. For illustration purposes, we limit the results to the model using

NLOGIT 5, using 1,000 Halton draws to provide a more accurate simulation for the random parameters (Train, 2009)[12].

Results

Before addressing our main research questions and to ensure appropriateness in comparing the WTP estimates from our treatments, we tested the joint equality between treatments using estimates from the MXL with error components models and the likelihood ratio test. The results of these tests indicate that the joint null hypotheses of equality between treatments in all three tests were rejected, suggesting that it would be appropriate to compare the WTP estimates between the query and non-query treatments, as well compare the treatments within the query and non-query treatments. We concluded that comparing the estimated parameters from the various treatments was appropriate when estimating the models separately. Next, we estimated equation (1) for our three query treatments[13]. Based on the estimated coefficients from these models, we calculated the marginal WTP (mWTP) for each attribute. The attributes' levels for the non-GMO, contains GM, and the local production attribute levels were significant with significant standard deviations in all three treatments. The only carbon footprint label found to be significant was the low carbon level only in the baseline and academic controls (QBC and QAC). Accordingly, we limit much of the discussion of the WTP results to the

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independent normal distributions for the random coefficients. Results from other models are available on request.

[12] Following Hensher and Greene (2003), all MXL models were estimated using 25, 50, 150, 250, 500, 1000, and 2000 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 1000 Halton draws, and thus we adopted this for all of the models presented here.

[13] Appendix Table A2 reports results from MXL models across the query treatments, and Table A3 reports the results for the three non-query treatments.

attribute levels found to be significant across all three treatments. In the following sections, we discuss each research question in detail and present the results of our analyses.

Question 1: Does the Honesty Oath Reduce Hypothetical Bias in Our DCE?

Establishing if hypothetical bias was present allowed us to measure the effectiveness of the honesty oath in returning significantly lower WTP values compared to the baseline and academic controls. To accomplish this, we assessed and compared treatments one and two by testing the following hypothesis:

$$H0_1 : (WTP^{QBC} - WTP^{QAC}) \neq 0, \text{ and}$$
$$H1_1 : (WTP^{QBC} - WTP^{QAC}) = 0 \quad (4)$$

If $H0_1$ is rejected, we provide evidence of the presence of hypothetical bias in the baseline control (QBC). Observing WTP values in both the QBC and QAC treatments, which are not statistically different, might confirm that hypothetical bias is present in both treatments, in light of respondents in the purely hypothetical treatment (QAC) having been instructed that their responses were hypothetical and would only be used for academic purposes. Concerning the ability of the honesty oath to mitigate hypothetical bias, we specify and test two hypotheses based on our experimental treatments. We tested the hypotheses that individuals who sign the oath indicate WTP values that are not different from those in the QBC and the QAC where respondents were not exposed to the oath:

$$H0_2 : (WTP^{QHO} - WTP^{QBC}) = 0, \text{ and}$$
$$H1_2 : (WTP^{QHO} - WTP^{QBC}) < 0 \quad (5)$$

$$H0_3 : (WTP^{QHO} - WTP^{QAC}) = 0, \text{ and}$$
$$H1_3 : (WTP^{QHO} - WTP^{QAC}) < 0 \quad (6)$$

If $H0_2$ is rejected, we would confirm that introducing the honesty oath in the hypothetical CE reduces hypothetical bias because the WTP values in the QHO treatment would be lower than in the QBC; likewise, if $H0_3$ is rejected, we would confirm that introducing the honesty oath in the

hypothetical CE reduces hypothetical bias because the WTP values from individuals under oath would be lower than in the academic control (QAC).

We tested hypotheses 1–3 using the combinatorial approach by Poe *et al.* (2005) to compare differences between mWTP estimates in the different treatments. The test requires the generation of a distribution of 1,000 WTP estimates, which was carried out using the statistical software package R (R Core Team, 2013) in combination with the Krinsky and Robb (1986) bootstrapping method. Coefficients and covariance matrices were estimated in NLOGIT 5 and then analyzed in R. For the random draws, we used a Bayesian estimator (James-Stein-type shrinkage estimator[14] in the R package 'corpcor') in order to return a positive, definite, and well-conditioned covariance matrix across all treatments (Schäfer and Strimmer, 2005; Schäfer et al., 2015). Table 3 lists the mWTP estimates and hypotheses tests using the combinatorial approach[15]. We observed that while the mWTP estimates from the academic control are higher than those from the baseline control for all three significant attribute levels (non-GMO, contains GM, and local), the WTP estimates are not significantly different. Therefore, we rejected hypothesis 1 and confirm the presence of hypothetical bias in the baseline control. Next, we were able to measure the effects of the honesty oath against both the baseline and academic controls.

The honesty oath treatment (QHO) produced the lowest WTP estimates for all of the significant attribute levels (non-GMO, contains GM, and local) (Table 3). The mWTP for the non-GMO attribute level was a $2.21/lb premium, $1.79/lb premium to avoid the "contains GM" label, and a $0.59/lb premium for the local production label. In contrast, the highest WTP values

[14] The James-Stein estimator improves upon the total mean square error (sum of expected errors of each component) and allows any particular component to improve for some parameter values and deteriorate for others. For this reason, such an estimator is preferred when three or more parameters are estimated.
[15] Table A5 in the appendix lists the mWTP results for the non-query treatments.

were from the academic control (QAC), with a \$3.65/lb premium for the non-GMO label, a \$2.55/lb premium to avoid GM, and a \$0.78/lb premium for the local production label. The p-values show that although the honesty oath resulted in generally lower WTP estimates, not all of the differences were significant.

Next, to test the robustness of our model specification, we estimated our models in WTP space. Train and Weeks (2005) suggest that it is important to recognize that the scale parameter in many situations can vary randomly over observations. Notably, holding price fixed in order to estimate WTP, errantly ignores variance in price across individuals, which can further lead to erroneous interpretation and policy conclusions. Additionally, estimating WTP directly using WTP space also reduces the incidence of large WTP values. In the context of evaluating methods to mitigate hypothetical bias, constraining the price coefficient (when it indeed varies) could falsely attribute the variation in price to variation in WTP. Therefore, we re-parameterize our models such that the parameters are the marginal WTP for the attributes. The results of our models in WTP space are shown in the Appendix in Table A4, where the coefficient estimates shown are the WTP estimates. The results indicate that again the coefficient estimates were significant in all three treatments for the non-GMO, contains GM, and local production attribute levels.

The lowest WTP estimates are again from the honesty oath treatment (QHO) for all significant attribute levels. Table 4 shows the results of our hypotheses tests to examine the statistical differences between our treatments' mWTP values; these results are similar to those from our preference space models. The honesty oath significantly reduces WTP estimates for the non-GMO attribute, as compared to both control groups, and reduces WTP to avoid the "contains GM" label, as compared to the academic control group. The results provide further evidence that

the honesty oath has the potential to produce substantially lower mWTP estimates. Although the honesty oath was effective at reducing hypothetical bias, we cannot conclude that the oath completely eliminated hypothetical bias[16] based on the preference space and WTP space results because not all differences were found to be statistically significant and we had no real or non-hypothetical treatment by which to compare our results.

Question 2: Does the Honesty Oath Change the Content of Queries

Having observed the ability of the honesty oath to reduce hypothetical bias in our DCE, we next used QT to understand how the oath may affect individuals in order to lower WTP estimates. Our first QT prediction states that listed aspects should differ, in content and size, depending on whether an individual takes the oath. Specifically, we hypothesize that respondents in the QHO treatment, list a greater number of value-decreasing aspects and a smaller number of value-increasing aspects than respondents in the QBC and QAC control groups. We test the following four hypotheses:

$$\begin{aligned} &H0_4 : (DEC^{QBC} - DEC^{QHO}) = 0, \text{ and} \\ &H1_4 : (DEC^{QBC} - DEC^{QHO}) < 0 \end{aligned} \tag{7}$$

$$\begin{aligned} &H0_5 : (INC^{QHO} - INC^{QBC}) = 0, \text{ and} \\ &H1_5 : (INC^{QHO} - INC^{QBC}) < 0 \end{aligned} \tag{8}$$

$$\begin{aligned} &H0_6 : (DEC^{QBC} - DEC^{QHO}) = 0, \text{ and} \\ &H1_6 : (DEC^{QBC} - DEC^{QHO}) < 0 \end{aligned} \tag{9}$$

$$\begin{aligned} &H0_7 : (INC^{QHO} - INC^{QAC}) = 0, \text{ and} \\ &H1_7 : (INC^{QHO} - INC^{QAC}) < 0 \end{aligned} \tag{10}$$

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[16] Appendix tables A1 and A2 list the results from our three non-query treatments. The non-query treatments are provided as a robustness test for our data to ensure that any WTP differences observed can be attributed to the honesty oath rather than to the aspect-listing task itself. The honesty oath produced similar results in the non-query treatments demonstrating the ability to reduce hypothetical bias by producing lower WTP values over the baseline and academic controls. Although the aspect-listing task could have influenced choices made by respondents, the results of the non-query treatments demonstrate that any difference between the query and non-query treatments is minimal.

If $H0_4$ and $H0_6$ are rejected, we would confirm that introducing the honesty oath increases the number of value-decreasing aspects listed by respondents, compared to the baseline control and the academic control. Accordingly, if $H0_5$ and $H0_7$ are rejected, we would confirm that the oath also decreases the number of value-increasing aspects listed by respondents.

Respondents who took the oath listed more value-decreasing aspects and fewer value-increasing aspects than those in the control (Table 2). A repeated measures ANOVA confirmed the interaction between treatment and the content of aspects. Because each choice task is different, it is important to examine the content of aspects at the choice task level. Table 5 shows the value-decreasing and increasing aspects listed by individuals in each of the eight choice tasks separately. Multivariate tests were significant (*p*-value 0.000), confirming that treatment membership has a significant effect on the aspects listed during each choice task. Additionally, Table 5 shows ANOVA results, confirming that for each choice task, treatment has a significant effect on the numbers of value-decreasing and increasing aspects listed. Our aspect-listing data demonstrate that people assigned to the oath treatment listed on average more value-decreasing aspects overall, as well as on all eight choice tasks separately. Additionally, respondents in the QHO treatments listed significantly fewer value-increasing aspects overall and on all eight choice tasks. Notably, these data provide the evidence to reject hypotheses 4–7.

Question 3: Does the Honesty Oath Change the Order of Queries?

The sequential nature of QT predicts that the kind of aspects (positive or negative) generated by people will change during the aspect listing (Johnson et al., 2007). Our second QT prediction states that the sequence of aspects should correspond to our hypothesized order of queries, which is dependent upon whether an individual takes the oath. Because participants

listed different numbers of aspects both overall and during each choice task, we tested this prediction by calculating a score at the respondent level and choice-task level that reflects an individual's tendency to produce value-increasing aspects before value-decreasing ones. The score, as proposed by Johnson *et al.* (2007) and Weber *et al.* (2007), is the Standardized Median Rank Difference of aspect types (SMRD) and is defined as follows:

$$2(MR_{\mathrm{i}} - MR_{\mathrm{d}})/n \qquad (11)$$

where MR_{d} is the median rank of value-decreasing aspects in a participant's sequence; MR_{i} is the median rank of value-increasing aspects in a participant's sequence; and n is the total number of aspects in a participant's sequence[17]. SMRD can take on values from -1 (all value-decreasing aspects listed before any value-increasing aspects) to 1 (all value-increasing aspects listed before value-increasing aspects).

We hypothesized that respondents in the QHO treatment would list value-decreasing aspects earlier in the aspect-listing task than respondents in the QBC and QAC control groups. In other words, we expected a lower SMRD of aspect types in the QHO treatment and tested the following two hypotheses:

$$H0_8 : (\mathrm{SMRD}^{\mathrm{QHO}} - \mathrm{SMRD}^{\mathrm{QBC}}) = 0, \text{ and}$$
$$H1_8 : (\mathrm{SMRD}^{\mathrm{QHO}} - \mathrm{SMRD}^{\mathrm{QBC}}) < 0 \qquad (12)$$

$$H0_9 : (\mathrm{SMRD}^{\mathrm{QHO}} - \mathrm{SMRD}^{\mathrm{QAC}}) = 0, \text{ and}$$
$$H1_9 : (\mathrm{SMRD}^{\mathrm{QHO}} - \mathrm{SMRD}^{\mathrm{QAC}}) < 0 \qquad (13)$$

[17] Following Johnson *et al.* (2007), any sequence (of length s) in which only one of the two response categories of interest, i.e., value-increasing or value-decreasing aspects, appears, the median rank of the unobserved response category is set to s+1, which is a conservative way of representing the low level of accessibility of thoughts of that type. In addition, for the purpose of calculating the SMRD score, n=s+1 for such single-category sequences. For sequences that include responses from both categories, n=s.

If $H0_8$ and $H0_9$ are rejected, we would confirm that introducing the honesty oath induces respondents to consider value-increasing aspects before value-decreasing ones. As predicted, the mean SMRD score in the honesty oath treatment (QHO) was significantly lower (-0.271) than those in the two control groups (QAC=-0.086, QBC=-0.070) (ANOVA F=14.624, p-value=0.000). Because we are interested in the choice-task level aspects listed, Table 6 lists the SMRD results for each of the eight choice tasks. As these data demonstrate, the mean SMRD score from respondents taking the oath is significantly lower on each choice task. These results indicate that the honesty oath prompts individuals to consider value-decreasing aspects earlier in their decision making process, and that this effect is evident during all eight choice tasks. Importantly, the effect of the honesty oath varies across choice task, with the lowest (most negative thoughts) SMRD observed for choice task three, and the highest (most positive) SMRD observed during choice task five. The QHO was the only treatment with a negative SMRD observed across all eight choice tasks. Based on these results, we reject hypotheses 8–9 and conclude that the honesty oath has a significant effect on the order of aspects listed by respondents in our DCE.

Question 4: Do Queries Predict Consumer Valuations?

Our final QT prediction is that aspects should predict valuation estimates. If the retrieval of aspects is used to determine value, then the aspects should predict WTP values. We test this question using WTP as a dependent variable in a multiple regression with number of value-decreasing and increasing aspects listed by individuals as the independent variables in the model. If the simple value-decreasing and increasing encoding we used in our experiment result in: 1) significant coefficients and 2) coefficients are in the expected direction, we can conclude that the

aspects listed by respondents in our experiment might predict the WTP values derived from the choice-task portion of the DCE. Our multiple regression is shown as follows:

$$WTP_{iz} = \beta_0 + \beta_1 PriceDEC_{iz} + \beta_1 PriceINC_{iz} + \beta_2 GMDEC_{iz} + \beta_2 GMINC_{iz} + \beta_3 CO_2DEC_{iz} + \beta_3 CO_2INC_{iz} + \beta_4 LocalDEC_{iz} + \beta_4 LocalINC_{iz} + \beta_5 OtherDEC_{iz} + \beta_5 OtherINC_{iz} \quad (14)$$

where *i* is the individual respondent; *z* is the attribute for which WTP is estimated; PriceDEC, PriceINC, GMDEC, GMINC, CO_2DEC, CO_2INC, LocalDEC, LocalINC, OtherDEC, and OtherINC are continuous variables representing the number of value-decreasing and increasing aspects listed by individual respondents and categorized by attribute[18]. The aspects by attribute are summarized in Table 2.

The results of our three multiple regressions (one for each of the significant WTP) indicate that our encoding of aspects predicts WTP for the non-GMO, contains GM, and local production attribute levels. The adjusted R square values indicate that our simple encoding explains over 50% of the variation in the WTP values for the non-GMO label, 49% for the GM label, and 36% for the local production label. However, not all aspects listing variables were found to significantly influence WTP estimates. Table 7 shows the regression results, and notably, the carbon footprint aspects had no effect on the WTP values for local production. Also, the carbon value-increasing aspects had only a small statistically significant effect on the WTP values for non-GMO and contains GM labels. Considering that carbon footprint was the attribute with the fewest aspects listed, this is not surprising. Furthermore, the signs of the coefficients for the non-GMO and contains GM were in opposite directions, which was expected based on the positive WTP for non-GMO and negative WTP (paying to avoid) contains GM label.

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[18] We do not include value-neutral aspects listed for two reasons: theoretically, expressions of indifference should have no increasing or decreasing effect on WTP values, and empirically, when neutral aspects are included, they are found to have no significant impact on WTP values in our study.

One of the more interesting findings is that the signs of coefficients for PriceDEC and PriceINC were the same (negative for non-GMO and positive for GM). Additionally, the coefficients were larger for the PriceINC variable across all three WTP measures. Price was arguably the most important attribute, which could indicate that individuals have a stronger emotional affection when saving money and focusing on the benefit of lower prices, rather than focusing on prices being too high. While two statements such as the negative “price for product 1 is too expensive” and the positive “price for product 2 is more affordable” seem to relay the same thought, the negative and positive connotation could represent two individual valuations of the same price comparison. If our results are any indication that these two statements truly are different in terms of a consumer’s valuation of a product, then it is important to note that the honesty oath produces more of the negative affectations of price, compared to the control groups. When treatment was controlled for in our multiple regressions, we found that in the honesty oath, the coefficient for PriceINC was lower, relative to the controls. Additionally, the PriceINC and PriceDEC coefficients were similar in size in the honesty oath (both near -1), while in the controls, the PriceINC was larger relative to PriceDEC[19]. This result provides additional support to the claim that the honesty oath produces more value-decreasing thoughts, which also appear to lead to lower WTP estimates, as shown by our preference-space and WTP-space results.

While these results provide evidence to support the QT prediction that aspects do predict valuation estimates, the signs of some of the coefficients in our models signal a need for further research on how to interpret (and properly categorize) the aspects listed by respondents. In addition, further research is required on how these aspects truly influence consumer choice

[19] The results of these multiple regressions controlling for treatment are available from the authors by request.

behavior. Identifying the attribute attended to by individuals is relatively straightforward; however, interpreting statements to determine positive or negative affectations is more subjective and could be subject to greater experimenter error in determining the correct categories. Because the attributes attended to are much clearer to identify than the value-decreasing or increasing sentiments of the aspects, a next logical step would be to explore how our MXL models could be improved by using these aspects as a predictor for attribute attendance. Further investigation could reveal a stronger connection between query content and consumer valuation.

Summary and Conclusions

Our study's main goals were to examine the effect of an honesty oath on mitigating hypothetical bias in a DCE and to use QT to better understand how the oath affects individuals' decision making in a DCE. To achieve these goals, we designed and carried out an experiment to answer four main questions. Our results provided necessary insight into these research questions. Our first conclusion is that the honesty oath reduces, but may not eliminate hypothetical bias. To explain, the honesty oath treatment returned the lowest WTP values across all attributes and significantly lowered WTP values by varying amounts, compared to the baseline and academic controls. However, because not all WTP values were found to be significantly lower (Tables 3 and 4) in the honesty oath treatment, we cannot definitively conclude that the oath totally eliminated hypothetical bias. What we have observed across our preference space and WTP space models is that the honesty oath succeeds in returning significantly lower WTP estimates. This provides support for our conclusion that the oath reduces hypothetical bias in our DCE.

Our second conclusion is that that the honesty oath changes the content of queries. The three QT predictions we tested were closely related to those tested by Johnson *et al.* (2007). The first QT prediction we tested was that listed aspects should differ, in content and size, depending

on whether an individual takes the oath. Our results provide strong evidence that the treatment did have a significant effect on the number of value-decreasing and increasing aspects listed by individuals (Tables 2 and 5). Overall, respondents in the honesty oath treatment listed more negative aspects (value-decreasing) and fewer positive aspects; these relationships were statistically significant. This observation held across all eight choice tasks as well (Table 5), with individuals in the honesty oath treatment listing the most negative aspects and fewest positive aspects in all eight choice tasks. Overall, these results provide strong evidence to support our conclusion that honesty oath changes the content of queries.

Our third conclusion is that the honesty oath changes the order of queries. The second QT prediction we tested was that the sequence of aspects should correspond to our hypothesized order of queries, which is dependent upon whether an individual takes the oath. Because participants listed different numbers of aspects, we used the SMRD score to test this prediction. SMRD reflects an individual's tendency to produce value-increasing aspects before value-decreasing ones. Our results indicated that individuals under oath had SMRD scores closer to -1, than individuals not under oath; this relationship was found to be significant (Table 6). This condition also held under each of the eight choice tasks; the honesty oath treatment was the only treatment to produce a negative SMRD score across all eight tasks. These results provide support for our conclusion that the honesty oath changed the order of aspects listed by individuals, and it influenced individuals to produce negative aspects before positive ones.

Our fourth conclusion is that the queries predict consumer valuation. Our third and final QT prediction was that aspects should predict valuation estimates. The results of our multiple regression model indicate that the crude encoding of aspects explain between 36 and 52% of the variation in our WTP estimates for the non-GMO, contains GM, and local production attribute

levels (Table 7). Not all aspects listed by attribute were found to be significant; most notably, the carbon footprint aspects were not significant predictors of WTP. These results are not surprising considering that the carbon footprint levels were not significant across our MXL models and individuals listed the fewest aspects on carbon footprint. It is no surprise that not all coefficients in our multiple regressions were significant, due to the complexity of our choice experiment where we ask individuals to complete eight choice tasks and list thoughts after each task.

We are also not surprised that the sign of the price coefficients for PriceINC and PriceDEC are in the same direction across our models. A vast body of empirical evidence and theory demonstrate clearly that, ceteris paribus, consumers have a significant preference for lower prices. Our results demonstrate this relationship as well. Importantly, the honesty oath shifts the balance of how individuals in our experiment represent price from a positive price affectation to a negative one. Whether an individual reports a positive statement like: "I like the cheaper price," or a negative one like: "this price is outrageous," may seem unimportant on the surface as both of these statements are significant predictors of WTP values according to our results (Table 7). However, QT proposes that the negative affection will lead to lower consumer valuations, and our evidence supports this.

Additionally, our results demonstrate that the negative aspects listed by individuals holds across all eight choice tasks. According to QT, due to output interference, the first query is a more heavily weighted representation than subsequent queries. The treatment with the highest level of value-decreasing aspects and the lowest (most negative SMRD score) order of queries was the honesty oath treatment—the treatment that also produced the lowest WTP values across all attribute levels. Our multiple regression results, when controlled for treatment effects, demonstrate that the PriceINC and PriceDEC are nearly identical in value, indicating that the

oath may shift the balance between positive and negative aspects to significantly lower WTP values, at least where WTP estimates are significant. Our results therefore support our conclusion that queries can predict consumer valuation.

Perhaps our most significant limitation is in the categorization of aspects. Gaps exist in how to best classify aspects listed by respondents in an experiment like ours. In our study, we did not allow individuals to self-classify their aspects into positive and negative categories for the purpose of decreasing the burden of our experiment and to avoid influencing responses on subsequent choice tasks. In future experiments, it may be worthwhile to decrease the complexity of the experiment so that individuals would not become fatigued by multiple choice tasks. This would allow for the assignment of the additional task to individuals to self-classify aspects. This change could reduce the ambiguity in the classification of aspects and potential researcher bias.

Our study is the first to use QT to decipher a possible mechanism behind the effectiveness of the honesty oath in reducing hypothetical bias in DCEs. We believe that this study will initiate further exploration of the potential use of QT in valuation and choice behavior research, in spite of it being based specifically within the context of honesty oath and DCE's. To illustrate, future research could explore the use of the QT in identifying the thought process behind the effectiveness or ineffectiveness of other ex-ante techniques, e.g., cheap talk, in reducing hypothetical bias not just in DCE's, but also in other stated-preference methods, e.g., multiple price list, dichotomous choice, payment cards. There are also potential applications in the use of QT to dig deeper into the thought process of subjects in non-hypothetical valuation studies such as those using experimental auctions.

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Tables

Table 1. Choice experiment attributes and levels with effects coding

Attributes	Levels	Coding
Price (4)	\$2.99	\$2.99
	\$6.99	\$6.99
	\$10.99	\$10.99
	\$14.99	\$14.99
	No-buy	0
GM Content (3)	No information	-1,-1
	Non-GMO verified	1, 0
	Contains GM	0, 1
	No-buy	0, 0
Carbon Footprint (4)	No information	-1,-1,-1
	79 oz CO2e/lb (low)	1, 0, 0
	90 oz CO2e/lb (medium)	0, 1, 0
	112 oz CO2e/lb (high)	0, 0, 1
	No-buy	0, 0, 0
Local (2)	No information	-1
	Local production	1
	No-buy	0

Table 2. Value-decreasing, value-increasing, and value-neutral aspects listed across query treatments

	Attributes	Honesty Oath (QHO)		Academic Control (QAC)		Baseline Control (QBC)		Hypothesis Tests
		Number	percent	Number	percent	Number	percent	
Value-Decreasing Aspects Listed	price	2438	34.3%	1948	29.1%	2043	29.4%	F = 15.668 p-value = 0.000
	gm	684	9.6%	534	8.0%	444	6.4%	
	carbon	208	2.9%	139	2.1%	130	1.9%	
	location	206	2.9%	142	2.1%	145	2.1%	
	other	731	10.3%	654	9.8%	628	9.0%	
	total	4267	60.0%	3417	51.1%	3390	48.8%	
Value-Increasing Aspects Listed	price	789	11.1%	1058	15.8%	1219	17.6%	F = 9.121 p-value = 0.000
	gm	460	6.5%	523	7.8%	646	9.3%	
	carbon	165	2.3%	135	2.0%	136	2.0%	
	location	442	6.2%	436	6.5%	470	6.8%	
	other	634	8.9%	817	12.2%	617	8.9%	
	total	2490	35.0%	2969	44.4%	3088	44.5%	
Value-Neutral Aspects Listed	price	7	0.1%	13	0.2%	41	0.6%	F = 3.840 p-value = 0.022
	gm	37	0.5%	47	0.7%	51	0.7%	
	carbon	64	0.9%	55	0.8%	117	1.7%	
	location	13	0.2%	19	0.3%	12	0.2%	
	other	235	3.3%	172	2.6%	243	3.5%	
	total	356	5.0%	306	4.6%	464	6.7%	
Average Aspects Listed per Respondent	decreasing	8.4	60.0%	6.7	51.1%	6.6	48.8%	F = 1.773[1] p-value = 0.170[1]
	increasing	4.9	35.0%	5.8	44.4%	6.1	44.5%	
	neutral	0.7	5.0%	0.6	4.6%	0.9	6.7%	
	Total	14.0	100.0%	13.2	100.0%	13.6	100.0%	

Notes: multivariate tests were all significant (p-value 0.000) confirming that treatment membership has a significant effect on the number of aspects listed.

ANOVA results confirm significant differences between treatments in value-decreasing, -increasing, and -neutral aspects listed.

[1] Results for total aspects listed per respondent (not significant)

Table 3. Marginal WTP ($/lb for boneless skinless chicken breast) across treatments and hypothesis tests

Hypotheses Tests	NGE	GME	LOE	MDE	HIE	LCE
$H0_1$ ($WTP^{QBC} - WTP^{QAC}) \neq 0$						
$^{b}WTP^{QBC}$	3.27	-2.19	0.69	-0.19	-0.08	0.64
$^{c}WTP^{QAC}$	3.65	-2.55	0.46	-0.14	0.20	0.78
mean difference	-0.38	-0.37	0.23	0.05	-0.12	-0.14
p-value[a]	0.251	0.135	0.216	0.428	0.167	0.225
$H0_2$ ($WTP^{QHO} - WTP^{QBC}) = 0$						
$^{d}WTP^{QHO}$	2.21	-1.79	0.21	-0.04	0.28	0.59
$^{c}WTP^{QBC}$	3.27	-2.19	0.69	-0.19	-0.08	0.64
mean difference	-1.06	-0.39	-0.48	-0.15	0.20	-0.05
p-value[a]	***0.032***	0.125	***0.057***	0.282	***0.089***	0.397
$H0_3$ ($WTP^{QHO} - WTP^{QAC}) = 0$						
$^{d}WTP^{QHO}$	2.21	-1.79	0.21	-0.04	0.28	0.59
$^{b}WTP^{QAC}$	3.65	-2.55	0.46	-0.14	0.20	0.78
mean difference	-1.44	-0.76	-0.25	-0.10	0.08	-0.19
p-value[a]	***0.005***	***0.013***	0.211	0.348	0.378	0.158

[1] p-values were estimated using the combinational method of Poe, Giraud, and Loomis (2005) with 1,000 Krinsky-Robb (1986) bootstrapped WTP estimates. The p-value reports results of the one-sided test for our hypotheses for each corresponding pair of attributes.
[2] WTP^{QBC} indicates mean WTP estimates from the baseline control
[3] WTP^{QAC} indicates mean WTP estimates from the Academic Control
[4] WTP^{QHO} indicates mean WTP estimates with honesty oath

Table 4. Hypotheses tests in WTP space ($/lb for boneless skinless chicken breast)

Hypotheses Tests	Coefficient[b]		Standard Error	p-value
H0$_1$[a] ($WTP^{QBC} - WTP^{QAC}$) ≠ 0				
nge x dtreat$_{QBC}$	-0.15		0.15	0.317
gme x dtreat$_{QBC}$	-0.12		0.10	0.230
loe x dtreat$_{QBC}$	0.07		0.10	0.463
mde x dtreat$_{QBC}$	-0.02		0.09	0.848
hie x dtreat$_{QBC}$	-0.09		0.08	0.256
lce x dtreat$_{QBC}$	-0.06		0.05	0.245
H0$_2$[a] ($WTP^{QHO} - WTP^{QBC}$) = 0				
nge x dtreat$_{QHO}$	-0.35	**	0.15	0.026
gme x dtreat$_{QHO}$	-0.15		0.10	0.143
loe x dtreat$_{QHO}$	-0.20	**	0.10	0.046
mde x dtreat$_{QHO}$	0.01		0.09	0.875
hie x dtreat$_{QHO}$	0.13		0.08	0.109
lce x dtreat$_{QHO}$	-0.01		0.06	0.921
H0$_3$[a] ($WTP^{QHO} - WTP^{QAC}$) = 0				
nge x dtreat$_{QHO}$	-0.51	***	0.15	0.001
gme x dtreat$_{QHO}$	-0.28	***	0.10	0.008
loe x dtreat$_{QHO}$	-0.12		0.10	0.206
mde x dtreat$_{QHO}$	0.00		0.08	0.970
hie x dtreat$_{QHO}$	0.04		0.08	0.616
lce x dtreat$_{QHO}$	-0.07		0.06	0.232

Notes: ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

[1] H0$_1$, H0$_2$, H0$_3$, H0$_4$, and H0$_5$ designates the effects of the treatment (dtreat) on the marginal WTP estimate.

[2] Designates the effects of the treatment (dtreat) on the marginal WTP estimate.

Table 5. Mean value-decreasing and value-increasing aspects listed per respondent by query treatment

Choice Task		Treatment			Hypothesis Tests
		QHO	QAC	QBC	
1	Decreasing	1.215	0.951	0.922	*F* = 12.796, *p-value* = 0.000
	Increasing	0.774	0.943	0.975	*F* = 7.201, *p-value* = 0.001
2	Decreasing	1.104	0.835	0.857	*F* = 13.121, *p-value* = 0.000
	Increasing	0.624	0.791	0.765	*F* = 5.050, *p-value* = 0.007
3	Decreasing	1.126	0.913	0.931	*F* = 7.895, *p-value* = 0.000
	Increasing	0.482	0.614	0.614	*F* = 4.403, *p-value* = 0.012
4	Decreasing	1.035	0.844	0.843	*F* = 6.781, *p-value* = 0.001
	Increasing	0.616	0.724	0.733	*F* = 3.165, *p-value* = 0.043
5	Decreasing	0.925	0.758	0.704	*F* = 7.977, *p-value* = 0.000
	Increasing	0.709	0.778	0.875	*F* = 5.182, *p-value* = 0.006
6	Decreasing	1.030	0.776	0.820	*F* = 10.794, *p-value* = 0.000
	Increasing	0.594	0.738	0.722	*F* = 4.408, *p-value* = 0.012
7	Decreasing	0.998	0.843	0.829	*F* = 5.190, *p-value* = 0.006
	Increasing	0.516	0.626	0.665	*F* = 4.705, *p-value* = 0.009
8	Decreasing	0.967	0.807	0.741	*F* = 8.042, *p-value* = 0.000
	Increasing	0.587	0.630	0.708	*F* = 3.110, *p-value* = 0.045

Notes: multivariate tests were all significant (*p*-value 0.000) confirming that treatment membership has a significant effect on the number of aspects listed.
ANOVA results confirm significant differences between treatments in value-decreasing, -increasing, and -neutral aspects listed.

Table 6. Standardized median rank difference (SMRD[1]) of aspect types, by choice task

Choice Task	Treatment QHO	QAC	QBC	Hypothesis Tests
1	-0.262	-0.058	-0.029	F = 8.255, *p-value* = 0.000
2	-0.349	-0.072	-0.096	F = 12.042, *p-value* = 0.000
3	-0.472	-0.274	-0.264	F = 7.668, *p-value* = 0.000
4	-0.252	-0.044	-0.062	F = 6.533, *p-value* = 0.001
5	-0.098	0.042	0.093	F = 4.719, *p-value* = 0.009
6	-0.281	-0.025	-0.056	F = 9.618, *p-value* = 0.000
7	-0.348	-0.141	-0.138	F = 7.326, *p-value* = 0.001
8	-0.278	-0.102	-0.009	F = 9.030, *p-value* = 0.000
overall	-0.271	-0.086	-0.070	F = 14.624, *p-value* = 0.000

Notes: ANOVA results indicate treatment had a significance effect on the mean SMRD at each choice task.

[1] SMRD is valued on a scale from -1 (all negative aspects) to +1 (all positive aspects)

Table 7. Multiple regression analysis for value-decreasing and value-increasing aspects listed by attribute predicting WTP values[1]

	WTPi NGE					WTPi GME				
Attribute	β		Std. Error	t	Sig.	β		Std. Error	t	Sig.
Price DEC	-0.934	***	0.054	-17.419	0.000	0.483	***	0.031	15.689	0.000
Price INC	-1.213	***	0.073	-16.516	0.000	0.643	***	0.042	15.254	0.000
GM DEC	1.296	***	0.115	11.281	0.000	-0.841	***	0.066	-12.762	0.000
GM INC	2.118	***	0.110	19.293	0.000	-1.104	***	0.063	-17.513	0.000
CO_2 DEC	-0.240		0.228	-1.055	0.292	0.142		0.131	1.091	0.276
CO_2 INC	0.477	*	0.262	1.821	0.069	-0.278	*	0.150	-1.851	0.064
Local DEC	-0.147		0.215	-0.682	0.496	0.231	*	0.124	1.871	0.062
Local INC	-0.717	***	0.128	-5.598	0.000	0.469	***	0.074	6.381	0.000
Other DEC	0.480	***	0.082	5.863	0.000	-0.227	***	0.047	-4.828	0.000
Other INC	0.651	***	0.073	8.957	0.000	-0.317	***	0.042	-7.606	0.000
Model Statistics	R Square 0.527			F 168.682	Sig. 0.000	R Square 0.491			F 146.124	Sig. 0.000

Notes: ***, **, * indicate significance at 1%, 5%, 10% level.

[1] NGE, GME and LCE have significant coefficient estimates across all preference and WTP space models and therefore are included here.

Table 7. Multiple regression analysis for value-decreasing and value-increasing aspects listed by attribute predicting WTP values[1] (Cont.)

	WTPi LCE				
Attribute	β		Std. Error	t	Sig.
Price DEC	-0.176	***	0.012	-14.379	0.000
Price INC	-0.248	***	0.017	-14.778	0.000
GM DEC	0.102	***	0.026	3.910	0.000
GM INC	0.194	***	0.025	7.740	0.000
CO_2 DEC	-0.003		0.052	-0.063	0.950
CO_2 INC	0.005		0.060	0.090	0.928
Local DEC	0.094	*	0.049	1.909	0.056
Local INC	0.286	***	0.029	9.794	0.000
Other DEC	0.080	***	0.019	4.268	0.000
Other INC	0.091	***	0.017	5.500	0.000
Model Statistics	R Square			F	Sig.
	0.361			85.643	0.000

Notes: ***, **, * indicate significance at 1%, 5%, 10% level.
[1] NGE, GME and LCE have significant coefficient estimates across all preference and WTP space models and therefore are included here.

Appendix Tables and Figures

Table A1. Examples of value-decreasing, value-increasing, and value-neutral 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 its 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. Mixed logit (MXL) models across three query treatments

Variables	Coeff.	Honesty Oath (QHO) Estimate		Standard Errors	*p*-values	Academic Control (QAC) Estimate		Standard Errors	*p*-values
Random Parameters									
NGE	μ	1.02	***	0.20	0.00	1.64	***	0.20	0.00
	σ	2.64	***	0.16	0.00	2.68	***	0.17	0.00
GME	μ	-0.83	***	0.12	0.00	-1.15	***	0.12	0.00
	σ	1.53	***	0.10	0.00	1.58	***	0.10	0.00
LOE	μ	0.09		0.10	0.37	0.21	**	0.10	0.04
	σ	0.68	***	0.14	0.00	0.79	***	0.14	0.00
MDE	μ	-0.02		0.08	0.83	-0.06		0.08	0.45
	σ	0.20	*	0.12	0.09	0.18		0.17	0.30
HIE	μ	0.13		0.08	0.11	0.09		0.09	0.34
	σ	0.64	***	0.14	0.00	0.93	***	0.15	0.00
LCE	μ	0.27	***	0.06	0.00	0.35	***	0.06	0.00
	σ	0.69	***	0.18	0.00	0.69	***	0.12	0.00
Nonrandom Parameters									
PRICE	μ	-0.46	***	0.01	0.00	-0.45	***	0.02	0.00
No-buy (NONE)	μ	-3.60	***	0.22	0.00	-3.86	***	0.24	0.00
Error Component	σ	3.08	***	0.17	0.00	3.29	***	0.19	0.00
N. parameters		30				30			
Log likelihood		-2926.91				-2987.78			
BIC		6146.50				6224.85			
BIC/N		1.50				1.53			
AIC		5913.81				6035.56			
AIC/N		1.46				1.49			
AIC3		5943.81				6065.56			
AIC3/N		1.46				1.49			

Notes: ***, **, * Significance at 1%, 5%, 10% level

Table A2. Mixed logit (MXL) models across three query treatments (Cont.)

		Baseline Control (QBC)			
Variables	Coeff.	Estimate		Standard Errors	*p*-values
Random Parameters					
NGE	μ	1.40	***	0.20	0.00
	σ	2.66	***	0.16	0.00
GME	μ	-0.94	***	0.12	0.00
	σ	1.49	***	0.11	0.00
LOE	μ	0.30	***	0.10	0.00
	σ	0.79	***	0.13	0.00
MDE	μ	-0.08		0.08	0.33
	σ	0.22		0.15	0.14
HIE	μ	-0.03		0.08	0.71
	σ	0.68	***	0.24	0.00
LCE	μ	0.27	***	0.06	0.00
	σ	0.62	***	0.23	0.01
Nonrandom Parameters					
PRICE	μ	-0.43	***	0.01	0.00
No-buy (NONE)	μ	-3.78	***	0.23	0.00
Error Component	σ	3.14	***	0.18	0.00
N. parameters		30			
Log likelihood		-2976.71			
BIC		6202.84			
BIC/N		1.52			
AIC		6013.43			
AIC/N		1.47			
AIC3		6043.43			
AIC3/N		1.48			

Notes: ***, **, * Significance at 1%, 5%, 10% level

Table A3. Mixed logit (MXL) models across three treatments without query

		Honesty Oath (QHO)			Academic Control (QAC)		
Variables	Coeff.	Estimate	Standard Errors	*p*-values	Estimate	Standard Errors	*p*-values
Random Parameters							
NGE	μ	1.24 ***	0.20	0.00	1.37 ***	0.18	0.00
	σ	2.76 ***	0.17	0.00	2.54 ***	0.16	0.00
GME	μ	-0.92 ***	0.12	0.00	-0.98 ***	0.11	0.00
	σ	1.67 ***	0.11	0.00	1.39 ***	0.11	0.00
LOE	μ	0.30 ***	0.10	0.00	0.21 **	0.10	0.03
	σ	0.85 ***	0.13	0.00	0.82 ***	0.13	0.00
MDE	μ	-0.16 *	0.08	0.05	-0.01	0.09	0.92
	σ	0.25 *	0.14	0.07	0.31 **	0.13	0.02
HIE	μ	-0.01	0.08	0.88	0.05	0.08	0.54
	σ	0.66 ***	0.18	0.00	0.83 ***	0.24	0.00
LCE	μ	0.30 ***	0.06	0.00	0.38 ***	0.05	0.00
	σ	0.75 ***	0.20	0.00	0.61 ***	0.07	0.00
Nonrandom Parameters							
PRICE	μ	-0.45 ***	0.02	0.00	-0.37 ***	0.01	0.00
No-buy (NONE)	μ	-4.74 ***	0.29	0.00	-3.79 ***	0.22	0.00
Error Component	σ	3.72 ***	0.24	0.00	3.19 ***	0.19	0.00
N. parameters		30			30		
Log likelihood		-2914.13			-3075.09		
BIC		6077.79			6399.29		
BIC/N		1.48			1.58		
AIC		5888.26			6210.17		
AIC/N		1.44			1.54		
AIC3		5918.26			6240.17		
AIC3/N		1.44			1.54		

Notes: ***, **, * Significance at 1%, 5%, 10% level

Table A3. Mixed logit (MXL) models across three treatments without query (Cont.)

Variables	Coeff.	Baseline Control (QBC)		
		Estimate	Standard Errors	*p*-values
Random Parameters				
NGE	μ	1.37 ***	0.19	0.00
	σ	2.65 ***	0.18	0.00
GME	μ	-0.82 ***	0.11	0.00
	σ	1.42 ***	0.10	0.00
LOE	μ	0.18 *	0.09	0.05
	σ	0.77 ***	0.12	0.00
MDE	μ	-0.06	0.07	0.40
	σ	0.25 *	0.14	0.07
HIE	μ	0.08	0.08	0.28
	σ	0.63 **	0.26	0.02
LCE	μ	0.25 ***	0.06	0.00
	σ	0.61 **	0.29	0.04
Nonrandom Parameters				
PRICE	μ	-0.37 ***	0.01	0.00
No-buy (NONE)	μ	-4.04 ***	0.23	0.00
Error Component	σ	3.29 ***	0.20	0.00
N. parameters			30	
Log likelihood			-3023.98	
BIC			6297.14	
BIC/N			1.56	
AIC			6107.96	
AIC/N			1.51	
AIC3			6137.96	
AIC3/N			1.52	

Notes: ***, **, * Significance at 1%, 5%, 10% level

Table A4. WTP space model estimates of mean WTP estimates ($/lb for Chicken)

Query Treatment	Coefficient		Standard Errors	*p*-value	Std. Dev.		Differences in WTP Estimates relative to: Baseline Control (QBC)	Hypothetical Control (QHC)
Honesty Oath (QHO)								
NGE	0.92	*	0.52	0.074	8.245	***	-1.66	-2.15
GME	-1.23	***	0.32	0.000	4.909	***	-0.69	-1.08
LOE	-0.31		0.29	0.294	2.295	***	-0.21	0.14
MDE	-0.18		0.26	0.500	1.372	***	-0.06	0.00
HIE	0.49	*	0.27	0.072	2.089	***	0.48	0.08
LCE	0.41	**	0.19	0.027	2.319	***	-0.05	-0.22
Academic Control (QAC)								
NGE	3.07	***	0.49	0.000	7.897	***	0.49	n/a
GME	-2.32	***	0.32	0.000	4.667	***	0.40	n/a
LOE	0.17		0.30	0.573	2.186	***	-0.35	n/a
MDE	-0.17		0.27	0.524	1.050	**	-0.06	n/a
HIE	0.40		0.27	0.139	2.126		0.40	n/a
LCE	0.63	***	0.18	0.001	2.023		0.17	n/a
Baseline Control (QBC)								
NGE	2.58	***	0.47	0.000	8.038	***	n/a	-0.49
GME	-1.92	***	0.29	0.000	4.546	***	n/a	-0.40
LOE	0.52	*	0.28	0.061	2.282	***	n/a	0.35
MDE	-0.24		0.27	0.388	0.942	*	n/a	0.06
HIE	0.01		0.25	0.975	1.528	***	n/a	-0.40
LCE	0.46	**	0.18	0.013	1.903		n/a	-0.17

Notes: ***, **, * Significance at 1%, 5%, 10% level

Table A5. Marginal WTP ($/lb for boneless skinless chicken breast) across non-query treatments and hypothesis tests

Hypotheses Tests	NGE	GME	LOE	MDE	HIE	LCE
$H0_1$ ($WTP^{BC} - WTP^{AC}$) $\neq 0$						
[b]WTP^{BC}	3.67	-2.20	0.49	-0.17	0.22	0.68
[c]WTP^{HC}	3.65	-2.62	0.55	-0.01	0.14	1.01
mean difference	0.02	-0.41	-0.06	0.16	0.08	-0.34
p-value[a]	0.481	0.129	0.436	0.303	0.396	***0.038***
$H0_2$ ($WTP^{HO} - WTP^{BC}$) $= 0$						
[d]WTP^{HO}	2.77	-2.07	0.67	-0.35	-0.03	0.66
[c]WTP^{BC}	3.67	-2.20	0.49	-0.17	0.22	0.68
mean difference	-0.90	-0.14	0.19	0.18	-0.19	-0.02
p-value[a]	***0.063***	0.344	0.279	0.252	0.171	0.454
$H0_3$ ($WTP^{HO} - WTP^{AC}$) $= 0$						
[d]WTP^{HO}	2.77	-2.07	0.67	-0.35	-0.03	0.66
[b]WTP^{HC}	3.65	-2.62	0.55	-0.01	0.14	1.01
mean difference	-0.88	-0.55	0.13	0.34	-0.11	-0.35
p-value[a]	***0.070***	***0.064***	0.346	0.124	0.269	***0.029***

[1] p-values were estimated using the combinational method of Poe, Giraud, and Loomis (2005) with 1,000 Krinsky-Robb (1986) bootstrapped WTP estimates. The p-value reports results of the one-sided test for our hypotheses for each corresponding pair of attributes.

[2] WTP^{BC} indicates mean WTP estimates from the baseline control

[3] WTP^{AC} indicates mean WTP estimates from the Academic Control

[4] WTP^{HO} indicates mean WTP estimates with honesty oath

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

Abstract

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 and a no-choice alternative (Hensher Rose and Green 2015). Conventionally, every 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 the 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; Carlsson, Kataria and Lampi 2010; Hensher 2014; Hensher and Rose 2009; Scarpa et al. 2009; Scarpa et al. 2013). Hence, accounting for the patterns of AA is essential in estimating reliable results.

Previous studies have examined the strategies used by respondents in choice experiments (Balcombe Fraser and McSorly 2015; Bello and Abdulai 2016; Erdem Campbell and Hole 2015; Hess and Hensher, 2010; Scarpa et al., 2009; Scarpa et al. 2013), and 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 uses 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 the content of these queries influences choice behavior. By

asking respondents to use a report method called *aspect-listing*, useful information is produced that can help us better understand the information processing strategies of individuals in a DCE.

Many approaches have been explored to account for AA; our study is limited to three approaches: 1) the inferred approach, 2) the stated approach, and 3) a proposed query approach. In the inferred approach, the inference of AA is accomplished 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 (Caputo Nayga and Scarpa 2013; Hensher and Greene 2010; Scarpa et al. 2009; 2013) is the equality constrained latent class method that imposes specific restrictions on the utility functions for each class of respondents by constraining some coefficients to zero for selected attribute respective classes. Hess and Hensher (2010) suggest 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 in order to identify large "signal-to-noise" ratios and thereby infer attribute non-attendance.

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 (Chalak Abiad and Balcombe 2016), which are that these data can be used directly within utility functions, or incorporated using a latent variable approach (Hess and Hensher, 2013). The latent variable structure approach was developed to avoid endogeneity issues with the direct approach. As noted by Chalak Abiad and Balcombe (2016), the latent approach depends on observable data (stated

attendance to attributes) to replace a hidden (latent) variable, implying misspecification. In our research, the stated approach was employed 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 extends 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 of the approaches best accounts for these patterns, and that overlooking the issue in choice experiments can have significant consequences for welfare estimates.

As an alternative to the two approaches discussed above, we posit that attribute processing strategies can be examined using psychological theories of choice (Hess and Hensher 2010). Specifically, we suggest that Query Theory could offer a psychological explanation for the decision heuristics used by individuals in DCEs. Furthermore, 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). It also suggests that preference construction and choice are an automatic and unconscious process of arguing with oneself (Weber and Johnson, 2011). According to the theory, people sequentially generate arguments for selecting each of the various choice options, with the first option considered having a major

advantage because arguments for the default choice option are generated first (Johnson Häubl and Keinan 2007). Accordingly, our study seeks to use Query Theory to examine respondents' attention to attributes, as well as how incorporating this information affects model structure and fit, patterns of heterogeneity, and willingness to pay measures.

The main goal of this study is to evaluate 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 two conventional approaches, i.e., inferred approach and stated approach, to the query approach, wherein we use the principles of Query Theory to account for the information processing strategies of individuals. Following Johnson, Häubl and Keinan (2007) and Weber *et al.* (2007), we use a verbal report method called "aspect listing" to obtain some indication of the aspects, i.e., thoughts, considered during each choice task of the experiment. We then use the aspect listing results to examine the attributes considered by individuals during the choice task. Specifically, our study employs a between-subjects design where respondents are randomly assigned to one of the two groups: the stated approach group, or the query approach group. The inferred approach is then applied to the estimation of the data from these two respective groups to compare all three approaches.

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 two common approaches. The remainder of this article is laid out as follows: the next section expands on Query Theory and outlines its key premises. Then, we describe the experimental design and methods including a discussion of our choice set design, experimental treatments, and econometric methods employed. This is followed by the findings of our analyses.

We conclude the article with a brief summary of our findings and a discussion around the implications of our research.

Query Theory

The four key principles of how preferences are formed according to Query Theory (QT) (Weber and Johnson 2011) are as follows: 1) people query past experience for evidence supporting different choice options; 2) these queries are executed sequentially and automatically; 3) 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 4) 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 the aspects predict valuations. Furthermore, 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 were successful in reducing people's discounting of future rewards by setting up an experiment where the decision was reframed in a way that directed attention to the delayed outcome. Even more, Kemper, Popp and Nayga (2016) provided a query account of the honesty oath in a DCE and concluded that the content and order of aspects were

significantly different in the treatment under oath, as compared to the two control groups. Additionally, they found that the content of aspects listed by individuals in the experiment predicted WTP measures.

Notably, 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. To illustrate, Johnson, Häubl and Keinan (2007) found that the content of queries predicted prices; Kemper, Popp and Nayga (2016) found that the order of queries helped explain how individuals respond to DCEs under oath and that the content of queries predict WTP values. In light of this, the premise of our study purports that the aspects listed by people should also predict AA. QT documents the cognitive mechanisms used in constructing preferences (Weber and Johnson 2006), so 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). Overall, our study examines the validity of the stated and query approaches, as well as the concordance of these approaches with inferred models using the same choice data.

Experimental Design and Methods

The data were collected through a national, web-based DCE survey built with the Sawtooth Software package (Sawtooth Software 2016) and then collected by Survey Sampling International (SSI) (SSI 2016) using their nationally representative consumer panel. The panel

consisted of 1,461 participants who were the primary grocery shoppers for their households and randomly placed into one of two treatments with approximately 500 participants per treatment. Notably, the sample from SSI is balanced by socio-demographic characteristics as well as the four main US Census regions for regional balance across the US. Furthermore, the experiment consisted of two tasks, with the first having respondents in both treatments participate 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. For the query approach group, respondents were asked during each choice task to list the things they were considering as they made their decisions. For the stated approach group, respondents were asked to report which attributes they were ignoring and/or considering during each choice task. The second task consisted of all respondents being asked a series of survey questions related to food preferences and demographic data.

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 used in our data analysis to avoid confounding effects that arise with dummy coding. Although interaction terms were not included across the design attributes in our analysis, we were still interested in estimating more than simple effects (Bech and Gyrd-Hansen 2005). 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 (USDA ERS 2015). For the genetically modified (GM) content attributes, a Non-GMO Project Verified label[1] was included and the mandatory labeling

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

style statement: “this product contains genetically engineered ingredients.” The “this product contains GM” language was chosen to measure how consumers respond to such language if it appears on products due to new federal regulations. Additionally, two more sustainability labels were included: carbon footprint[2] and local production. 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 (Bliemer and Rose 2010) obtained in two stages. The first stage was an orthogonal design (Addelman 1962) for the pilot that used 250 respondents. Next, a Multinomial Logit Model (MNL) was estimated using data from the pilot to obtain coefficient estimates to 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). All designs involved 32 choice tasks arranged in four blocks of eight tasks each.

Econometric Methodology

To examine respondents' preferences, a discrete choice framework was employed that is consistent with random utility theory (McFadden 1974), as well as 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 2005). The utility function is specified as follows:

$$(1)\ U_{ijt} = \mathrm{NONE} + \beta_1 PRICE_{ijt} + \beta_2 \mathrm{NGE}_{ijt} + \beta_3 \mathrm{GME}_{ijt} + \beta_4 \mathrm{LOE}_{ijt} + \beta_5 \mathrm{MDE}_{ijt} + \beta_6 \mathrm{HIE}_{ijt} + \beta_7 \mathrm{LCE}_{ijt} + \eta_{ijt} + \varepsilon_{ijt}$$

[2] The CO_2 levels followed those used by Van Loo, *et al.* (2014).

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) is dummy coded, taking the value 1 for the no-buy option and 0 otherwise. *PRICE* is a continuous variable represented by the four experimentally designed price levels ($2.99, $6.99, $10.99, $14.99). The non-price 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 the value 1 if the product carries the corresponding labels, the value of -1 if the absence of the label, and 0 for the no-buy option. 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, an error component, η_{ijt}, was included that is normally distributed, but with a mean of zero, inflating the variance of utility for choice options apart from the no-buy option. Furthermore, ε_{ijt} is an unobserved random term that is distributed following an extreme value type-I (Gumbel) distribution independent and identically distributed (i.i.d.) over alternatives.

In all models, the attribute parameters, including price, were assumed to be random and follow a normal distribution. However, when WTP was estimated across models for the purpose of comparison, the assumption that price has a fixed coefficient was employed when estimating Equation (1) (Layton and Brown 2000; Lusk and Schroeder 2004; Revelt and Train 1998). Notably, fixing the price coefficient ensures that the estimated WTP will be normally distributed and all respondents will have a negative price coefficient. The coefficient and variance estimates

of these WTP models are used to generate a distribution of 1,000 WTP values for the purpose of discussing the welfare implications of accounting for patterns of AA.

Treatment Descriptions

A between-subjects design was used, where respondents are assigned to only one of the two treatments. Because we target the primary household grocery consumer rather than students, our subject pool is considered non-standard (Harrison and List 2004). The first treatment represents the stated approach group where respondents were asked after each choice task to state the consideration or ignoring of each attribute. The second treatment represents the query approach group where respondents were asked to list their thoughts during each choice task.

Modeling Attendance to Attributes

In choice experiments, some respondents may not attend to certain attributes, which is further outlined by Hensher, Rose and Green (2005) who argued that if a respondent ignores an attribute in a choice task, then the coefficient for the attribute should be zero in the utility function. Accordingly, in all of our models conditioned for AA, a zero restrictions was imposed on the utility parameters, βs, in Equation (1) for individuals not attending to (ignoring) attributes. Additionally, models can be estimated at the serial level, or the choice task level. Scarpa, Thiene and Hensher (2010) noted that the individual processing strategies of respondents 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 non-attendance (ANA) to vary from one choice task to another. However, when inferring AA, Mariel, Hoyos and Meyerhoff (2013) noted that at the choice-task level, the inferred approach to identifying patterns of AA did not correctly predict the true patterns, as defined by a generated hypothetical

dataset. Therefore, when the Stated and Query Approaches were taken in our study, the models were estimated at the serial level[3] and the choice task level. Notably, when these data were analyzed using the inferred approach, only the serial level models were estimated. Additionally, when the individual level concordance is compared with the inferred approach and the stated and query approaches, this comparison is carried out at the serial level (table 2).

Inferred Approach

To identify patterns of AA, the procedures proposed by Hess and Hensher (2010) were followed using MXL models. Similar to Scarpa *et al.* (2013), error components were also included. This method is based on the coefficient of variation of individual specific posterior means and variances. It is assumed that respondent *n* has a normally distributed coefficient for attribute *k*, then $\beta kn \sim N(\mu_{kn}, \sigma^2_{kn})$, where μ_{kn} is the estimated mean and σ^2_{kn} is the variance. The coefficient of variation (*CV*) $\kappa_{kn} = \sigma_{kn}/\mu_{kn}$ is then interpreted as the "noise-to-signal" ratio on the variation relating to taste intensity for attribute *k*, as evidenced by the individual's responses in the choice tasks (Scarpa et al. 2013). If the noise-to-signal ratio is high, then the individual's normal distribution is considered to be over-dispersed and the pattern of choice is consistent with the respondent not attending to attribute *k* in their choices. Hess and Hensher (2010) used the *CV* value of two, so that respondent *n* is considered as not attending to attribute *k* if their estimated value of κ_{kn} greater than 2. The choice of using the *CV* value of two is based on the observation that normal distributions with ratios higher than two are over-dispersed (Scarpa et al. 2013)[4]. The

[3] To simulate serial level stated data, we aggregate responses such that attendance to any attribute during at least one choice task is equivalent to attendance to the respective attribute throughout the entire experiment.

[4] The selection of a *CV* value of 2 is somewhat arbitrary; however, the choice is made here to remain consistent with previous literature because the inferred approach is included here in order to provide a benchmark for comparison to the stated and query approaches.

sample proportion of AA is then obtained by aggregating these values. By adopting this value we have established a baseline with which to compare our other approaches, although the proper value of *CV* for the purpose of inferring AA is debatable. Table 2 reports the percent of respondents attending attributes (AA) in both the query and stated approach treatments.

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.” In our stated approach model estimated at the serial level, the individual’s AA was not allowed to vary across choice tasks. Notably, a report of attendance of an attribute in any of the eight choice tasks was considered as attendance to the attribute in all eight choice tasks. In our stated approach model estimated at the choice task level, attendance was allowed to vary across the eight tasks. Consequently, the self-reported data were used as indicated after each choice task. The distribution of AA with the stated approach at the serial and choice-task levels is reported in table 2. Importantly, the decision of whether to assume a serial or choice-task level of behavior of respondents has important implications, as the results demonstrate based on the differences in the percentage of observations attended to by respondents.

Query Approach

To obtain information on the aspects considered during each choice task of the experiment, a verbal report method called an *aspect listing* was used, following Johnson, Häubl and Keinan

(2007) and Weber *et al.* (2007). Respondents were asked to list what they were thinking as they made decisions. 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. This process provided 24 total opportunities for each respondent to list their thoughts during the experiment[5]. Notably, the aspects listed are an approximation of the thoughts that actually occur as the respondents made decisions, particularly given that the queries themselves may be automatic and difficult to observe directly (Johnson Häubl and Keinan 2007). Specifically, the 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.

Other QT studies (Johnson Häubl and Keinan 2007; Weber et al. 2007) 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, the individual responses were coded by us[6]. Additionally, the aspect listing task was left more open and allowed for any comments regarding the individual's decision to be entered[7]. Completion time grew by nine minutes on average (from 10 to 19 minutes) when aspect-listing task was requested; while the task of manually coding responses from 500 respondents who provided up to three responses per task across eight choice tasks (over 12,000 opportunities to enter text in total) required a great

[5] 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 therefore we could be underreporting the number of aspects considered by some respondents.
[6] Johnson, Häubl and Keinan (2007) note that aspects coded by novice raters produce similar results in their experiments.
[7] 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. We tested multiple software programs and found that it took more time to learn the software and check for and correct errors than to manually hand code the data.

deal of time. Aspect responses were coded by the attributes used in the study (price, gm content, carbon footprint, location), or by “other” in cases where responses listed aspects not related to the attributes of our study, such as “I don’t like white meat” or “prefer all-natural.” Table 2 summarizes the distribution of AA in the query group alongside the inferred and stated approaches. As shown, price is estimated to be ignored between six and 33% of the time using the serial query and choice task query approaches, respectively. 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 attribute was attended by that individual. It is acknowledged that by adopting this decision rule, in effect, it should also be assumed that attributes not mentioned by individuals are not being attended to. This approach is conservative for attribute attendance, one we consider “*attendance to attributes with certainty*” in that the aspects listing task provides some confidence in which attributes are being considered by individuals in our DCE. However, it is not known whether the attributes not mentioned are being ignored. Because of the problems associated with relying on the stated “ignoring” of attributes and inferred methods, this conservative strategy was used of focusing on AA with certainty and comparing the performance of this approach with the stated and inferred methods. In using the query approach, if a respondent mentions an attribute, it was assumed that the person derives either positive or negative utility from the attribute mentioned. If a respondent does not attend an attribute, the coefficient was restricted to zero, thereby removing it from the choice set[8]. To test the robustness of our results, this restriction was relaxed in a

[8] We cannot assume to know why the respondent did not mention the attribute that we remove; we do not know if they do not care about the attribute or if the choice task was too complex. Respondents may not understand some attribute levels. We observed numerous comments in our aspect listing tasks from respondents who did not understand our carbon footprint attribute.

subsequent analysis described below. If a person truly ignored an attribute, no assumptions can be made about the utility they derive from the ignored attribute. The attributes that are mentioned in the aspects listing task were the main point of focus, wherein there is a high level of certainty that these attributes were considered by respondents while they were querying their memory to make a decision. This approach was taken because the true reason our respondents ignored attributes is unknown.

Contrastingly, with the stated approach, respondents indicated both considered and ignored attributes, whereas with the query approach, the “ignoring” information was not collected directly. Nevertheless, the reliability of the stated approach could be questioned because it 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. 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 likely leads to underreporting of AA, this smaller amount of data gained from our query approach is more reliable and can be used with a high level of certainty.

Validity of Attendance to Attributes

To test the validity of using our three approaches to identify patterns of AA and the robustness of our results, six additional models were estimated, where the coefficients (β) of attributes not attended to are not restricted to zero in Equation (1). Although a person may report that they have ignored an attribute, they may still have a marginal utility for that attribute that differs from zero (Carlsson Kataria and Lampi 2010). Likewise, with the query data, if a respondent does not mention an attribute, this may actually indicate low attendance to the attribute, rather than

necessarily indicating that the attribute was ignored. To accommodate this reality, researchers have estimated models with two coefficients for each attribute (Hess and Hensher 2010; Scarpa et al. 2013). 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 attend to or do not attend to attributes (NA). Notably, comparing the coefficient estimates across these models provides a clearer understanding of the validity of our approaches in distinguishing true patterns of AA from heterogeneity.

Results

This study incorporated 978 respondents in the two treatments, with each respondent completing eight choice tasks with three choices or alternatives per set, for a total number of 23,472 observations. We also tested if there were differences in socio-demographic profiles across treatments using a chi-square test. The results show no significant differences in observable characteristics across treatments, which suggests that our randomization was successful in providing a balanced sample across the treatments[9]. We estimated Equation (1) using a 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. Subsequently, estimations were conducted using NLOGIT 5 with 1,000 Halton draws to provide more accurate simulation for the random parameters (Train 2009)[10].

[9] Demographic characteristics of the samples can be obtained from the authors upon request.
[10] Following Hensher and Greene (2003) all MXL models were estimated using 25, 50, 150, 250, 500, 1,000 and 2,000 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 and thus we adopted this for all of the models presented here.

In our results, we contrasted the performance of the inferred and stated approaches in identifying patterns of AA with that of the query approach. Our assertion is that the query approach provides the most reliable estimates of AA patterns; therefore, we can compare the results of the other two approaches to the query approach to evaluate the performance of these approaches. Similar to Hess and Hensher (2013), we compared the three approaches based on: 1) the rates of AA between the various models (concordance), 2) differences in model fit between models, and 3) the heterogeneity patterns for individual coefficients. We also discussed the implications of our findings on the estimation of WTP; however, as noted by Hess and Hensher (2013), the computation of WTP is complicated in the presence of non-attended attributes, particularly when price is one of the attributes involved. Accordingly, we focused on the above measures and provide only a brief discussion of the WTP estimations.

Stated Approach Models

We define concordance as the agreement between the inferred and the stated approaches in identifying the same individual as attending to an attribute. The results of the four models using data from the stated approach treatment are presented in table 3 and discussed here. We abbreviated the respective models using the following notation: SAB refers to the baseline model, SAI refers to the model where the inferred approach was used, SAS is the stated approach model at the serial level, and SAT is the stated approach model at the choice task level. The highest level of "agreement" between the stated approach models (SAI and SAS in Table 3) is for the price attribute, where the two approaches were in line on the classification of 80% of the same respondents. This result was expected given the importance of price to consumers. Less agreement was found for the other attributes of the study, with around 69% agreement with the GM content attribute, 52% with carbon footprint, and 67% with the local production attribute.

The largest discrepancy here relates to the carbon footprint attribute. As shown in table 2, the inferred approach identifies only about 21% of respondents as attending to carbon footprint, while the stated approach signals between 55 and 75% of respondents attending to this attribute—based on the choice task and serial level models, respectively. This result indicates that the stated approach data may be overestimating attendance to the carbon footprint attribute.

Next, we compared the model fit of the four models presented in Table 4. All four models were developed using the stated approach treatment data. 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 4. The model with the greatest improvement with respect to the baseline is the SAI with a BIC/N of 1.34 and AIC/N of 1.29. The SAS model offers only minor improvements based on these criteria, while the SAT model offers more substantial improvements with a BIC/N of 1.45 and AIC/N of 1.39. These results are in line with previous studies where accounting for AA improved model fit (Campbell Hutchinson and Scarpa 2008; Hensher Rose and Greene 2005).

Moving from the baseline model (SAB) to the inferred approach with the stated treatment data (SAI), we observed that all coefficients increase in magnitude with the most substantial rise in the low and high carbon footprint attribute levels. Considering carbon footprint had the lowest inferred AA, these mixed results are not surprising. In terms of coefficient estimates, moving from the baseline to the stated approach at the serial level (SAS), we saw similar improvements as in the inferred (SAI) model (table 4); however, increases in our coefficients were not of the same magnitude as before. Using SAS resulted in an increase in the estimated number of individuals attending to all attributes in the experiment. With fewer individuals to "remove," due

to not attending, it is not surprising to see more modest changes to the size of coefficients. Finally, we examine changes when moving from the baseline model (SAB) to the choice-task level model using the stated approach (SAT). These results indicate that all coefficients again increase in magnitude using the stated approach at the choice-task level, with the most substantial increases in three carbon footprint attribute levels. We also note that all coefficients in our SAT model are significant and have the expected signs.

Finally, we compared the stated approach models in terms of patterns of heterogeneity. We observed a decrease in heterogeneity (*CV*) when moving from the base to the SAI model for all coefficients in the model. This finding indicates that what was previously captured as heterogeneity is now accommodated by our model conditioned for AA using the inferred approach. The SAS model with serial-level stated approach data also shows substantial decreases in heterogeneity, with a lower (absolute) value of *CV* for all attributes, as compared to the base. Finally, the heterogeneity patterns for the SAT model indicate that the *CV* for price remained the same, while all other measures decreased.

Query Approach Models

Using the proposed query approach, AA is based on the direct observations of attributes attended to with certainty, as these represent the aspects listed by respondents. This approach differs from the stated approach, where respondents indicate both considered and ignored attributes. Additionally, we noted possible issues with the reliability of the stated approach because it forces respondents to ponder the attributes they are ignoring. As with the stated approach results, we present the results of four models from our query treatment in table 4. The respective models were abbreviated using the following notation: QAB refers to the baseline model, QAI refers to the model where we used the inferred approach, QAS is the query approach model at the serial

level, and QAT is the query approach model at the choice-task level. Concordance results (agreement between the inferred and the query approaches in identifying the same individual as attending to an attribute) indicate that the highest level of "agreement" between the query approach models (QAI and QAS in table 3) is for the price attribute with 87% of the same respondents identified as attending price across these two models. We also found a 59% agreement between the QAI and QAS models for the GM content attribute, 72% for carbon footprint, and 53% for local production.

Next, we compared the model fit of the four models presented in table 5, using measures of estimation criteria that focus on the BIC/N and AIC/N. The QAI (inferred) and QAT (query choice task) models experienced similar model improvements with respect to the baseline. While the QAS also shows model improvements, they are not as substantial. In terms of coefficient estimates, we observed that all coefficients increase in magnitude, in moving from the baseline model (QAB) to the inferred model (QAI). Moving from the baseline to the query approach at the serial level (QAS), improvements occurred, but the increases in our coefficients were not of the same magnitude as with the inferred approach. When moving from the baseline model (QAB) to the choice-task level model using the query approach (QAT), all coefficients increased in magnitude with substantial increases observed in the medium and high carbon footprints and the local production attribute.

Finally, we 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 QAI model for all coefficients of medium carbon footprint and local production (table 5). We also observed a decrease in heterogeneity when moving from the base to the QAS model for all coefficients of attributes, indicating the ability of the query approach at the serial level to accurately distinguish

patterns of AA and heterogeneity in our data. The heterogeneity patterns for the QAT model indicate that the *CV* for all attributes decreased, as compared to the baseline model. These results suggest that the query approach at the choice task level (QAT) is a reliable means of addressing AA in our data.

Validity of Modeling Approaches

To test the validity of using these three approaches to identify patterns of AA, we estimated Equation (1) without restricting the coefficients (β) of attributes where respondents are not attending attributes to zero. 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 again estimated models using the stated and query approaches at the serial and task level. Comparing across these models provided a clearer understanding of the validity of our approaches in identifying true patterns of AA. In the interest of brevity, the full results of these models can be obtained from authors upon request. We limited our presentation of results to the patterns of heterogeneity for both sets of coefficients, as a key indicator of how effective each approach is at identifying true AA.

Table 6 summarizes the heterogeneity patterns for the dual coefficient models. The "AA" columns in table 6 refer to coefficients where respondents are considered to be attending to attributes, while the "NA" columns refer to coefficients where attendance to attributes is uncertain. Additionally, we used the noise-to-signal ratio criteria (*CV*>2) to evaluate the effectiveness of each approach in identifying AA. Based on this criteria, we expected the AA attributes to have CVs of less than two and NA attributes to have CVs of greater than two. Only when both of these conditions are met do we consider the approach as effective at identifying patterns of AA for the attribute. When both CV criteria are met for an attribute under one of our

approaches, we note this using the symbol "ǂ". As shown in table 6, of the three stated approach models, the inferred approach (SAI) is the most effective at identifying patterns of AA based on the patterns of heterogeneity. Notably, three attributes in the SAI model met the noise-to-signal ratio criteria: price, low carbon, and medium carbon. The stated approach at the serial level (SAS) only met the criteria for the price attribute. The remaining six attributes had CVs of less than two, which indicates that some of what respondents reported as the ignoring of attributes using the stated approach, is actually low attendance to attributes.

As for the query approach models with dual coefficients, the results reveal that the QAS is the top performer, in using our noise-to-signal ratio criteria. The heterogeneity patterns for this model indicate that 6 of the 7 AA and NA attributes' CVs meet the criteria; the only exception is the medium carbon footprint attribute where the CVs for the AA and NA coefficients are close to meeting the criteria as well. The query data at the choice-task level (QAT) on the surface appears to also perform well, with five attributes meeting the criteria; however, the price coefficient does not meet the CV criteria, which is concerning and indicates that the query approach at the choice task level may be underreporting AA to the price attribute.

Implications for Willingness to Pay

We estimated model (1) again, but this time we held the price coefficient constant in order to facilitate the estimation of WTP. Fixing the price coefficient ensures that the estimated WTP will be normally distributed and all respondents will have a negative price coefficient. We then calculated the WTP based on the average coefficient estimates from the AA models only, rather than the models with two coefficients. The negative values in table 7 can be thought of as WTP to avoid the attribute in question. Looking first at the stated treatment models, all three AA approaches increased the magnitude of the WTP estimates. The serial approach (SAI) appears to

be associated generally with the highest WTP values across all attributes (in absolute value); WTP values for the non-GM attribute level, for instance, range from $3.98/lb for the base, up to $6.38/lb in the SAI. Of the two models where the stated approach was applied (SAS and SAT), the choice- task level model resulted in larger WTP values across all attributes. The SAT model also provided the only stated-treatment model with significant WTP estimates for all attributes. We examined these differences in WTP not to identify a "best" approach, but rather to discuss the ramifications of how the modeling approach in accounting for AA can affect welfare measures, which are usually an important outcome of DCEs.

The query treatment models at the bottom of table 7 reveal similar results to the stated treatment models, but there are some important differences. All three models adjusted for AA result in larger absolute value WTP values across all attributes, although not all WTP values are significant. Because our models increased the magnitude of coefficient estimates for all the non-price attributes, the increases in WTP were expected. Notably, the highest WTP estimates were found using the query approach at the choice task level (QAT), which are substantially higher than for the baseline model. For instance, the non-GM attribute is $7.00/lb, as compared to $3.22/lb in the base; while the attribute for local was $0.63/lb in the base and jumps to $4.79/lb in the QAT model. Importantly, the QAT model provides significant WTP estimates for all attributes; however, these large WTP estimates likely indicate that the query approach at the choice- task level understates respondents' true attendance to attributes.

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. Our study uses Query Theory to examine the thought processes of individuals in a DCE by asking respondents to use a report method called *aspect-listing*. We implemented the *aspect-listing* task by allowing individuals to report any thought that was 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, as compared to the other common approaches presented in this article—the stated and inferred approaches. 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. Nevertheless, our results appear to support the conclusion that aspects listed indeed represent patterns of attendance.

Our comparison across the three approaches highlights the challenges faced by researchers in identifying AA, as well as the difficulties that arise in properly modeling the phenomenon. Notably, Hess and Hensher (2010) question the accuracy of the attributes being reported as attended to in studies using the stated approach. The results of our validity tests (using the dual coefficient models) 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 models' coefficients indicate that some individuals stating they are ignoring attributes are actually not ignoring the 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 a relatively high level of certainty of attendance to attributes; our results support this conclusion. Importantly, this conclusion is based on the assumption that when respondents

mention attributes, they are attending to these attributes. While our approach represents a conservative one in identifying AA, we do not argue that it is a flawless one capable of producing absolute predictions.

Our results show that the inferred, stated, and query approaches all improve model fit statistics; however, in terms of the improvement to model coefficients, the query approach outperforms both the inferred and stated approaches by returning coefficients for attributes with patterns of heterogeneity (*CV*) that indicate the query approach has effectively identified patterns of AA (table 5). The query approach at the serial level (QAS) appears to do a better job than the approach at the choice task level (QAT). Additionally, the stated approach at both the serial and choice-task levels (SAS and SAT) also appear to do an effective job at identifying patterns of AA; however, the CVs listed in tables 4 and 5 indicate that the query approach models outperformed the stated approach models in this regard.

The heterogeneity estimates from our dual coefficients models offer perhaps the strongest support for the use of the query approach to attribute attendance with certainty (table 6). When we relax the assumption that an individual's AA is "all or nothing", we then see more clearly how reliable our methods are in identifying patterns of AA. Our query approach at the serial level (QAS) outperformed the stated approach at both the serial and choice-task levels (SAS and SAT). Our findings are in support of our assertion that the query approach represents attendance to attributes with certainty. Our results also demonstrate that while the stated approach does improve model performance, the approach may still suffer from the misrepresentation of true patterns of AA due to the confounding of attributes truly ignored and those to which low attention is given. The stated approach may therefore be more likely to produce misleading results.

Although the query approach has an advantage in returning reliable patterns of AA with certainty, the inferred and stated approaches have an advantage over the query approach in terms of ease of use. The stated approach questions are easy to implement in an online setting such as ours, although questions still remain as to how to properly ask the questions and how to interpret responses. Furthermore, the query approach is time consuming, requiring additional steps to collect and synthesize text responses to open- ended questions, thereby potentially opening up new sources of error due to researcher bias and data entry errors. Hence, the costs associated with the query approach relative to the other approaches are high. The query approach may lower respondent bias compared to the stated approach because individuals are not involved in the classification of their own responses in the query approach. Even more, the stated approach asks respondents to respond to a question regarding what attributes they ignored, and so the question remains as to whether one can really be confident about the respondent's ability to observe what he/she has ignored. Moreover, there is also the question of how a respondent can respond to the ignored question in a choice task without biasing his/her responses on the other choice tasks that follow. The query approach may not be free from bias, but the aspect-listing task is open and allows for 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 in that it may allow for a more accurate representation of the thoughts considered in a decision. One of the major implications is that there is no "one-size-fits-all" approach for modeling AA. Attributes have different meanings for individuals and carry varying affective values; how important these values are to the decision being made influences what we would define as AA.

Perhaps our most important limitation is how we conducted our aspect-listing task. We did not force people in our experiment to list aspects for each attribute, or to provide more than one response per choice task. Leaving this out could lead to underreporting, although our query approach generally provided more reliable results. Much remains to be learned about how to gather the aspects data and how to classify aspects in an experiment such as ours. In future experiments, it would be worthwhile to decrease the complexity of the experiment in order to allow individuals to offer more detailed responses on a greater number of aspects. It would be interesting to observe if 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 2016; Van Loo et al. 2016) 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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Tables and Figures

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
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
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
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

Table 2. Distribution of Attendance to Attributes across Approaches

Attributes		Stated Approach: Serial Inferred (SAI)	Stated Approach: Serial Stated (SAS)	Stated Approach: Choice Task Stated (SAT)	Query Approach: Serial Inferred (QAI)	Query Approach: Serial Query (QAS)	Query Approach: Choice Task Query (QAT)
	no. obs.	4040	4040	4040	3784	3784	3784
Price	no.	3408	3800	3411	3568	3152	2543
	percent	*84.4%*	*94.1%*	*84.4%*	*94.3%*	*83.3%*	*67.2%*
GM Content	no.	2352	3528	2753	2368	1880	976
	percent	*58.2%*	*87.3%*	*68.1%*	*62.6%*	*49.7%*	*25.8%*
Carbon Footprint	no.	832	3016	2197	1032	720	347
	percent	*20.6%*	*74.7%*	*54.4%*	*27.3%*	*19.0%*	*9.2%*
Local	no.	2768	3360	2503	2016	1296	571
	percent	*68.5%*	*83.2%*	*62.0%*	*53.3%*	*34.2%*	*15.1%*

Table 3. Concordance between Serial Level Models

Attributes	Concordance	**Stated Approach** Agreement between SAI and SAS	**Query Approach** Agreement between QAI and QAS
Price	no. agree	404	409
	percent agree	*80.0%*	*86.5%*
GM Content	no. agree	347	278
	percent agree	*68.7%*	*58.8%*
Carbon Footprint	no. agree	262	342
	percent agree	*51.9%*	*72.3%*
Local	no. agree	339	251
	percent agree	*67.1%*	*53.1%*

note: inferred approach is only carried out at the serial level, therefore concordance with the stated and query approaches is at serial level only.

Table 4. Stated Approach Data Models using Three Approaches for Attributes Attended (AA)

		Stated Base (SAB) Baseline			Serial Inferred (SAI) Stated Data			Serial Stated (SAS) Stated Data			Choice Task Stated (SAT) Stated Data		
Variables	Coeff.	Estimate		S.E.	Estimate		S.E.	Estimate		S.E.	Estimate		S.E.
PRICE	μ	-0.40	***	0.03	-0.52	***	0.02	-0.46	***	0.03	-0.44	***	0.03
	σ	0.40	***	0.03	0.35	***	0.02	0.41	***	0.03	0.43	***	0.03
NON-GM (NGE)	μ	1.27	***	0.15	2.95	***	0.16	1.71	***	0.15	2.06	***	0.15
	σ	1.72	***	0.14	1.82	***	0.16	1.75	***	0.14	1.98	***	0.16
GM (GME)	μ	-0.74	***	0.10	-1.79	***	0.12	-1.00	***	0.10	-1.06	***	0.10
	σ	1.02	***	0.10	1.23	***	0.13	1.13	***	0.10	1.16	***	0.11
LOWCO2 (LOE)	μ	0.22	**	0.09	1.22	***	0.24	0.34	***	0.11	0.55	***	0.11
	σ	0.29	*	0.15	0.70	**	0.32	0.43	***	0.16	0.48	***	0.18
MEDIUMCO2 (MDE)	μ	0.06		0.09	0.33		0.23	0.13		0.11	0.22	*	0.12
	σ	0.22		0.16	0.46		0.34	0.30	*	0.16	0.48	***	0.17
HIGHCO2 (HIE)	μ	-0.03		0.08	-1.07	***	0.27	-0.15		0.10	-0.26	**	0.12
	σ	0.43	***	0.17	1.18	***	0.40	0.65	**	0.25	0.73	**	0.31
LOCAL (LCE)	μ	0.27	***	0.05	0.57	***	0.06	0.36	***	0.06	0.54	***	0.07
	σ	0.37		0.25	0.32		0.42	0.45	*	0.23	0.60	***	0.21
No-buy (NONE)		-5.76	***	0.35	-5.99	***	0.27	-6.08	***	0.33	-6.00	***	0.32
Error Component	σ	3.64	***	0.32	3.03	***	0.26	3.75	***	0.30	4.06	***	0.30
Model Fit Measures													
Obs.		4040			4040			4040			4040		
Log likelihood		-2684.23			-2559.88			-2852.75			-2766.67		
BIC		5673.28			5427.00			6012.74			5840.59		
BIC/N		1.50			1.34			1.49			1.45		
AIC		5442.46			5193.75			5779.49			5607.34		
AIC/N		1.44			1.29			1.43			1.39		
AIC3		5479.46			5230.75			5816.49			5644.34		
AIC3/N		1.45			1.29			1.44			1.40		

***, **, * Significance at 1%, 5%, 10% level

Table 4. Stated Approach Data Models using Three Approaches for Attributes Attended (AA) (Cont.)

		Stated Base (SAB)	**Serial Inferred (SAI)**	**Serial Stated (SAS)**	**Choice Task Stated (SAT)**
		Baseline	Stated Data	Stated Data	Stated Data
Patterns of Heterogeneity					
PRICE	*cv*	-0.98	-0.67	-0.89	-0.99
NON-GM (NGE)	*cv*	1.36	0.62	1.02	0.96
GM (GME)	*cv*	-1.37	-0.69	-1.13	-1.09
LOWCO2 (LOE)	*cv*	1.34	0.57	1.26	0.87
MEDIUMCO2 (MDE)	*cv*	3.68	1.38	2.23	2.23
HIGHCO2 (HIE)	*cv*	-12.95	-1.10	-4.43	-2.77
LOCAL (LCE)	*cv*	0.63	0.49	0.56	0.75

***, **, * Significance at 1%, 5%, 10% level

Table 5. Query Approach Data Models using Three Approaches for Attributes Attended (AA)

		Query Base (QAB) Baseline			**Serial Inferred (QAI)** Query Data			**Serial Query (QAS)** Query Data			**Choice Task Query (QAT)** Query Data		
Variables	Coeff.	Estimate		S.E.	Estimate		S.E.	Estimate		S.E.	Estimate		S.E.
PRICE	μ	-0.53	***	0.03	-0.61	***	0.02	-0.57	***	0.03	-0.46	***	0.02
	σ	0.35	***	0.03	0.31	***	0.03	0.34	***	0.03	0.26	***	0.02
NON-GM (NGE)	μ	1.44	***	0.21	3.43	***	0.29	2.33	***	0.27	3.25	***	0.19
	σ	2.67	***	0.18	3.44	***	0.23	2.84	***	0.30	3.58	***	0.30
GM (GME)	μ	-1.02	***	0.13	-2.42	***	0.21	-1.75	***	0.19	-2.08	***	0.19
	σ	1.49	***	0.13	2.31	***	0.24	1.79	***	0.24	2.50	***	0.29
LOWCO2 (LOE)	μ	0.31	***	0.12	0.86	***	0.30	0.96	***	0.33	2.21	***	0.31
	σ	0.74	***	0.15	1.32	***	0.44	0.90	**	0.46	0.83	*	0.49
MEDIUMCO2 (MDE)	μ	-0.05		0.10	-0.07		0.30	0.16		0.26	0.62	*	0.36
	σ	0.14		0.21	0.39		0.39	0.29		0.57	1.32	***	0.49
HIGHCO2 (HIE)	μ	-0.10		0.08	-0.76	***	0.28	-0.81	***	0.27	-2.06	***	0.40
	σ	0.52	***	0.17	1.21	**	0.47	0.97	*	0.50	2.28	***	0.57
LOCAL (LCE)	μ	0.26	***	0.06	0.69	***	0.09	0.40	***	0.10	2.23	***	0.18
	σ	0.54	***	0.09	0.57	***	0.16	0.34		0.37	1.70	***	0.21
No-buy (NONE)		-4.98	***	0.27	-5.12	***	0.21	-4.69	***	0.23	-3.83	***	0.23
Error Component	σ	2.60	***	0.24	2.19	***	0.20	3.04	***	0.23	3.23	***	0.16
Model Fit Measures													
Obs.		3784			3784			3784			3784		
Log likelihood		-2684.23			-2421.10			-2631.29			-2490.66		
BIC		5673.28			5147.02			5567.41			5286.15		
BIC/N		1.50			1.36			1.47			1.40		
AIC		5442.46			4916.19			5336.59			5055.32		
AIC/N		1.47			1.30			1.41			1.34		
AIC3		5479.46			4953.19			5373.59			5092.32		
AIC3/N		1.45			1.31			1.42			1.35		

***, **, * Significance at 1%, 5%, 10% level

Table 5. Query Approach Data Models using Three Approaches for Attributes Attended (AA) (Cont.)

		Query Base (QAB) Baseline	**Serial Inferred (QAI)** Query Data	**Serial Query (QAS)** Query Data	**Choice Task Query (QAT)** Query Data
Patterns of Heterogeneity					
PRICE	*cv*	-0.67	-0.51	-0.60	-0.56
NON-GM (NGE)	*cv*	1.85	1.00	1.22	1.10
GM (GME)	*cv*	-1.46	-0.95	-1.03	-1.20
LOWCO2 (LOE)	*cv*	2.40	1.53	0.95	0.38
MEDIUMCO2 (MDE)	*cv*	-2.77	-5.36	1.86	2.15
HIGHCO2 (HIE)	*cv*	-5.05	-1.59	-1.19	-1.11
LOCAL (LCE)	*cv*	0.51	0.57	0.41	0.98

***, **, * Significance at 1%, 5%, 10% level

Table 6. Heterogeneity Patterns for Dual Coefficients Models

Variables		Serial Inferred (SAI)			Serial Stated (SAS)			Choice Task Stated (SAT)		
		AA	NA		AA	NA		AA	NA	
PRICE	*cv*	-0.65	2.82	ǂ	-0.94	-3.76	ǂ	-0.90	-2.23	ǂ
NON-GM (NGE)	*cv*	0.59	-1.58		1.16	-0.36		0.99	-1.40	
GM (GME)	*cv*	-0.60	0.99		-1.27	0.35		-1.14	3.86	ǂ
LOWCO2 (LOE)	*cv*	0.56	22.46	ǂ	1.49	-1.28		0.99	-2.71	ǂ
MEDIUMCO2 (MDE)	*cv*	1.35	-30.51	ǂ	2.02	-1.44		2.81	-3.27	
HIGHCO2 (HIE)	*cv*	-1.00	1.39		-4.26	0.79		-2.44	1.55	
LOCAL (LCE)	*cv*	0.50	-0.33		1.27	-1.23		1.14	-1.68	

Table 6. Heterogeneity Patterns for Dual Coefficients Models (Cont.)

Variables		Serial Inferred (QAI)			Serial Query (QAS)			Choice Task Query (QAT)		
		AA	NA		AA	NA		AA	NA	
PRICE	*cv*	-0.60	1.20		-0.45	8.18	ǂ	-0.37	-1.73	
NON-GM (NGE)	*cv*	0.94	-1.43		1.34	2.98	ǂ	1.18	2.51	ǂ
GM (GME)	*cv*	-0.93	1.12		-1.11	-2.89	ǂ	-1.30	-2.23	ǂ
LOWCO2 (LOE)	*cv*	1.45	11.87	ǂ	0.89	7.91	ǂ	0.98	4.98	ǂ
MEDIUMCO2 (MDE)	*cv*	7.02	35.15	ǂ	2.32	-4.10		1.07	-7.74	ǂ
HIGHCO2 (HIE)	*cv*	-1.99	10.65	ǂ	-1.35	7.26	ǂ	-1.21	108.58	ǂ
LOCAL (LCE)	*cv*	0.86	-1.16		0.86	5.49	ǂ	0.79	24.85	

ǂ indicates that both AA and NA coefficient of variations (CVs) meet the noise-to-signal criteria of CV<2 for AA and CV>2 for NA

Table 7. Marginal WTP ($/lb for Boneless Skinless Chicken Breast) Across Treatments

	NON-GM (NGE)	GM (GME)	LOW CO2 (LOE)	MEDIUM CO2 (MDE)	HIGH CO2 (HIE)	LOCAL (LCE)
Stated Base (SAB)	3.98 ***	-2.21 ***	0.77 ***	0.01	0.08	0.94 ***
Serial Inferred (SAI)	6.38 ***	-3.71 ***	2.54 ***	0.76	-2.55 ***	1.50 ***
Serial Stated (SAS)	4.76 ***	-2.61 ***	1.11 ***	0.22	-0.23	1.12 ***
Choice Task Stated (SAT)	5.76 ***	-2.82 ***	1.66 ***	0.53 **	-0.52 *	1.71 ***
Query Base (QAB)	3.22 ***	-2.17 ***	0.67 ***	-0.18	-0.06	0.63 ***
Serial Inferred (QAI)	5.54 ***	-3.67 ***	1.07 **	-0.27	-0.48	1.28 ***
Serial Query (QAS)	4.07 ***	-3.05 ***	1.67 ***	0.27	-1.42 ***	0.70 ***
Choice Task Query (QAT)	7.00 ***	-4.47 ***	4.76 ***	1.33 *	-4.42 ***	4.79 ***

***, **, * Significance at 1%, 5%, 10% level

Appendices

Appendix 1

Table A1. Stated Approach Mixed Logit (MXL) Models with dual Coefficients for Attributes Attended (AA) and Not Attended (NA)

		Serial Inferred (SAI)						**Serial Stated (SAS)**				
		Attended (AA)			Not Attended (NA)			Attending (AA)			Not Attended (NA)	
Variables	Coeff.	Estimate		S.E.	Estimate		S.E.	Estimate		S.E.	Estimate	S.E.
PRICE	μ	-0.49	***	0.03	0.11		0.17	-0.42	***	0.03	-0.05	0.08
	σ	0.32	***	0.03	0.32	***	0.07	0.40	***	0.03	0.19	0.28
NON-GM (NGE)	μ	2.77	***	0.20	-0.88	*	0.47	1.67	***	0.17	-0.88	1.27
	σ	1.63	***	0.20	1.38	***	0.36	1.93	***	0.16	0.32	7.00
GM (GME)	μ	-1.69	***	0.13	0.48	*	0.26	-0.98	***	0.12	0.36	1.22
	σ	1.01	***	0.17	0.47		0.62	1.25	***	0.11	0.13	5.95
LOWCO2 (LOE)	μ	1.12	***	0.24	0.02		0.15	0.31	***	0.10	-0.17	0.59
	σ	0.62	*	0.38	0.38		0.34	0.46	***	0.16	0.22	2.22
MEDIUMCO2 (MDE)	μ	0.34		0.26	-0.01		0.14	0.14		0.11	-0.10	0.78
	σ	0.45		0.53	0.43		0.46	0.29	*	0.17	0.14	4.68
HIGHCO2 (HIE)	μ	-1.11	***	0.34	0.26	**	0.13	-0.16		0.10	0.29	0.46
	σ	1.11		0.81	0.36		0.73	0.68	***	0.25	0.23	1.72
LOCAL (LCE)	μ	0.59	***	0.08	-0.50	**	0.20	0.34	***	0.07	-0.14	0.43
	σ	0.30		0.34	0.17		0.79	0.44	**	0.21	0.17	1.98
No-buy (NONE)		-5.51	***	0.38				-5.67	***	0.38		
Error Component	σ	2.74	***	0.34				3.07	***	0.35		

***, **, * Significance at 1%, 5%, 10% level

Table A1. Stated Approach Mixed Logit (MXL) Models with dual Coefficients for Attributes Attended (AA) and Not Attended (NA) (Cont.)

	Serial Inferred (SAI)		**Serial Stated (SAS)**	
	Attended (AA)	Not Attended (NA)	Attending (AA)	Not Attended (NA)
Model Fit Measures				
Obs.	4040		4040	
Log likelihood	-2560.40		-2837.41	
BIC	6067.46		6679.61	
BIC/N	1.50		1.65	
AIC	5348.81		5916.82	
AIC/N	1.32		1.46	
AIC3	5462.81		6037.82	
AIC3/N	1.35		1.49	

Table A1. Stated Approach Mixed Logit (MXL) Models with dual Coefficients for Attributes Attended (AA) and Not Attended (NA) (Cont.)

		Choice Task Stated (SAT)					
		Attended (AA)			Not Attended (NA)		
Variables	Coeff.	Estimate		S.E.	Estimate		S.E.
PRICE	μ	-0.52	***	0.04	-0.18	***	0.06
	σ	0.46	***	0.04	0.39	***	0.11
NON-GM (NGE)	μ	2.47	***	0.23	-0.72	**	0.31
	σ	2.43	***	0.22	1.01	*	0.58
GM (GME)	μ	-1.34	***	0.15	0.11		0.21
	σ	1.53	***	0.14	0.44		0.50
LOWCO2 (LOE)	μ	0.77	***	0.15	-0.18		0.23
	σ	0.76	***	0.26	0.50		0.69
MEDIUMCO2 (MDE)	μ	0.25	*	0.15	-0.14		0.20
	σ	0.70	***	0.22	0.46		0.62
HIGHCO2 (HIE)	μ	-0.42	***	0.16	0.33	*	0.20
	σ	1.02	***	0.37	0.51		0.58
LOCAL (LCE)	μ	0.69	***	0.10	-0.22	*	0.13
	σ	0.79	***	0.11	0.37		0.32
No-buy (NONE)		-6.50	***	0.45			
Error Component	σ	3.71	***	0.39			

***, **, * Significance at 1%, 5%, 10% level

Table A1. Stated Approach Mixed Logit (MXL) Models with dual Coefficients for Attributes Attended (AA) and Not Attended (NA) (Cont.)

	Choice Task Stated (SAT)	
	Attended (AA)	Not Attended (NA)
Model Fit Measures		
Obs.	4040	
Log likelihood	-2674.80	
BIC	6354.38	
BIC/N	1.57	
AIC	5591.60	
AIC/N	1.38	
AIC3	5712.60	
AIC3/N	1.41	

Table A2. Query Approach Mixed Logit (MXL) Models with dual Coefficients for Attributes Attended (AA) and Not Attended (NA)

		Serial Inferred (QAI)						Serial Query (QAS)					
		Attended (AA)			Not Attended (NA)			Attending (AA)			Not Attended (NA)		
Variables	Coeff.	Estimate		S.E.	Estimate		S.E.	Estimate		S.E.	Estimate		S.E.
PRICE	μ	-0.52	***	0.02	0.39		0.28	-0.72	***	0.04	0.04		0.06
	σ	0.31	***	0.02	0.46		0.30	0.33	***	0.04	0.33	***	0.10
NON-GM (NGE)	μ	2.88	***	0.16	-1.37	***	0.37	2.53	***	0.36	0.66	***	0.25
	σ	2.72	***	0.15	1.96	***	0.18	3.40	***	0.39	1.96	**	0.93
GM (GME)	μ	-2.15	***	0.14	0.45	**	0.20	-1.97	***	0.26	-0.40	**	0.16
	σ	2.01	***	0.13	0.50	*	0.30	2.20	***	0.29	1.15		0.87
LOWCO2 (LOE)	μ	0.65	***	0.21	0.05		0.15	1.10	***	0.39	0.10		0.15
	σ	0.93	***	0.26	0.58	***	0.19	0.98		0.63	0.79		0.55
MEDIUMCO2 (MDE)	μ	0.06		0.23	0.02		0.13	0.22		0.31	-0.09		0.13
	σ	0.40	*	0.24	0.53	***	0.19	0.52		0.92	0.38		0.56
HIGHCO2 (HIE)	μ	-0.51	**	0.24	0.05		0.12	-0.98	***	0.35	0.07		0.11
	σ	1.01	***	0.27	0.49	***	0.16	1.31	**	0.58	0.52		0.37
LOCAL (LCE)	μ	0.63	***	0.08	-0.26	**	0.12	0.54	***	0.13	0.10		0.10
	σ	0.54	***	0.08	0.30		0.18	0.46		0.41	0.55	*	0.32
No-buy (NONE)		-4.30	***	0.16				-5.67	***	0.36			
Error Component	σ	1.11	***	0.14				3.04	***	0.34			

***, **, * Significance at 1%, 5%, 10% level

Table A2. Query Approach Mixed Logit (MXL) Models with dual Coefficients for Attributes Attended (AA) and Not Attended (NA) (Cont.)

	Serial Inferred (QAI)		Serial Query (QAS)	
	Attended (AA)	Not Attended (NA)	Attending (AA)	Not Attended (NA)
Model Fit Measures	QAI		QAS	
Obs.	3784		3784	
Log likelihood	-2504.76		-2498.24	
BIC	5948.72		5993.35	
BIC/N	1.57		1.58	
AIC	5237.53		5238.48	
AIC/N	1.38		1.38	
AIC3	5351.53		5359.48	
AIC3/N	1.41		1.42	

Table A2. Query Approach Mixed Logit (MXL) Models with dual Coefficients for Attributes Attended (AA) and Not Attended (NA)

		Choice Task Query (QAT)					
		Attended (AA)			Not Attended (NA)		
Variables	Coeff.	Estimate		S.E.	Estimate		S.E.
PRICE	μ	-1.11	***	0.10	-0.44	***	0.08
	σ	0.41	***	0.06	0.76	***	0.10
NON-GM (NGE)	μ	7.41	***	0.95	1.38	***	0.36
	σ	8.74	***	1.13	3.48	***	0.48
GM (GME)	μ	-5.06	***	0.76	-0.92	***	0.23
	σ	6.59	***	0.97	2.06	***	0.37
LOWCO2 (LOE)	μ	4.02	***	1.10	0.29		0.25
	σ	3.94	***	1.45	1.43	***	0.51
MEDIUMCO2 (MDE)	μ	1.65	**	0.74	-0.09		0.21
	σ	1.77	*	1.01	0.68		0.57
HIGHCO2 (HIE)	μ	-4.61	***	1.31	0.01		0.21
	σ	5.57	***	2.05	1.34	**	0.55
LOCAL (LCE)	μ	6.58	***	0.99	0.04		0.14
	σ	5.20	***	1.10	1.03	***	0.26
No-buy (NONE)		-7.40	***	0.70			
Error Component	σ	4.83	***	0.50			

***, **, * Significance at 1%, 5%, 10% level

Table A2. Query Approach Mixed Logit (MXL) Models with dual Coefficients for Attributes Attended (AA) and Not Attended (NA) (Cont.)

	Choice Task Query (QAT)	
	Attended (AA)	Not Attended (NA)
Model Fit Measures		
Obs.	3784	
Log likelihood	-2206.90	
BIC	5410.66	
BIC/N	1.43	
AIC	4655.79	
AIC/N	1.23	
AIC3	4776.79	
AIC3/N	1.26	

Appendix 2

We explore the potential connection between choice response time and the number of attributes attended by individuals in our experiment. Using z-scores, Uggeldahl et al. (2016) found a negative and significant relationship between stated choice certainty and choice set response time. They argued that the greater the time spent responding to choice sets, the higher is the level of uncertainty. Additionally, their results suggest that response time provides a better proxy for stated choice certainty than responses on certainty scale questions provided by respondents. Similar to Uggeldahl et al. (2016), we transform respondent specific variables to z-scores within subjects to remove any individual variance. The z-scores are calculated as seen below in equation (2):

(2) $Z_{in} = X_{in} - \bar{X}_{in} / \sigma_{in}$

where X_{in} is the raw amount of time (or number of attributes attended) spent by respondent *i* in choice set *n*, $\bar{X}_{in}$ is the mean time (attributes attended) for respondent *i* over the 8 choice sets and σ_{in} is the standard deviation. In the event that all observations were the same across all choice tasks and, thus, no variance in the individual's data, the value of "1" was inserted which forces the z-score to be a zero for the individual. We use the calculated z-scores to test whether choice task time has any effect on z-scores for attributes attended. We use two linear regressions (one for each treatment) as follows:

(3) $A_{in} = \beta_0 + \beta_1 Z_{in}$

where A_{in} is the z-score corresponding to the number of attributes attended to by respondent *i* over *n* the choice sets. We expect there to be a negative relationship between time spent on choice tasks and the number of attributes attended in the stated treatment; however, we expect the opposite to be true in the query treatment. In the stated approach group, it is reasonable to

expect that an increase in time spent on a choice task is due to a higher level of uncertainty and therefore more time devoted to making the decision (Uggeldahl et al. 2016). This logic extends to respondents across all treatments in choice experiments; however, in our query approach group, AA is dependent upon the aspects listed by respondents. This means that the more attributes considered by an individual, the more aspects listed and, therefore, the more time spent in typing the response. We do not have the ability to separate out the aspect listing task and the choices made because we collected the responses on the same page of the survey. So while the method for assessing AA is consistent across the stated approach, where all respondents respond “considered” or “ignored” to all attributes in the experiment, in the query approach, the time was dependent upon the attendance given to attributes.

The results of our regression models indicate that our expectations about the relationship between choice task time and AA are correct. The coefficients signs are in the expected direction and significant (Query β: 0.178, p-value: 0.000 and Stated β: -0.023 and 0.002). Choice response time holds more explanatory power for the query group compared to the stated group (about 4% vs. 0.1%). We also specified a third regression model using the z-scores from both treatments at the same time and found a positive and significant coefficient estimate (0.076) with a model adjusted R^2 of 0.008.

Cultural Cognition, Query Theory and Preferences for Genetically Modified Food Policy

Abstract

In recent years, there has been an intensifying campaign by some stakeholders to highlight food safety and environmental concerns over genetically modified (GM) foods in the U.S. As a result, the issue of labeling in on the federal agenda. Traditionally, the average U.S. consumer has not considered GM foods as much of a risk, particularly in relation to other risks (e.g., nuclear power, gun violence, climate change) and opinions have been fairly consistent across various cultural worldviews and political affiliations. However, with the increasing public profile of GM food labeling, there may now be more cultural conflict on the topic than historically observed. A number of state and federal policies regarding GM food and the reaction from consumer advocacy groups and the media coverage of these regulations serve as indicators of a potential shift in the cultural cognition of GM food. We use cultural cognition theory to examine the influence cultural worldview has on: 1) preferences for GM labeling policy in the U.S. and 2) the discounts required by individuals to consume GM foods. We also employ query theory to further our understanding of how people with different worldviews form values for GM labels. Our results demonstrate that cultural worldview influences individuals' preferences for GM policy and consumer valuations. As predicted by cultural cognition theory, the most dramatic differences exist between those with relatively *Egalitarian-Communitarian* and *Hierarchical-Individualistic* worldviews. Our results also support our query theory prediction that cultural worldview influences individual's affective reactions to choice options leading to significantly different valuations of GM foods. Our findings show that an important part of the GM labeling debate is driven by an individual's predisposition to support or oppose GM foods due to their cultural worldview.

Cultural Worldview, Query Theory and Preferences for Genetically Modified Food Policy

Introduction

Concerns over genetically modified (GM) foods have helped to place GM food labeling on the federal government's policy agenda. Even with 88 percent of American scientists viewing GM organisms (GMOs) as generally safe (Rainie and Funk, 2015), President Obama recently signed a bill in July 2016 requiring GM labeling in the U.S. (Enoch, 2016). Historically, U.S. consumers in general have not viewed GM foods as much of a risk, particularly in relation to other risks (e.g., nuclear power, gun violence, and climate change) (Kahan et al., 2011). Policy for regulating GM products has evolved overtime, beginning as a very cautious approach, protecting against both real and hypothetical hazards (NIH, 2015). Since the 1990s however, U.S. policy has remained largely unchanged and can be best described as a preventative approach, which aims to minimize harm once harm is scientifically demonstrated (Patterson and Josling, 2005). The U.S. system of GM food labeling has traditionally focused on voluntary labeling where companies label products for GM content based on the perceived demand for GM (or non-GM) attributes of consumers. However, the recently signed labeling law will change the way in which GM foods are labeled in the U.S.

GM labeling has also reached the policy agenda at the state level. Two ballot initiatives in 2012 and 2013 in California and Washington helped spark renewed debate over mandatory GM labeling in the U.S. (Costanigro and Lusk, 2014). Both ballot initiatives failed, but were well-covered in the national news. In 2014, Vermont successfully passed a *mandatory* food labeling law, the first of its kind in the U.S., followed by legislatures in Connecticut and Maine which passed labeling laws (pending a threshold of other states passing similar measures). According to the American Farm Bureau, between 2013 and 2015 as many as 175 labeling laws in over 30

states have been introduced (AFB, 2015). On July 29, 2016, President Obama signed bill S.764, which put a federal standard for labeling GM foods into place (Enoch, 2016). The bill requires food containing GM ingredients to be labeled; however, companies can comply with this requirement via the use of smartphone scanning codes as an alternative to written text on the package. The bill also prevents states from requiring labeling of GM ingredients. The legislation is viewed as a victory for farm advocacy groups, food companies, and the biotechnology industry. The bill requires the U.S. Department of Agriculture (USDA) to implement the disclosure standard within two years. Opponents of the new law have encouraged food companies that were already labeling GM ingredients, due to Vermont law, to continue to label the ingredients while the USDA creates the new Federal guidelines (Halloran, 2016).

In order to raise the state of concern over GM labeling, proponents of mandatory GM labeling successfully mobilized supporters by emphasizing the themes of 1) food safety, 2) the collusion of big business and government, and 3) the "right to know" if food contains GM ingredients (Lendman, 2015). This resembles the organic movement that led to the National Organic Program (Ingram and Ingram, 2005) during which the theme of the "right to know" was critical. Food labeling for the consumers' "right to know" has ties to the basic founding principles of democracy and encompasses issues such as the right to religious freedom, the right to information, and the ethics of transparency and societal concerns (Klintman, 2002). The success of labeling advocates appears to defy research findings that suggest the U.S. consumers tend to have positive attitudes towards GM foods. Frewer et al. (2013) conducted a meta-analysis and found that on average, U.S. consumers have high trust in regulators and the institutions responsible for protecting consumer and environmental health related to food production. The perceived risk of GM foods is an important factor in its acceptance (Rodriguez-Entrena et al.,

2015), but the public's beliefs about risk are often very different from the beliefs of experts (Curtis et al., 2004; Jenkins-Smith and Bassett, 1994; Kahan et al., 2011). A Pew research poll indicates that 57 percent of Americans view GM foods as unsafe to eat (Rainie and Funk, 2015), while over 90 percent of Americans support the mandatory labeling of GM foods (ABC News, 2015). This indicates that a sizable portion of the public who view GM foods as safe also support mandatory labeling. Therefore, the arguments for mandatory labeling rely on gaining broad public support for labeling.

Mintz's (2016) analysis of headlines from 200 articles on GMOs published in major national newspapers from 2011 and 2013, shows that there were 207 favorable and 250 unfavorable mentions of GMOs with some of the major arguments focusing on technical performance and the potential for environmental harm. Receiving the most media coverage were the biotechnology industry and the U.S. government. There was a sharp increase in GM coverage in mid-2013 caused by two important events: (1) Proposition 37 in California and (2) the discovery of unapproved GM wheat being grown on a farm in Oregon. Farmers sued Monsanto over the GM wheat event, Japan and South Korea even suspended U.S. wheat imports. Monsanto claimed that the event was suspicious, which led to further media coverage (Mintz, 2016). These occurrences and their media coverage may have placed GM labeling on the federal agenda. As seen in the polling numbers reported above, media coverage can have a polarizing impact on the views of the average American. However, a better understanding of how different groups of individuals form preferences on GM food policy is important for understanding the policy making process.

Because fundamental differences in cultural values exist between individuals, polarizing issues like GM foods are rarely resolved through the provision of more scientific data (Kahan et

al., 2011). The tendency for individuals to conform beliefs to values defined by cultural identities is known as cultural cognition and this plays a significant role in how people evaluate risk and interpret information from experts and the media (Kahan et al., 2011). Consequently, we use cultural cognition theory to explore how individuals' cultural worldviews result in divergent preferences for GM policy. We accomplish this by carrying out a four-part study. First, we examine the preferences for GM food labeling using cultural worldview (CWV) as a key independent variable in two ordinal regression analyses. Second, we investigate the effects of CWV on the GM discounts required for individuals to consume GM foods by using a choice experiment and mixed logit models (MXL) to examine consumers' preferences and valuation for GM food labels. Third, we use query theory (Johnson *et al.*, 2007; Weber *et al.*, 2007) to examine how an individual's affective responses to GM food labels depends upon the person's CWV, leading to significantly different product valuations. One prediction of query theory is that individuals evaluate options by sequential queries about the options under consideration and the first query retrieved by individuals is weighted more heavily in the decision than subsequent queries. Using an aspect listing task, we determine if people with different CWVs have a statistically different order of queries which could help explain GM discount valuations. Finally, we use multiple regression to examine how CWV and query order affect the GM discount required by individuals to consume GM foods.

Our study contributes to the literature in a number of ways. First, it provides evidence that the relative acceptance of GM foods by Americans observed in previous research may have fractured over the past several years due to increased media coverage and attention from the public in general. Second, to our knowledge, this is the first study to attempt to use cultural cognition theory to estimate both preferences for GM foods policy and consumer preferences for

GM labels. Finally, to our knowledge, this is the first study using query theory to help understand the choice behavior of individuals from different CWVs as defined by cultural cognition theory. The remainder of our paper is laid out as follows: we offer a brief discussion of cultural cognition theory and how we apply the theory. Then, we present our research design including discussion of the data and methods employed in the consumer preference portion of the study as well as how query theory is used to examine differences between CWVs. Finally, we discuss our results and our conclusions.

Cultural Cognition Theory

Cultural cognition theory (CCT) is a widely used framework for explaining differences in public perceptions of the risks posed by technologies (Kahan et al., 2011). Individuals tend to conform their beliefs to values defined by cultural identities. Because beliefs about GM foods are also subject to this tendency, scientific consensus alone is not enough to influence public opinion towards a single agreed upon view of GM foods. Cultural cognition also affects an individual's perception of credibility (Kahan et al., 2011). Hossain et al. (2003) found that greater distrust of government is associated with a greater likelihood of disagreeing with the use of GM. An individual's position for or against GM foods can be reinforced by an expert who shares their values (Mintz, 2016).

Cultural cognition builds on the cultural theory of risk (Douglas and Wildavsky, 1982) which suggests that people can be expected to form risk perceptions that reflect and reinforce an idealized "way of life." Figure 1 shows the "group" and "grid" typology of CWVs used in this study (Douglas and Wildavsky, 1982; Kahan and Braman, 2006). A "low group" worldview coheres with an *individualistic* social order, in which individuals are expected to provide for their own needs without collective assistance and enjoy immunity from regulation aimed at securing

collective interests. At the opposite end of the continuum, a “high group” worldview supports a *communitarian* social order where the collective needs are valued more than individual initiative, and society is expected to secure the conditions that allow individuals the opportunity to prosper. A “high grid” worldview favors a *hierarchical* society where resources and opportunities are distributed on the basis of conspicuous and fixed social characteristics (gender, race, class, etc.). A “low grid” worldview favors an *egalitarian* society where social characteristics should not influence the distribution of resources and opportunities.

We extend CCT to the study of preferences for GM foods policy. Personal values and beliefs influence policy preferences in a number of domains (Doan and Kirkpatrick, 2013; Sabatier and Jenkins-Smith, 1993; Song et al. 2014). Rather than the result of a benefit-cost calculation, according to CCT, an individual’s preference for a particular public policy derives from the individual’s evaluation of the nature of influence a policy has upon their way of life. Over the past 25 years, as GM foods have become more common and familiar to the public, the calls for increased regulation and mandatory labeling of GM foods have increased. The familiarity hypothesis would suggest that just the opposite should occur; that as people become more familiar with a novel technology, they should become more supportive (Kahan et al., 2009). We maintain that members of the public who hold different worldviews perceive GM foods differently and, therefore, have differing preferences on GM foods policy.

Experimental Design and Methods

Survey and Choice Experiment

The data for this project were collected via a national online survey using Sawtooth Software (Sawtooth Software, 2016). Respondents to the survey were provided by Survey Sampling International (SSI, 2016) using a nationally representative consumer panel. Our panel

consisted of 569 participants identified as primary grocery shoppers for their respective households. The sample is balanced by socio-demographic characteristics and the four main U.S. Census regions. The data were collected in November of 2015. The experiment consists of two parts: a survey and a choice experiment. The survey consisted of a series of questions relating to policy and food labeling preferences as well as demographic questions. The choice experiment involved participants making choices between poultry products carrying two different GM labels as well as with information on production location and carbon footprint. All participants were presented with eight separate choice tasks.

Table 1 shows the attributes and levels in the choice experiment. We used effects coding to provide clear estimates of the main effects (Bech and Gyrd-Hansen, 2005). Price has four levels collected from retail outlets and USDA price reports for chicken (USDA ERS, 2015). The second attribute was the GM content of the products which had three levels: (1) Non-GMO Project Verified[1]; (2) this product contains genetically engineered ingredients; and (3) no information. The three labels chosen for analysis represent valid labels under a voluntary system of labeling as used in the U.S. The “this product contains GM” label was included in anticipation of a change to federal labeling policy. President Obama’s recent signing of a law requiring the labeling of GM foods emphasizes the importance of including language regarding the GM content of food in our experiment. We also included labels regarding the carbon footprint of the products following the levels used by Van Loo et al. (2014), and a local production attribute (table 1).

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

Each individual in the experiment completed eight choice tasks that included two experimentally designed options and a no-buy option. The allocation of attribute levels to alternatives was designed using a sequential design and D-efficient criteria (Bliemer and Rose, 2010). The first stage was an orthogonal design and was implemented for the pilot utilizing 250 respondents. The coefficient estimates from the pilot survey data were then used as priors for the data collected in the first wave. The final design involved 32 choice tasks arranged in four blocks of eight tasks each.

Cultural Worldview Measures

All respondents' CWVs are measured with abbreviated versions of the cultural cognition worldview scales consisting of only four items (Kahan, 2012; Kahan et al., 2016). The scales characterize an individual's preferences for how society should be organized along two orthogonal dimensions. The first dimension, *hierarchy-egalitarianism*, assesses how much an individual supports approaches of an organization that tie authority to clearly delineated social roles and characteristics versus viewing such roles and characteristics as illegitimate bases for the distribution of power and resources. The second dimension, *individualism-communitarianism*, assesses the degree to which people prefer modes of organization that treat individuals as responsible for securing the conditions of their own prosperity versus modes that treat individual well-being as a collective responsibility that takes precedence over individual interests (Kahan, 2012). We implemented the four item scale in order to reduce the burden on respondents in our experiment and because prior research by Kahan et al. (2016) shows that the four item scale provides reliable CWV identification (table 2). These four items displayed acceptable psychometric properties shown in previous studies to have the highest correlation with the latent construct associated with the respective scales from which they were drawn

(Kahan et al., 2016). Factor analysis is used to assess the covariance patterns of the indicators of CWV. This analysis confirms that the variance in our respondents' responses to the four items is best explained by two separate orthogonal factors. The *individualism-communitarianism* scale formed with the two items described in table 2 reflected acceptable levels of measurement precision (Cronbach's α= 0.779). The *hierarchical-egalitarian* scale formed with second two items in table 2 also reflected acceptable levels: Cronbach's α= 0.710. Factor scores were used as measures of the subjects' *hierarchy–egalitarian* and i*ndividualism–communitarian* worldviews. The scores are standardized with means at 0 and arranged so that negative scores denoted either a relatively hierarchical or a relatively individualistic disposition, while positive scores denoted either a relatively egalitarian or communitarian disposition. The factor scales are formed as continuous measures and represent the reality that individuals can vary in how strongly they fall into one classification versus another. However, for the purpose of a succinct presentation of results and to simplify the discussion, we use the factor scores to categorize individuals into the four CWVs shown in figure 1. The number of individuals in each respective group is reported in table 2.

Query Theory and Aspect-Listing Task

To better understand the processes that may be responsible for the differences in how individuals with different CWVs value GM labels, we apply query theory (Johnson *et al.* 2007 and Weber *et al.*, 2007). Query theory assumes that individuals evaluate options by sequential queries that retrieve different aspects (both negative and positive) of relevant knowledge about the options under consideration. One important prediction of query theory is that because of output interference, the order of queries matters. The first query retrieved by individuals typically generates a richer set of answers than the subsequent queries. If people with different

CWVs have statistically different valuations associated with GM labels, these difference may be explained in part by the order of queries. Query theory has been used to examine a range of behaviors including the endowment effect (Johnson *et al.,* 2007) where ownership changed the order of queries, in studies of intertemporal choice (Weber *et al.*, 2007) where the default date of consumption determined the order of queries, and in Hardisty *et al.* (2010) where attribute framing was shown to change the order of queries. In all three studies, thought listings provided by decision makers explained the observed behavioral effects. We therefore use aspects listed by individuals to examine how CWV may affect valuations in our study. Using a verbal report method called aspect listing, we follow Johnson *et al.* (2007) and Weber *et al.* (2007). After each choice task, respondents were asked to list the reasons for their decision. Next, the content and order of the responses were recorded to approximate the thought processes of respondents in each CWV.[2] Using these listed aspects, we calculated a score that reflects an individual's tendency to produce *value-increasing* (positive) aspects before *value-decreasing* (negative) ones. The score is the Standardized Median Rank Difference of aspect types (SMRD) (Johnson *et al.*, 2007; Weber *et al.,* 2007) measured as follows:

$$2(MR_i - MR_d)/n$$

where MR_d is the median rank of value-decreasing aspects in a participant's sequence; MR_i is the median rank of value-increasing aspects in a participant's sequence; and n is the total number of aspects in a participant's sequence. SMRD can take on values from -1 (all value-decreasing aspects listed before any value-increasing aspects) to 1 (all value-increasing aspects listed before value-increasing aspects).

[2] Each respondent completed eight choice tasks with three text fields for the aspect listing available for each task.

Variables and Measures

We first employ ordinal logistic regression with robust standard errors to examine the relationships between individuals' CWVs and GM foods labeling policy preferences. The dependent variables in the regression models are the preferences for voluntary (status quo) and mandatory labeling programs. For the two GM policies, each respondent's preference is measured on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The first model addresses the following question: "Do you agree or disagree that the voluntary approach with third-party certification should be left as is and NOT changed?" This question offers an examination of how individuals view the current state of GM labeling in the U.S. as this has been the system of labeling used since the 1990s. The second model addresses the question: "Do you agree or disagree that the federal government should require mandatory labeling?" giving us an estimate of individuals' preferences for change in our system of labeling. The primary independent variables include the four CWVs described in table 2: egalitarian communitarian (EC), hierarchical communitarian (HC), egalitarian individualist (EI) and hierarchical individualist (HI). Because of the theoretical expectations of a stark contrast between the polar opposite worldviews of EC and HI, the HI worldview is used as the base in the ordinal regressions with the other CWVs evaluated by comparison to the HI worldview. We expect those with an HI worldview to be less likely to support change in GM foods labeling policy and to demand less GM discount to consume GM foods. Our theoretical expectations are discussed further in a following section. We also examine other explanatory variables expected to have an impact on policy preferences based on prior research including: socio-demographic (gender, age, children in the household, education, race, income, home environment)

(Constanigro and Lusk, 2014), political (social and fiscal conservatism) (Constanigro and Lusk, 2014; McFadden and Lusk, 2015), risk preference (Lusk and Coble, 2005), reading food labels (Dannenberg *et al.*, 2008), knowledge of prior consumption of GM foods (Dannenberg *et al.*, 2008), and trust in different sources of information regarding the benefits and risks of GM foods (Dannenberg *et al.*, 2008; Dannenberg *et al.*, 2011). Because the effects of these variables have been exhaustively covered in the literature, we minimize their discussion, and focus instead on the results relating to CWV, GM discount, and query theory.

Second, we analyzed consumer preferences and estimate GM discount using a discrete choice framework consistent with random utility theory (McFadden, 1974) and Lancaster consumer theory (Lancaster, 1966). A Mixed (Random Parameters) Logit (MXL) model with correlated errors and error components was employed. We assume price to have a fixed coefficient to facilitate the estimation of willingness to pay (WTP), which is common practice in discrete choice experiments (Layton and Brown, 2000; Lusk and Schroeder, 2004; Revelt and Train, 1998). For a more in depth discussion of econometric methods using our data, see Kemper et al. (2016). To calculate the GM discount, we take the simple mean difference of the estimates for WTP for the non-GMO Project Verified label and the WTP to avoid GM from the "this product contains GM ingredients" label. Both measures represent an individual's WTP to avoid GM foods; however, the "contains GM" label is typically associated with a negative utility (hence, WTP to avoid GM). We reverse the sign of the "contains GM" label before calculating the mean GM discount value in order to have comparable measures for analysis. For instance, a negative WTP value for "contains GM" indicates a positive WTP to avoid GM (discount). The resulting mean WTP values and GM discount values represent the results of 1,000 bootstrapped estimates based on the coefficient estimates and variance from our MXL models.

Finally, we use multiple regression analysis to examine the influence of CWV and the other independent variables from the ordinal regression described above on the GM discount estimated in the consumer demand analysis. We also include SMRD to explore the influence of the query order on GM discount.

Hypotheses

Table 3 summarizes our hypotheses. For a succinct presentation of results, we limit our hypotheses to those applying to the HI and EC worldviews. Individuals whose values are *hierarchical* and *individualistic* have a tendency to be skeptical of environmental risks (Kahan et al., 2011). The acceptance of such risks would justify restricting commerce and industry which are highly prized by people with these viewpoints. Individuals with such values may also be expected to be skeptical of the risks of GM foods and therefore they may prefer the status quo, voluntary GM foods labeling. Therefore, we expect individuals from the *hierarchical individualistic* worldview to be less likely to prefer drastic change in how the U.S. regulates GM foods, and also to require little or no GM discount in order to consume GM foods.

In contrast, people with more *egalitarian* and *communitarian* values would be more likely to deem commerce and industry as self-seeking and inequitable and worthy of regulation (Kahan et al., 2011; Wildavsky and Dake 1990; Adams, 1995). Individuals with these values (EC worldview) may be expected to be skeptical of the companies promoting GM foods, such as Monsanto, and therefore may more strongly support stricter regulation of GM foods. We expect that individuals from the EC worldview will demand stricter regulation regarding the labeling of GM foods and express a higher discount required to consume GM foods.

An individual's perception of the relative safety of GM foods is informed by emotional reactions triggered by GM foods; whether those reactions are positive or negative is determined

largely by cultural values (Sherman and Cohen, 2002). Query theory holds that while making a choice, an individual makes a series of queries which include affective reactions to choice options. Due to the sequential nature of the queries, the first query is given more weight than subsequent tasks. Therefore, whether an individual has negative (value-decreasing) or positive (value-increasing) affective reactions first will influence the choice made. We proximate these emotional reactions using the SMRD to investigate the influence of CWV on query order. We expect individuals with a relatively *hierarchical individualistic* worldview to also have lower (more negative) SMRDs; we expect just the opposite for those with an *egalitarian communitarian* worldview. Lower SMRDs are expected to be observed by individuals with lower GM discounts. If hierarchical individualists do have relatively lower SMRDs, we might conclude that these individuals are calling on more negative affective information (value-decreasing) while making decisions about what products to choose. By contrast, for egalitarian communitarians, who are expected to have the highest GM discounts, having a relatively higher SRMD might indicate that these individuals tend to think first about the positive affective aspects (value-increasing) of the decision. If CWV influences whether reactions to GM food labels are positive or negative, then our SMRD data should reflect this influence.

Results

Table 4 presents a cross tabulation of our socio-demographic and political variables with CWV. The chi-square and significance values shown in table 4 and discussed here compare the HI and EC worldviews only. CWV varies widely across a number of our variables. Notably, individuals from the HI worldview are significantly more likely to be older, to be white, and to be socially and fiscally conservative than those individuals from the EC worldview (all *p*-values: 0.000). Table 5 presents a cross tabulation of how people from each CWV responded to the two

GM policy preference questions. Again the test statistics compare only the HI and EC worldviews. Thirty-five percent of individuals in the HI worldview agree or strongly agree that the voluntary approach should be changed, whereas 52 percent of those in the EC worldview agree with the statement (*p*-value: 0.000). Preferences for mandatory GM policy is also lower with individuals with the HI worldview with 53 percent of people in the HI agreeing that the federal government should require mandatory labeling and 83 percent of EC individuals agreeing or strongly agreeing (*p*-value: 0.000). Next, we explore further the influence of CWV and the other variables on GM policy preference.

GM Policy Preferences

Table 6 summarizes the results of our ordinal (ORD) regression models. Because we expect individuals with a HI worldview to express relatively lower support for change in GM labeling policy, we use the HI worldview as the base for comparison. The contrast between the EC and HI worldviews are the focus of the presentation of results that follow. The results in table 6 indicate that individuals with an EC worldview are over 2 times more likely than those with an HI worldview to agree with the statement “should the current voluntary approach with third-party certification be changed?” Individuals more likely to support change are also more likely to be female (1.41 times), to have incomes under $120,000 (48 percent more likely), to have a suburban or urban living environment (50 percent more likely), and to trust information from consumer advocacy groups regarding the safety and benefits of GM foods (70 percent more likely). Individuals more likely to support change in the voluntary system were also 1.59 times more likely to read food labels than those who do not read food labels. Individuals less likely to support change in the voluntary system of labeling are those with a lower preference for taking risks with the food they eat (8 percent less likely), to not trust information from the government

about the safety of GM foods (36 percent less likely) and to not trust information from private companies about the safety of GM foods (36 percent less likely).

Results for the second model in table 6 summarize the preferences of individuals for mandatory labeling of GM food ingredients. The dependent variable is responses to the question: "should the federal government require mandatory labeling?" Consistent with the hypothesis, the results indicate that people from the EC worldview are 2.51 times (151 percent) more likely to agree that we need a mandatory labeling program than people with a HI worldview. Those more likely to support mandatory labeling are also more likely to be female (55 percent more likely), under the age of 45 (38 percent), to have children (52 percent), to be a race other than white (62 percent), to be fiscally non-conservative (73 percent), and to read food labels (90 percent). Notably, individuals who view consumer advocacy groups and the media as trusted sources of information about the safety of GM foods are approximately 2 times more likely to support federal mandatory labeling than those who do not trust these sources. Individuals less likely to support mandatory labeling tend to be more risky with the food they eat (11 percent) and to not trust the government as a source of information regarding the safety of GM foods (31 percent).

These results support our hypotheses regarding the influence of CWV on GM food policy preference. Compared to individuals with an HI worldview, individuals with an EC worldview are more likely to agree that the current voluntary program needs to be changed and are also more likely to agree that the federal government should require mandatory labeling of GM foods. By contrast, our results in table 6 confirm that those with a relatively HI worldview are more likely to disagree with both propositions. Other factors are also important predictors of the likelihood of supporting change in GM foods labeling. Notably, trust in media, consumer advocacy groups, and the government as sources of information about the benefits and risks of

GM foods are significant predictors. A cross tabulation analysis examining differences between the HI and EC worldviews reveals a stark contrast between individuals with these worldviews and their trust in these sources of information. Only four percent of the individuals with a HI worldview reported viewing the government as a trustworthy source of information about GM foods safety compared to 46 percent of individuals with a EC worldview ($\chi2$: 65.848, *p*-value: 0.000). Individuals with a HI worldview also put less trust in consumer advocacy groups, with 49 percent reporting they trust these groups compared to 70 percent in the EC ($\chi2$: 14.797, *p*-value: 0.000). Trust in the media is low with individuals from both worldviews; however, only four percent of individuals from the HI worldview report trust in the media versus 22 percent from the EC worldview ($\chi2$: 20.227, *p*-value: 0.000). These results underscore the importance of individuals' worldviews in how they interpret information about the safety and benefits of GM foods. The next section explores the impact of CWV on consumer preferences for GM labels and the GM discount required by individuals to consume GM foods.

Consumer Preference Results

The full results of the mixed logit models (MXL) can be found in the appendix. We focus our discussion on the marginal WTP and GM discount estimates corresponding to the HI and EC worldviews as presented in Table 7. The values represent the means of 1,000 bootstrapped estimates and show that individuals from the EC CWV require a significantly larger average GM discount (25 cents per pound of boneless skinless breast meat) in order to consume GM (*p*-value: 0.010). Further, those with an EC worldview are willing to pay a higher premium for the non-GMO attribute ($3.42/lb), and also have a larger WTP to avoid GM ingredients ($2.31/lb) compared to those with a HI worldview. The negative value (-$0.11/lb) for individuals with a HI worldview indicates that on average these individuals would rather consume a product labeled as

containing GM ingredients than to pay for the non-GMO label. The comparison of WTP and GM discount between the HI and EC CWVs are as hypothesized.

Figure 1 presents the results from our aspect listing tasks and the SMRD values by each respective CWV. SMRD can take on values from -1 (all value-decreasing aspects listed before any value-increasing aspects) to 1 (all value-increasing aspects listed before value-increasing aspects). We hypothesized that respondents with a HI CWV would list value-decreasing aspects earlier in the aspect-listing task than individuals with an EC worldview. In other words, we expected a lower SMRD of aspect types from individuals with an HI worldview. The results indicate that individuals with a HI CWV have significantly lower (more negative) SMRDs than those with an EC CWV. In other words, HI individuals are significantly more likely to think value-decreasing thoughts first than are individuals with an EC worldview (ANOVA F: 5.118, p-value: 0.024). This aligns with the GM discount results as we expect the lower SMRDs to be associated with lower WTP values and lower GM discounts (Kemper et al., 2016). We also compared the SMRDs from the EC and HI worldviews using independent samples t-tests based on 1,000 bootstrapped estimates. These results indicate that individuals from these two CWVs had significantly different SMRDs, providing support our final hypothesis in table 3 that individuals with a HI worldview tend to think value-decreasing thoughts first while evaluating the products in our choice experiment.

To explore further the factors that influence consumer GM discount, in table 8 we report the results of our multiple regression analysis. The independent variables in this analysis are the same as in the ordinal regression with one exception: we include SMRD as an explanatory variable due to its expected influence on WTP and GM discount. The coefficient for the EC CWV is positive and significant indicating that individuals with this worldview require higher

mean GM discounts than do those in the base CWV (HI). SMRD is also significantly related to GM discount and the sign indicates that higher (more positive) SMRDs are associated with larger GM discounts (and larger WTP for non-GMO labels). The results also indicate that having children in the household, being a race other than white, and reading food labels are significantly related to higher GM discounts. Having a household income lower than $120,000, a relatively higher preference for taking risks with food, and high level of trust in the government as a source of information about the risks of GM foods are significantly related to lower GM discounts.

Conclusion and Discussion

A 2015 Pew survey indicated that 88 percent of American scientists view GM food as generally safe (Rainie and Funk, 2015). However, 82 percent of the respondents in our study reported agreeing: "*...that labeling the genetically modified ingredients in food should be required.*" After over twenty years of experience with GM foods in the U.S., relative consensus among scientists, and relatively high support from the public in general, why has the call for mandatory labeling increased rather than dissipated? This reality has puzzled many from the academic and scientific community. The familiarity hypothesis would suggest that as people gain more experience with GM foods, the more accepting they will become. However, recent events in the U.S. indicate that the reasoning behind the familiarity hypothesis does not explain behavior regarding preferences for GM foods. Because fundamental differences in cultural values exist between individuals, polarizing issues like GM foods are rarely resolved through more scientific data and campaigns to raise the awareness of the real risks and benefits of GM foods (Kahan et al., 2011). Even if one takes a hardline rational individualist perspective, where all decisions are linked to self-interested rational behavior, one might expect some preferences regarding the issue of GM foods to be culturally skewed. Even self-interested individuals need to

figure out which policies and activities best promote their interests. Our study uses cultural cognition theory to better understand the social psychological processes that influence the demand for GM policy and the discounts required to by individuals to consume GM foods as well as how CWV can explain cultural conflict regarding GM foods.

Our results demonstrate that CWV has a significant influence on the likelihood that an individual will support or oppose voluntary and mandatory labeling policy change. Individuals with a relatively HI worldview were not only less likely to support mandatory labeling, they also expressed very low trust in a number of sources of information about the safety of GM foods. Only four percent of the individuals with a HI worldview expressed trust in the government as a source of information about GM foods safety (EC: 46 percent), only 49 percent trusted consumer advocacy groups (EC: 70 percent), and only four percent viewed the media as trustworthy (EC: 22 percent). These results underscore the importance of individuals' worldviews, in how they interpret information about the safety and benefits of GM foods. Efforts by the government and policy advocates to raise the level of awareness of GM foods risks are likely to have varying effects depending upon a person's CWV. Those individuals with a relatively higher preference for mandatory GM labeling are also those who have a significantly higher level of trust in consumer advocacy groups and the media; these are often sources of negative information regarding GM foods. This helps to explain some of the polarizing results between worldviews.

The results of our consumer demand analysis further demonstrate this polarization and indicate that CWV also has a significant impact on the WTPs of individuals for the two GM labels (non-GMO and "this product contains GM ingredients). Perhaps the most interesting finding of the consumer analysis is that the WTP for the non-GMO attribute is actually lower than that for the "contains GM" attribute among individuals with an HI CWV. This is not a

common finding among consumers in general, where the WTP for the non-GMO attribute is typically larger. However, these results demonstrate the important influence that cultural biases play in the formation of values. Our query results using the SMRD to compare individuals from different CWVs confirm that individuals with a HI CWV tend to consider relatively negative (value-decreasing) aspects first. By contrast, individuals with an EC worldview are more likely to be thinking first about aspects that increase their WTP for non-GMO and GM discount. This is an important finding because query theory assumes that individuals evaluate aspects sequentially and that due to output interference, the first query is weighted more heavily by individuals. Our results provide support for the conclusion that an individual's CWV influences the order of queries.

Two psychological mechanisms help to connect CWV and query theory: *cognitive-dissonance avoidance* and *affect* (Kahan and Braman, 2006). Cognitive-dissonance avoidance, applied to our study, means that individuals are likely to align their beliefs about GM to their cultural evaluations of GM. *Affect* relates to how individuals perceive the safety of GM foods. These perceptions about the relative safety of GM foods are informed by emotional reactions triggered by GM foods; whether those reactions are positive or negative is determined largely by cultural values (Sherman and Cohen, 2002). Our query theory results demonstrate that individuals who have negative affective (value-decreasing) reactions first also require lower GM discounts. While we cannot directly connect these negative affectations (SMRD) to CWV, our results do provide evidence that an individual's CWV influences the order of queries and GM discounts. The multiple regression results emphasized the influence of query order and CWV on GM discounts.

The GM labeling policy debate is not based solely on scientifically demonstrated risk associated with consuming GM foods or on a societal cost-benefit analysis. Rather, the GM foods debate is driven considerably by individuals' predispositions to support or oppose GM foods due to their CWV. This is important for the USDA to consider as it develops the new labeling program for GM foods. If advocates for GM technologies believe that people oppose GM foods due to lack of experience or false information, they may find their efforts to try and enlighten the public disappointing. This does not mean that there is no role for science in this debate. Knowledge from the scientific community regarding the safety and benefits of GM foods is essential and Americans historically have shown a high regard for science; however, our results demonstrate that preferences for GM food policies are influenced significantly by an individual's CWV. More than a characteristic of individuals, CWV represents a set of heuristics used by people to process information in order to form preferences for GM policies and valuations for products bearing GM labels. A person's worldview represents a filter through which all new information must be viewed and through which some sources are deemed unacceptable and untrustworthy.

People engage in politics to translate their beliefs into action (Sabatier and Jenkins-Smith, 1993). Coalitions of members with different beliefs often interact and compete to drive the direction of policy subsystems to produce the outcomes preferred by coalition members. From a policy learning perspective, the principle arguments adopted by coalitions both for and against GM labeling have evolved over time. When the technology was new, the conflict regarding the safety of GM foods was based on conflict from within the scientific community; however, as large numbers of studies began to document the relative safety of GM foods and consumers became less concerned over the risk of consuming these foods (Frewer et al., 2013) the

arguments concerning their use have also changed. Some of the current themes adopted by opponents of GM labeling focus on the economic benefits of GM technologies while labeling proponents often focus on the social, ethical and environmental arguments against GM foods and concerns about the collusion between the biotech industry and government (Mintz, 2016). Perhaps one of the most important areas of emphasis adopted by the coalition supporting the labeling of GM foods is the consumer empowerment theme of the "right-to-know". This theme has broad based appeal and helps to explain why some Americans who believe GM foods to be safe still support GM labeling. Additionally, consumer advocacy groups and the media have taken on important roles of generating and disseminating policy ideas in the policy subsystem and these actors have considerable influence in the pro-labeling coalition.

During the development of the new GM labeling rules, it will be crucial for policymakers to consider the influence of CWV on the preference for GM labeling. Thoughtful planning can help make the final rules a policy solution that moves us towards public consensus on GM foods. This certainly represents a challenge as evidenced by the strong negative reaction from some consumer advocacy groups to the recently signed GM labeling law. The Consumers Union is one advocacy group which criticized the new federal law because of the feared loss of GM labeling that many companies had already adopted in response to the Vermont labeling law. The federal law nullifies the Vermont law and there is now a two-year period for developing the new labeling standards. The labels being used to accommodate the Vermont law were similar to those in our choice experiment; for example, Campbell Soup has used "produced with genetic engineering" on some products (Halloran, 2016). The new federal law allows for companies to use smartphone scanning codes instead of written text which some argue allows companies to hide the GM content of foods. *Pluralistic advocacy* emphasizes that individuals will tend to

reject messages from experts with whom they do not share cultural values, and individuals more likely to trust those with whom their values align (Earle and Cvetkovich, 1995). Moreover, individuals are more likely to assimilate information that appears to reinforce their own worldviews and reject that which undermines their values (Cohen *et al.*, 2000). Developing a framework to include multiple stakeholders in the development of the GM rules and to disseminate information may lead to a more widely accepted program and considering CWV could help identify key stakeholders for input.

Our findings also suggest that there may be some common ground between individuals with differing CWVs. Although individuals with a HI CWV express significantly less support for mandatory labeling, approximately 71 percent of these individuals indicate that they agreed that labeling the GM ingredients in food should be required, compared to 88 percent of the individuals with an EC CWV and 82 percent overall for people in our study. These results clearly indicate a high level of support for mandatory GM labeling across all CWVs. We also asked individuals about their preferences for the location of GM labeling and the preferred location of information about GM content across all CWVs was on the front of the food packaging as a plain statement. Less popular label locations were front label warning, back label as part of the ingredients list, and back label separate statement. While individuals from different CWVs have different preferences these results highlight important similarities which could form a base for common ground in identifying labeling standards that satisfy a broad range of people.

Our research is limited in a number of ways. First, it only examines two GM policy statements with fairly broad questions. These may not represent enough options for many individuals to adequately express their true GM preferences. Second, our use of four questions to build CWV scales limits some of the nuances which can be observed when using a more robust

set of questions to determine CWV. We also do not fully explore the connections between other demographic, political, and attitudinal variables and CWV and the influence of one on the other. We did explore the collinearity issues associated with using these variables in logistic and linear regression settings, but the complex interactions between these variables and CWV were not explored here. Finally, our data on how CWV influences GM policy preferences are not robust enough to make specific label recommendations to inform policy formation in the active development of the new GM labeling rules. However, our results do provide evidence that it may be wise for policy makers to seek out a wide range of experts and stakeholders with diverse CWVs in the testing phase for GM labels. How will consumers from various CWVs react to scanning codes versus written label statements? How will such labels effect product valuations? Does a government endorsement of information, like with the USDA organic program, help or hinder the GM labeling program? How does this vary by CWV? All of these questions could be addressed in a future study and would greatly inform the GM policy labeling process being carried out by the USDA.

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Tables and Figures

Table 1. Attributes and Levels in Choice Experiment

Attributes	**Levels**
Price	\$2.99
	\$6.99
	\$10.99
	\$14.99
GM Content	No information
	Non-GMO verified
	Contains GM
Carbon Footprint	No information
	79 oz CO2e/lb (low)
	90 oz CO2e/lb (medium)
	112 oz CO2e/lb (high)
Local	No information
	Local production

Table 2. Cultural Cognition Worldview Scales, Short Form

Variable name	Variable Type	Description	
Group or Individualism-Communitarianism [1]			
CHARM (reverse code)	1=strongly agree to 5=strongly disagree	Sometimes government needs to make laws that keep people from hurting themselves.	
IPRIVACY	1=strongly disagree to 5=strongly agree	The government should stop telling people how to live their lives.	
Grid or Hierarchy-Egalitarianism [2]			
HEQUAL	1=strongly disagree to 5=strongly agree	We have gone too far in pushing equal rights in this country.	
EWEALTH (reverse code)	1=strongly agree to 5=strongly disagree	Our society would be better off if the distribution of wealth was more equal.	
Cultural Worldview Groups	**Scale Interpretation**	**Frequencies**	
		n	*percent*
Individualism	Negative Group Factor Score	370	65.0%
Communitarianism	Positive Group Factor Score	199	35.0%
Hierarchical	Negative Grid Factor Score	299	52.5%
Egalitarian	Positive Grid Factor Score	270	47.5%
Hierarchical Individualist	Negative Group x Negative Grid	126	22.1%
Egalitarian Communitarian	Positive Group x Positive Grid	226	39.7%
Hierarchical Communitarian	Positive Group x Negative Grid	73	12.8%
Egalitarian Individualist	Negative Group x Positive Grid	144	25.3%

note: respondents were not forced to agree or disagree with the above statements. Non-responses and neutral positions on these issues were removed from the cultural worldview analyses.

[1]The individualism-communitarianism scale reflected acceptable levels of measurement precision with a Cronbach's $\alpha = 0.779$

[2]The hierarchy-egalitarianism scale reflected acceptable levels of measurement precision with a Cronbach's $\alpha = 0.710$

Table 3. Cultural Worldview and Hypothesized Preferences for GM Food Labeling Policy, GM Discount, and SMRD

	Should the Current Voluntary Approach with Third-Party Certification be Changed?	Should the Federal Government Require Mandatory Labeling?	GM Discount	SMRD
Hierarchical Individualist (HI)	more likely to disagree	more likely to disagree	Lower	Lower
Egalitarian Communitarian (EC)	more likely to agree	more likely to agree	Higher	Higher

Table 4. Demographic and Political Characteristics of Individuals in Four Cultural Worldviews

		Hierarchical Individualist	Egalitarian Communitarian	Hierarchical Communitarian	Egalitarian Individualist	Hypothesis Test[1]
female	Count	84	152	47	106	
	%	67%	67%	64%	74%	$\chi2$: 0.906
male	Count	42	74	26	38	*p*-value:
	%	33%	33%	36%	26%	0.501
under 45 years	Count	31	98	34	70	
	%	25%	43%	47%	49%	$\chi2$: 12.262
45 years and over	Count	95	128	39	74	*p*-value:
	%	75%	57%	53%	51%	0.000
children	Count	26	62	29	46	
	%	21%	27%	40%	32%	$\chi2$: 1.994
no children	Count	100	164	44	98	*p*-value:
	%	79%	73%	60%	68%	0.099
high school or below	Count	41	62	22	52	
	%	33%	27%	30%	36%	$\chi2$: 1.019
associate's or above	Count	85	164	51	92	*p*-value:
	%	68%	73%	70%	64%	0.187
not white	Count	5	47	10	24	
	%	4%	21%	14%	17%	$\chi2$: 18.196
white	Count	121	179	63	120	*p*-value:
	%	96%	79%	86%	83%	0.000

[1]Test statistics compare the HI and EC worldviews.

Table 4. Demographic and Political Characteristics of Individuals in Four Cultural Worldviews (Cont.)

		Hierarchical Individualist	Egalitarian Communitarian	Hierarchical Communitarian	Egalitarian Individualist	Hypothesis Test[1]
income under $120,000	Count	100	187	52	134	
	%	79%	83%	71%	93%	χ2: 0.613
income over $120,000	Count	26	39	21	10	*p*-value:
	%	21%	17%	29%	7%	0.260
suburban or urban	Count	89	185	59	108	
	%	71%	82%	81%	75%	χ2: 5.908
rural	Count	37	41	14	36	*p*-value:
	%	29%	18%	19%	25%	0.011
social non-conservative	Count	40	200	50	116	
	%	32%	89%	69%	81%	χ2: 120.093
social conservative	Count	86	26	23	28	*p*-value:
	%	68%	12%	32%	19%	0.000
fiscal non-conservative	Count	29	190	43	101	
	%	23%	84%	59%	70%	χ2: 128.282
fiscal conservative	Count	97	36	30	43	*p*-value:
	%	77%	16%	41%	30%	0.000

[1]Test statistics compare the HI and EC worldviews.

Table 5. Responses to Two Policy Preference Questions by Individuals from Four Cultural Worldviews

VOLUNTARY: Should the Current Voluntary Approach with Third-Party Certification be Changed?

Worldview		Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	Hypothesis Test[1]
Hierarchical Individualist	Count	16	32	35	26	17	
	%	13%	25%	28%	21%	14%	
Egalitarian Communitarian	Count	9	32	67	70	48	
	%	4%	14%	30%	31%	21%	$\chi 2$: 20.169
Hierarchical Communitarian	Count	6	14	20	17	16	*p*-value:
	%	8%	19%	27%	23%	22%	0.020
Egalitarian Individualist	Count	10	26	51	36	21	
	%	7%	18%	35%	25%	15%	

MANDATORY: Should the Federal Government Require Mandatory Labeling?

Worldview		Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	Hypothesis Test
Hierarchical Individualist	Count	17	16	26	44	23	
	%	14%	13%	21%	35%	18%	
Egalitarian Communitarian	Count	6	6	27	87	100	
	%	3%	3%	12%	39%	44%	$\chi 2$: 47.573
Hierarchical Communitarian	Count	0	8	6	25	34	*p*-value:
	%	0%	11%	8%	34%	47%	0.000
Egalitarian Individualist	Count	8	16	15	58	47	
	%	6%	11%	10%	40%	33%	

[1]Test statistics compare the HI and EC worldviews.

Table 6. Ordinal Logistic Regression Model Results

		Should the Current Voluntary Approach with Third-Party Certification be Changed?			***Should the Federal Government Require Mandatory Labeling?***		
Category	Level	Parameter	Robust SE	Odds	Parameter	Robust SE	Odds
Cultural Worldview	Hierarchical Individualist	-	-	-	-	-	-
	Egalitarian Communitarian	0.706 **	0.295	2.03	0.920 ***	0.290	2.51
	Hierarchical Communitarian	0.568 **	0.261	1.76	1.072 ***	0.275	2.92
	Egalitarian Individualist	0.244	0.271	1.28	0.514 *	0.281	1.67
Demographic	female	0.344 **	0.171	1.41	0.441 **	0.187	1.55
	under_45	0.047	0.197	1.05	0.323 *	0.189	1.38
	child	-0.041	0.195	0.96	0.418 **	0.200	1.52
	edu_coll	0.106	0.171	1.11	0.062	0.183	1.06
	not_white	0.109	0.241	1.12	0.484 **	0.246	1.62
	low_inc	0.390 *	0.234	1.48	0.306	0.237	1.36
	not_rural	0.408 **	0.188	1.50	-0.130	0.206	0.88
Political Views	soc_not_con	-0.083	0.242	0.92	-0.338	0.286	0.71
	fis_not_con	0.227	0.217	1.25	0.545 *	0.283	1.73
Risk Preference	frisk	-0.079 **	0.037	0.92	-0.115 ***	0.036	0.89
Food Labeling	read_labels	0.466 ***	0.170	1.59	0.642 ***	0.177	1.90
	eat_knowledge	-0.130	0.160	0.88	0.185	0.170	1.20
	ginfo_t	-0.440 **	0.201	0.64	-0.374 *	0.218	0.69
	uinfo_t	0.195	0.195	1.22	0.064	0.205	1.07
	cinfo_t	0.528 ***	0.165	1.70	0.817 ***	0.192	2.26
	minfo_t	-0.279	0.245	0.76	0.688 ***	0.250	1.99
	pinfo_t	-0.441 **	0.198	0.64	-0.289	0.200	0.75

*,**,*** indicates significance at the 10%, 5%, and 1% levels, respectively.

Table 6. Ordinal Logistic Regression Model Results (Cont.)

	Should the Current Voluntary Approach with Third-Party Certification be Changed?	***Should the Federal Government Require Mandatory Labeling?***
Log pseudolikelihood	-826.486	-700.354
Pseudo R^2	0.045	0.097
Wald χ^2	71.37 (0.000)	151.92 (0.000)
no. respondents	569	569

Except for frisk all independent variables are dummy variables: frisk willingness to take risks with food; female: female subjects; under_45: age under 45 years; child: children aged 14 and under living in household; edu_coll: associate's degree (2-year degree) or above; not_white: non-white subjects; low_inc: household annual after tax income below $120,000; not_rural: suburban or urban living environment; soc_not_con: not conservative on social issues; fis_not_con: not conservative on fiscal issues; read_labels: frequently or always read food labels; eat_knowledge: yes, I have eaten food containing GM ingredients; ginfo_t: government is a trustworthy source of information on the benefits and risks of GM foods; uinfo_t: universities are a trustworthy source of information on the benefits and risks of GM foods; cinfo_t: consumer advocacy group is a trustworthy source of information on the benefits and risks of GM foods; minfo_t: media is a trustworthy source of information on the benefits and risks of GM foods; pinfo_t: private companies are a trustworthy source of information on the benefits and risks of GM foods.

Table 7. Marginal WTP and GM Discount from Four Cultural Worldviews and Hypothesis Tests

Hypotheses Tests	**non-GMO^{WTP}**	**GM^{WTP}**	**GM Discount**
HI (Hierarchical Individualist)	1.37	-1.68	-0.11
EC (Egalitarian Communitarian)	3.42	-2.31	0.25
p-value[a]	***0.025***	0.185	***0.010***
HI (Hierarchical Individualist)	1.37	-1.68	-0.11
HC (Hierarchical Communitarian)	4.56	-3.04	0.25
p-value[a]	***0.008***	***0.048***	***0.015***
HI (Hierarchical Individualist)	1.37	-1.68	-0.11
ES (Egalitarian Individualist)	2.59	-1.99	0.17
p-value[a]	0.135	0.335	***0.056***

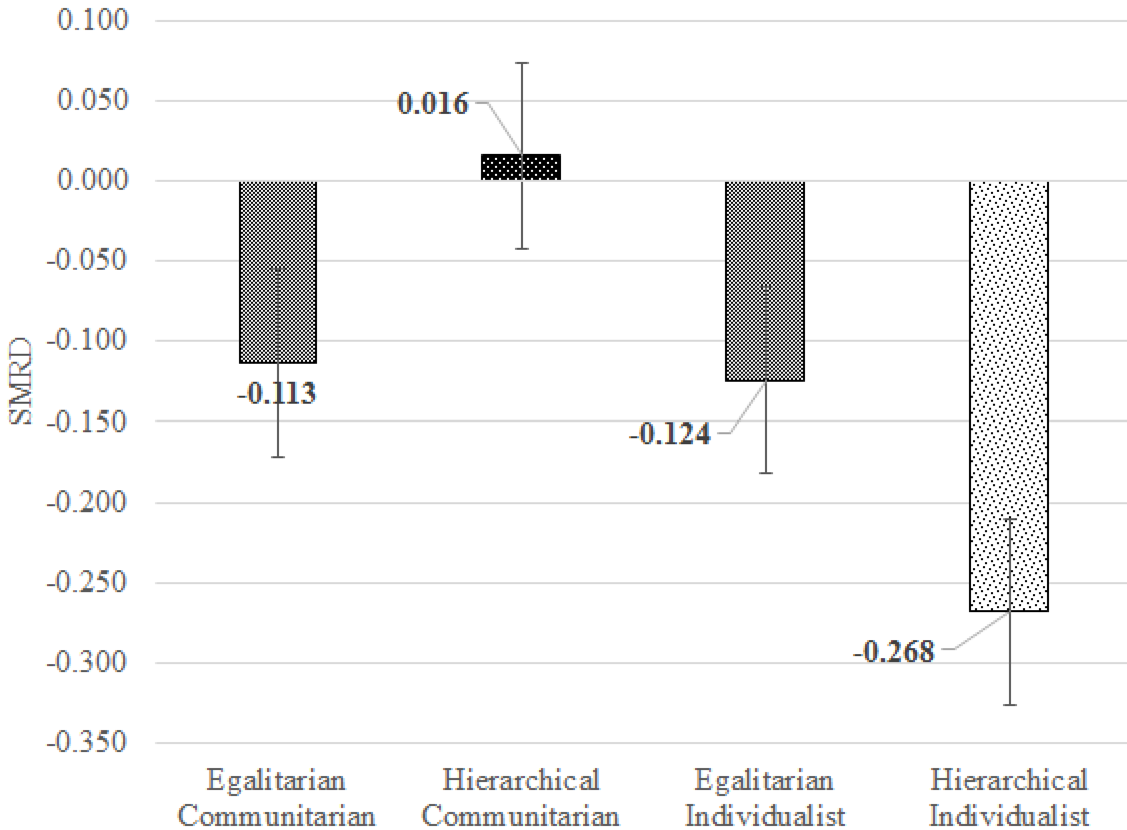
[a] *p*-values were estimated using the combinational method of Poe, Giraud, and Loomis (2005) with 1,000 Krinsky-Robb (1986) bootstrapped estimates. The p-value reports results of the one-sided test for our hypotheses for each corresponding pair of attributes.

Table 8. Multiple Regression Model Results

		GM Discount		
Category	Level	Parameter		Robust SE
Cultural Worldview	Hierarchical Individualist	-		-
	Egalitarian Communitarian	1.344	**	0.587
	Hierarchical Communitarian	1.651	***	0.518
	Egalitarian Individualist	0.614		0.489
Demographic	female	0.186		0.328
	under_45	0.282		0.388
	child	0.811	**	0.383
	edu_coll	-0.337		0.323
	not_white	1.166	**	0.480
	low_inc	-1.197	***	0.433
	not_rural	0.381		0.339
Political Views	soc_not_con	-0.352		0.464
	fis_not_con	0.408		0.436
Risk Preference	frisk	-0.256	***	0.066
Food Labeling	read_labels	1.644	***	0.320
	eat_knowledge	-0.235		0.309
	ginfo_t	-0.823	**	0.386
	uinfo_t	-0.440		0.365
	cinfo_t	0.230		0.321
	minfo_t	0.226		0.440
	pinfo_t	0.087		0.382
	SMRDm	1.098	***	0.263
	constant	2.709	***	0.833
	R^2	0.220		
	Adjusted R^2	0.190		
	F (21, 539)	8.65		
	no. respondents	561		

*,**,*** indicates significance at the 10%, 5%, and 1% levels, respectively.

Figure 1. Standardized Median Rank Difference (SMRD[1]) of Aspect Types



note: ANOVA results indicate that: 1) cultural worldview had a significant effect on SMRDs t-tests comparing the SMRDs from the hierarchical communitarian worldview to the other three worldviews based on 1,000 bootstrapped estimates and 2) the SMRDs from individuals in this worldview were significantly lower than the other three worldviews.

[1]SMRD is valued on a scale from -1 (all negative aspects) to +1 (all positive aspects)

Appendix

Table A1. Mixed Logit (MXL) Model Results for Four Cultural Worldviews

		Hierarchical Individualist			**Egalitarian Communitarian**			**Hierarchical Communitarian**			**Egalitarian Individualist**		
Variables	Coeff.	Estimate		S.E.	Estimate		S.E.	Estimate		S.E.	Estimate		S.E.
NON-GM (NGE)	μ	1.01	*	0.60	1.52	***	0.34	1.50	***	0.36	1.51	***	0.45
	σ	2.70	***	0.43	3.06	***	0.29	2.21	***	0.46	3.07	***	0.46
GM (GME)	μ	-1.22	***	0.45	-1.03	***	0.20	-1.00	***	0.21	-1.17	***	0.30
	σ	2.09	***	0.42	1.66	***	0.20	1.10	***	0.23	1.99	***	0.42
LOWCO2 (LOE)	μ	-0.05		0.26	0.54	***	0.17	0.28		0.19	0.05		0.23
	σ	0.59		0.51	1.00	***	0.23	0.70	***	0.25	0.88	**	0.39
MEDIUMCO2 (MDE)	μ	-0.04		0.31	-0.25		0.15	-0.12		0.15	0.14		0.20
	σ	0.27		1.89	0.54		0.46	0.26		0.21	0.65		0.43
HIGHCO2 (HIE)	μ	0.36		0.26	-0.12		0.15	-0.09		0.18	0.08		0.20
	σ	0.46		2.27	0.66	**	0.32	0.89	***	0.26	0.79	***	0.24
LOCAL (LCE)	μ	0.38	**	0.19	0.25	**	0.10	0.19		0.12	0.37	**	0.16
	σ	0.61		1.00	0.66	*	0.37	0.52	**	0.26	1.00	*	0.53
Price	μ	-0.73	***	0.04	-0.44	***	0.02	-0.33	***	0.04	-0.58	***	0.05
No-buy (NONE)	μ	-5.94	***	0.54	-3.92	***	0.30	-3.38	***	0.82	-5.14	***	0.57
Error Component	σ	2.67	***	0.39	2.46	***	0.25	2.42	***	0.27	2.92	***	0.43
Respondents		126			226			73			144		
Log likelihood		-601.85			-1316.70			-481.31			-830.36		
BIC		1411.18			2858.40			1153.72			1872.20		
BIC/N		1.40			1.58			1.98			1.63		
AIC		1263.71			2693.40			1022.63			1720.72		
AIC/N		1.25			1.49			1.75			1.49		
AIC3		1293.71			2723.40			1052.63			1750.72		
AIC3/N		1.28			1.51			1.80			1.52		

***, **, * Significance at 1%, 5%, 10% level

Conclusion

This research uses Query Theory to provide a deeper understanding of the demand for genetically modified (GM) foods and the preferences for GM policy. In the first article, Query Theory is applied to the formation of hypothetical bias in the estimation of consumers' willingness-to-pay. To address this, the honesty oath is used as an ex-ante technique to reduce hypothetical bias. Paper one provides a query account of the honesty oath in a discrete-choice experiment setting by using Query Theory to examine the mechanism behind the effectiveness of the honesty oath in reducing hypothetical bias in discrete choice experiments.

We conclude that the honesty oath reduces, but may not eliminate, hypothetical bias. Further, the honesty oath changes the content of queries. Our results provide strong evidence that experimental treatment did have a significant effect on the number of value-decreasing and increasing aspects listed by individuals. Overall, respondents in the honesty oath treatment listed more negative aspects (value-decreasing) and fewer positive aspects; these relationships were statistically significant. These results provide strong evidence to support our conclusion that honesty oath changes the content of queries.

We also conclude that the honesty oath changes the order of queries. Because participants listed different numbers of aspects, we used the standardized median rank difference (SMRD) score to test this prediction. SMRD reflects an individual's tendency to produce value-increasing aspects before value-decreasing ones. In our study, individuals under oath had SMRD scores closer to -1, than individuals not under oath; this difference was found to be significant. These results provide support for our conclusion that the honesty oath changed the order of aspects listed by individuals, and it influenced individuals to produce negative aspects before positive ones. Our fourth conclusion is that the queries predict consumer valuation. The results of our

multiple regression model indicate that the encoding of aspects explain between 36% and 52% of the variation in our willingness to pay (WTP) estimates for the non-GMO, contains GM, and local production attribute levels.

In the second paper, we apply Query Theory to the attendance to attributes (AA). Failure to account for patterns of AA in choice models can affect coefficient estimates, model fit and performance measures, and welfare estimates. We observe that the majority of all aspects listed relate to the attributes in our experiment. This gives us a high level of certainty that the aspects listed can be considered as predictors of attribute attendance. In this regard, the query approach represents a conservative one compared to the other common approaches presented in the paper: the stated and inferred approaches. Our comparison across the three approaches highlight the challenge faced by researchers in identifying AA and the difficulties that arise in properly modeling the phenomenon. Our results show that the inferred, stated and query approaches all improve model fit statistics. However, in terms of the improvement to model coefficients, the query approach outperforms both the inferred and stated approaches by returning coefficients for attributes with patterns of heterogeneity that indicate the query approach has effectively identified patterns of AA. The query approach at the serial level appears to do a better job than the approach at the choice task level. The stated approach at both the serial and choice task levels also appear to do an effective job at identifying patterns of AA; however, the query approach models outperforms the stated approach models in distinguishing between patterns of AA and heterogeneity. In fact, the heterogeneity estimates from our dual coefficients models offer perhaps the strongest support for the use of the query approach to attribute attendance with certainty. Our findings provide support to our assertion that the query approach represents attendance to attributes with certainty. Our results also demonstrate that while the stated

approach does improve model performance, the approach may still suffer from the misrepresentation of true patterns of AA due to the confounding of attributes truly ignored and those simply given low attention.

Finally, in the third paper, Query Theory is applied the study of the influence of cultural worldview on preferences for GM policy and the demand for GM foods. After decades of experience with GM foods in the U.S., relative consensus among scientists, and relatively high support from the public in general, the call for mandatory labeling has increased rather than dissipated. This reality has puzzled many from the academic and scientific community. Because fundamental differences in cultural values exist between individuals, polarizing issues like GM foods are rarely solved through more scientific data and campaigns to raise the awareness of the real risks and benefits of GM foods. Our GM policy preference results demonstrate that cultural worldview has a significant influence on the likelihood that an individual will support or oppose voluntary and mandatory labeling policy change. Individuals with a relatively hierarchical and individualistic worldview are not only less likely to support mandatory labeling, they also expressed very low trust in a number of sources of information about the safety of GM foods. These results underscore the importance of individuals' worldview in how they interpret information about the safety and benefits of GM foods. Efforts by the government and policy advocates to raise the level of awareness of GM foods risks are likely to have varying effects depending upon a person's worldview. Our results demonstrate that those individuals with a relatively higher demand for mandatory GM labeling are also those who have a significantly higher level of trust in consumer advocacy groups and the media; these are often sources of negative information regarding GM foods as evidenced by recent efforts to raise the state of concern over GM foods and increased media coverage of negative GM events. This helps

explain some of the polarizing results between worldviews. The results of our consumer demand analysis further demonstrate this polarization and indicate that cultural worldview also has a significant impact on the WTPs of individuals for non-GMO and contains GM labels. Perhaps the most interesting finding of the consumer analysis is that the WTP for the non-GMO attribute is actually lower than that for the "contains GM" attribute among individuals with a *hierarchical-individualistic* worldview. This is not a common finding among consumers in general, where the WTP for the non-GMO attribute is typically larger with respect to "this product contains GM" types of labels. However, these results demonstrate the important influence that cultural biases play in the formation of values. Our query results using the SMRD to compare individuals from different worldviews confirm that individuals with a *hierarchical-individualistic* worldview tend to consider relatively negative (value-decreasing) aspects first. By contrast, this means that individuals from the *egalitarian-communitarian* worldview are more likely to be thinking first about aspects that increase their WTP for non-GMO and GM discount. This is an important finding because Query Theory assumes that individuals evaluate aspects sequentially and that due to output interference the first query is weighted more heavily by individuals. Our results provide support for the conclusion that an individual's worldview influences the order of queries.

Our three papers provide important insights for policy makers. DCEs are a popular method for estimating the welfare measures often sought by policy makers conducting cost-benefit analyses. Our first two papers offer methodological suggestions for improving DCEs (by use of the honesty oath in survey design and by accounting for patterns of attendance to attributes) so that they may provide more reliable welfare measures. Our third paper emphasizes the importance of CWV on GM policy preferences. As the USDA develops the new federal

mandatory labeling program for GM foods, it is important to consider the preferences of individuals with different worldviews and search for common ground among groups. Our results demonstrate that preferences for GM food policies are influenced significantly by an individual's CWV, which represents a lens through which all new information must be viewed and through which some sources are deemed unacceptable and untrustworthy. People engage in politics to translate their beliefs into action and coalitions of members with different beliefs often interact and compete to produce the policy outcomes preferred by coalition members. The advocacy coalition supporting mandatory GM labeling has done an effective job framing the arguments for labeling by focusing on social and ethical concerns associated with GM foods and the consumer's "right-to-know" the GM content of food. The broad appeal of these themes help to explain why scientific consensus on the safety of GM foods is not enough to cease the calls for mandatory GM labeling. While scientific evidence does play an important role in how people form risk perceptions, people also form preferences based on their beliefs and values. In the case of GM food labeling, advocates for labeling have arguably done an effective job of changing the focus of the debate such that even a large share of individuals who believe GM foods to be safe still support GM labeling. As individuals have moved from being opponents of GM labeling to proponents, they have signaled that their values align more closely with the messages of the pro-labeling movement.

As the new rules for GM labeling are developed, a framework is needed that will include individuals with a broad spectrum of worldviews. Our results demonstrate that individuals less likely to support change in GM food labeling policy still, in fact, support mandatory GM labeling at a high level. This shows that although many differences do exist, there is common ground between individuals with differing CWVs. Finding this common ground could greatly improve

the chance of success of a final program that has broad appeal and reduces contention between groups in the GM labeling policy subsystem. Individuals with a *hierarchical individualist* worldview express less support for mandatory labeling; however, 71 percent of these individuals indicate that they agreed that labeling the GM ingredients in food should be required. This is compared to 82 percent of the total participants in our third paper supporting mandatory GM labeling. The preferences for types of labels are also similar across groups with individuals from all worldviews preferring plain text (not a warning) front of package GM labels. The inclusion of individuals with differing points of view in the process of developing the GM labeling rules could potentially identify more areas of common ground. Importantly, such an open and engaging process could lead to a long-lasting solution to GM food labeling and reduce the contention between the coalitions who advocate and oppose GM food technologies.

Appendix

Research Approval Letter

UNIVERSITY OF ARKANSAS

Office of Research Compliance
Institutional Review Board

November 11, 2015

MEMORANDUM

TO:	Nathan Kemper Jennie Popp
FROM:	Ro Windwalker IRB Coordinator
RE:	PROJECT MODIFICATION
IRB Protocol #:	15-10-192
Protocol Title:	*Consumer Preferences Regarding GMO-Free Labeling for Fresh Chicken*
Review Type:	☒ EXEMPT ☐ EXPEDITED ☐ FULL IRB
Approved Project Period:	Start Date: 11/11/2015 Expiration Date: 10/18/2016

Your request to modify the referenced protocol has been approved by the IRB. **This protocol is currently approved for 8,000 total participants.** If you wish to make any further modifications in the approved protocol, including enrolling more than this number, you must seek approval *prior to* implementing those changes. All modifications should be requested in writing (email is acceptable) and must provide sufficient detail to assess the impact of the change.

Please note that this approval does not extend the Approved Project Period. Should you wish to extend your project beyond the current expiration date, you must submit a request for continuation using the UAF IRB form "Continuing Review for IRB Approved Projects." The request should be sent to the IRB Coordinator, 109 MLKG Building.

For protocols requiring FULL IRB review, please submit your request at least one month prior to the current expiration date. (High-risk protocols may require even more time for approval.) For protocols requiring an EXPEDITED or EXEMPT review, submit your request at least two weeks prior to the current expiration date. Failure to obtain approval for a continuation *on or prior to* the currently approved expiration date will result in termination of the protocol and you will be required to submit a new protocol to the IRB before continuing the project. Data collected past the protocol expiration date may need to be eliminated from the dataset should you wish to publish. Only data collected under a currently approved protocol can be certified by the IRB for any purpose.

If you have questions or need any assistance from the IRB, please contact me at 109 MLKG Building, 5-2208, or irb@uark.edu.

109 MLKG • 1 University of Arkansas • Fayetteville, AR 72701-1201 • (479) 575-2208 • Fax (479) 575-6527 • Email irb@uark.edu

Research Continuation Letter

UNIVERSITY OF ARKANSAS

Office of Research Compliance
Institutional Review Board

October 4, 2016

MEMORANDUM

TO:	Nathan Kemper Jennie Popp
FROM:	Ro Windwalker IRB Coordinator
RE:	PROJECT CONTINUATION
IRB Protocol #:	15-10-192
Protocol Title:	*Consumer Preferences Regarding GMO-Free Labeling for Fresh Chicken*
Review Type:	☒ EXEMPT ☐ EXPEDITED ☐ FULL IRB
Previous Approval Period:	Start Date: 10/19/2015 Expiration Date: 10/18/2016
New Expiration Date:	10/18/2017

Your request to extend the referenced protocol has been approved by the IRB. If at the end of this period you wish to continue the project, you must submit a request using the form *Continuing Review for IRB Approved Projects*, prior to the expiration date. Failure to obtain approval for a continuation on or prior to this new expiration date will result in termination of the protocol and you will be required to submit a new protocol to the IRB before continuing the project. Data collected past the protocol expiration date may need to be eliminated from the dataset should you wish to publish. Only data collected under a currently approved protocol can be certified by the IRB for any purpose.

This protocol has been approved for 8,000 total participants. If you wish to make *any* modifications in the approved protocol, including enrolling more than this number, you must seek approval *prior to* implementing those changes. All modifications should be requested in writing (email is acceptable) and must provide sufficient detail to assess the impact of the change.

If you have questions or need any assistance from the IRB, please contact me at 109 MLKG Building, 5-2208, or irb@uark.edu.

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Data Collection Instrument

IMPLIED CONSENT INFORMATION

[Participants will be given this information as well as a link to the survey.]

Dear Consumer,

This research is being conducted by researchers at the University of Arkansas. The purpose of this survey is to better understand how you make decisions on purchasing food products and what types of food labels you prefer. There are no anticipated risks to participating. The survey should take 20 minutes to complete. Your participation is completely voluntary. Your responses will be recorded anonymously and no identifying personal information will be collected on the survey. Responses will be aggregated for presentation.

The survey has three parts. The first part is a choice experiment where you will be asked to make choices between different sets of products. The second part is a series of questions to help us better understand your purchasing decisions in the choice experiment and your preferences for different approaches to labeling food. The third part is a short series of demographic questions. You are free to refuse to participate in the research and to stop completing the survey at any time.

If you have any questions about this survey itself, please contact Nathan Kemper by email or phone at nkemper@uark.edu or 479-575-2697. You may also contact the University of Arkansas Research Compliance office listed below if you have questions about your rights as a participant, or to discuss any concerns about, or problems with the research: Iroshi (Ro) Windwalker, CIP, IRB/RSC Coordinator Research Compliance, 109 MLKG Building, Fayetteville, AR 72701, Ph. 479.575.2208, Fax 479.575.6527

Sincerely,

Nathan Kemper

IRB #15-10-192
Approved: 10/19/2015
Expires: 10/18/2016

Part 1. Choice Experiment

[*Participants will first be presented with a set of instructions that are common across all surveys*]

Instructions:

The United States does not follow a mandatory approach to the labeling of genetically modified food. Therefore, food producers are not required to label the genetically modified content of their food. As a result, under our current voluntary system the foods that typically carry a label are those carrying a non-genetically modified label. In the choice experiment portion of this survey, you will be asked to choose between food products that may or may not carry label statements regarding the genetically modified content of the food. Please consider all information provided for each product before making each purchase decision. Thank you.

Label Terms Defined:

Genetically Modified Organism (GMO): in this survey, genetic modification (GM) refers to the production of heritable improvements in organisms for specific uses via genetic engineering (GE) and a genetically modified organism (GMO) is a plant produced through GM. The GM information on the labels in this survey refer only to the ingredients in the diet fed to the chickens.

The Non-GMO Project: a non-profit organization committed to preserving and building the non-GMO food supply, educating consumers, and providing verified non-GMO choices. Poultry carrying a Non-GMO Project Verified label indicates the bird was raised on a diet containing non-GMO feed.

Carbon Footprint: the total amount of Greenhouse Gas Emissions associated with a product, along its supply chain, including emissions from consumption, end-of-life recovery and disposal. Expressed in ounces (oz) of carbon dioxide equivalent (CO_2e) per pound (lb) of meat.

Production State: the production location refers to BOTH the production of the feed AND the location of where the birds were raised.

Screening Questions

1. In my household…
   _____I am solely responsible for making all grocery purchasing decisions *[proceed]*
   _____I have shared responsibility for making grocery purchasing decisions *[proceed]*
   _____I do not have any responsibility for making grocery purchasing decisions *[discontinue]*

2. How many times have you purchased *chicken breast meat* in the past 12 months?
   _____0 *[discontinue]*   _____1-6 *[proceed]*
   _____7-12 *[proceed]*   _____13 or more *[proceed]*

Part 2. Survey

1. Perceived Consequentiality

1. To what extent do you believe that answers from this survey will be taken into consideration by decision makers such as producers, manufacturers, retailers, and/or policy makers?

   Not taken into account (1) (2) (3) (4) (5) Definitely taken into account

2. To what extent do you believe that answers from this survey will be taken into consideration by decision makers who bring food products to market?

   Not taken into account (1) (2) (3) (4) (5) Definitely taken into account

3. To what extent do you believe that answers from this survey will be taken into consideration by decision makers in a way that can change the price of food (thus impacting your budget)?

   Not taken into account (1) (2) (3) (4) (5) Definitely taken into account

2. Risk Preferences

4. How do you see yourself: are you generally a person who is willing to take risks or do you try to avoid taking risks? Please select a number on the scale, where the value 0 means: 'not at all willing to take risks' and the value 10 means: 'very willing to take risks'.

Not at all willing to take risks — Very willing to take risks

0	1	2	3	4	5	6	7	8	9	10

5. People can behave differently while engaged in different activities. How would you rate your willingness to take risks while engaged in the following activities? Please select a number on the scale, where the value 0 means: ‘not at all willing to take risks’ and the value 10 means: ‘very willing to take risks’.

	Not at all willing to take risks										Very willing to take risks
How willing are you to take risks...	0	1	2	3	4	5	6	7	8	9	10
…while driving?											
…when making investments?											
…in recreation and sports?											
…concerning your career?											
…with your health?											
…with the food you eat?											

3. Preferences for GM Labeling Programs

The United States uses a voluntary approach to the labeling of genetically modified food. Foods that are labeled under the current voluntary approach are products displaying a non-genetically modified statement and/or label certified by a third-party agent. Some argue that the United States Department of Agriculture should play a more active role in the voluntary approach by setting national standards for the certification of genetically modified (non-bioengineered) food.

6. Do you agree or disagree that the current voluntary approach with third-party certification should be left as is and NOT be changed?
_____Strongly Disagree (1)
_____Disagree (2)
_____Neither Agree nor Disagree (3)
_____Agree (4)
_____Strongly Agree (5)

7. Do you agree or disagree that the USDA should become more involved in the voluntary approach by developing a national certification program?
_____Strongly Disagree (1)
_____Disagree (2)
_____Neither Agree nor Disagree (3)
_____Agree (4)
_____Strongly Agree (5)

Some citizens in the United States argue that the federal government should adopt a mandatory labeling approach that requires labels on any food containing genetically modified ingredients.

8. Do you agre or disagree that the federal government should require mandatory labeling?
_____Strongly Disagree (1)
_____Disagree (2)
_____Neither Agree nor Disagree (3)
_____Agree (4)
_____Strongly Agree (5)

9. Do you agree or disagree that taxpayers should pay for the cost of a federal mandatory labeling program?
_____Strongly Disagree (1)
_____Disagree (2)
_____Neither Agree nor Disagree (3)
_____Agree (4)
_____Strongly Agree (5)

10. How would you rate your trust in the different sources of label certification for food products?

	Very Untrustworthy (1)	Untrustworthy (2)	Neutral (3)	Trustworthy (4)	Very Trustworthy (5)
Private Company					
Independent Third Party (non-governmental)					
Government – Local or State					
Government – National					

4. Food Label Information

11. Beyond looking at the brand name, how often do you read food labels?
_____Never (1)
_____Rarely (2)
_____Sometimes (3)
_____Frequently (4)
_____Always (5)

12. As far as you know, have you ever eaten any food containing genetically modified ingredients?
_____Yes
_____No
_____I am not sure

13. Do you agree or disagree that labelling the genetically modified ingredients in food should be required?
_____Yes
_____No

14. If genetically modified ingredients were required to be labeled, where do you feel is the best place to display these ingredients on a food product label?
_____On the back of the package in the list of ingredients (1)
_____On the back of the package separate from the ingredients (2)
_____On the front of the package (3)
_____On the front of package prominently displayed as a warning (4)

15. Different institutions publish research or report information on the advantages and disadvantages of genetically modified food. How trustworthy are each of the following sources?

	Very Untrustworthy (1)	Untrustworth y (2)	Neutra l (3)	Trustworth y (4)	Very Trustworth y (5)
Government					
Private Sector					
University					
Nonprofit Consumer Advocacy Group					
Food Manufacturer					
Media					

5. Cultural and Political Views

People in our society often disagree about how far to let individuals go in making decisions for themselves. How strongly do you agree or disagree with the following two statements?

16. Sometimes government needs to make laws that keep people from hurting themselves.
_____Strongly Disagree (1)
_____Disagree (2)
_____Neither Agree nor Disagree (3)
_____Agree (4)
_____Strongly Agree (5)

17. The government should stop telling people how to live their lives.
_____Strongly Disagree (1)
_____Disagree (2)
_____Neither Agree nor Disagree (3)
_____Agree (4)
_____Strongly Agree (5)

People in our society often disagree about issues of equality and discrimination. How strongly do you agree or disagree with the following two statements?

18. We have gone too far in pushing equal rights in this country.
_____Strongly Disagree (1)
_____Disagree (2)
_____Neither Agree nor Disagree (3)
_____Agree (4)
_____Strongly Agree (5)

19. Our society would be better off if the distribution of wealth was more equal.
_____Strongly Disagree (1)
_____Disagree (2)
_____Neither Agree nor Disagree (3)
_____Agree (4)
_____Strongly Agree (5)

20. How would you describe your political views on social issues?
_____Very liberal
_____Liberal
_____Moderate
_____Conservative
_____Very Conservative
_____none of these

21. How would you describe your political views on fiscal issues?
_____Very liberal
_____Liberal
_____Moderate
_____Conservative
_____Very Conservative
_____none of these

6. Demographic Information

22. In what state do you currently live?
________state [*drop down list*]

23. How would you describe your home environment?
_____Rural
_____Suburban
_____Urban

24. What is your age?
[census age categories]

25. What is your gender?
_____Male
_____Female

26. Do you live alone or with others?
_____Live alone
_____Live with others

[Skip Logic: if live alone, skip next question]

27. How many people in your household are in the following age categories?
_____Adults and children age 15 and older
_____Children age 7 to 14 years old
_____Children 6 years old and younger

28. What is your highest level of education? (check one):
_____Some High School
_____High School Diploma
_____Associate’s Degree (2-year degree)
_____Bachelor’s Degree (4-year degree)
_____Master’s Degree
_____Doctoral Degree

29. What is your race?
[census race/ethnicity]

30. What is your total net (after tax) household income?
[census income categories]

Table A1. Experimental Treatments and Numbers of Respondents in Treatments

Paper	Treatment	Without Aspect-Listing	With Aspect-Listing	Totals
1	Honesty Oath	500	500	1,000
1	Academic Control	500	500	1,000
1	Experimental Control	500	500	1,000
2	Stated Approach	500	0	500
2	Query Approach	0	500[1]	0
3	Cultural Cognition	0	1,000	1,000
	Totals	2,000	2,500	4,500

[1] The query approach treatment is the same as the experimental control with aspect-listing. The number of respondents in the total rows and columns have been adjusted to reflect this.