Consumer Choice Models Applied on a Biobased Product

By

Haotian Cheng

Bachelor of Science in Plant Protection
Hai-Nan University
China
2014

Master of Science in Agricultural Economics
Oklahoma State University
Stillwater, Oklahoma
2017

Submitted to the Faculty of the
Graduate College of the
Oklahoma State University
in partial fulfillment of
the requirements for
the Degree of
DOCTOR OF PHILOSOPHY
July, 2021

Consumer Choice Models Applied on a Biobased Product

Dissertation Approved:

Dissertation Adviser's Name Dr. Dayton Lambert

Dissertation Adviser

Committee Member Name Dr. Wade Brorsen

Committee Member Name Dr. Bailey Norwood

Outside Committee Member Name Dr. Danielle Bellmer

.

Name: HAOTIAN CHENG

Date of Degree: JULY, 2021

Title of Study: Consumer Choice Models Applied On Biobased Product

Major Field: Agricultural Economics

Abstract:

Biobased products are non-food/non-fuel goods derived from plants and other renewable agricultural and forestry materials. Everyday household products made from biobased materials could replace products made with petroleum-based inputs. This research estimates consumer willingness to pay (WTP) for extrinsic attributes (Source, Biodegradable, Biobased label, and Origin) in single-used eating-ware (SUEW) made from a biobased product using data from nationally representative surveys.

Study I applies the generalized multinomial logit (GMNL) model based on the data collected by the conjoint surveys. A split sample survey is used to address availability bias and attention bias. Study II extends a rank ordered logit (ROL) regression to a generalized rank ordered logit model (GROL). Best-worst scaling data collected from a survey is used in this study. Study III extents the hybrid mixed choice model (HMC) to a hybrid generalized multinomial logit (HGML) model based on the data collected from a conjoint survey. The choice models of studies 2 and 3 are estimated using Bayesian procedures.

Results suggest that the rapidity of product degradability and using non-plastic materials to make SUEW plates were valued most by consumers. Availability bias (e.g., the order of information provided to participants before choice set completion) did not affect WTP estimates in the study I while did affect WTP estimates in the study II. Inattention bias decreases consumer WTP for SUEW plates study I, while it did not affect WTP estimates in study II. This difference may be due to difference in the samples, on differences in the methods used to elicit WTP.

TABLE OF CONTENTS

Chapter Page

LIST OF TABLES

LIST OF FIGURES

Figure Page

CHAPTER I

INTRODUCTION

Biobased products include an array of consumer goods such as lubricants, cleaning products, packaging, cosmetics, fertilizers, and eating-ware. The United States Department of Agriculture (USDA) defines biobased products as non-food or non-fuel goods derived from plants and plant biomass from agriculture and forestry (Federal Register, 2015). Biomass materials are inputs for some types of bioplastics. Bioplastics are produced from plant or woody biomass, from which numerous polymers are used to make food packaging or molded products (Harmsen, Hackmann, and Bos, 2014).

In 2017, global production of bioplastics was 4.2 million tons, which accounted for just over 1-percent of total plastic production (European Bioplastics 2017). Products made with bioplastics are an alternative to consumer goods made wholly or in part from plastics or other petroleum-based inputs. In 2013, the bioproduct industry added $369 billion in value to the United States (US) economy (Golden et al., 2015). The estimated market value for biobased products was $104 billion in 2016 (Wood, 2017). The biobased industry supported 1.5 million jobs directly in 2015, with an additional 2.5 million employed through backward linked supply chains (Golden et al., 2015). Industry research on and development of biomaterial inputs will continue while profit margins remain, but consumer demand for products made from biobased inputs will play an important role in the scope and depth of this developing market.

This research estimates consumer willingness to pay (WTP) for extrinsic attributes of a molded bioplastic product; single-use eating-ware (SUEW) produced with the renewable biomaterial, wheat straw. Extrinsic attributes are features of a product that consumers value apart from the product's function (Li et al., 2017). SUEW products include cups, straws, plates, bowls,

and utensils. The environmental footprint of SUEW is substantial. Single-use eating-ware typically ends up in landfills. The US Environmental Protection Agency (USEPA) estimated that 1.05 million tons of solid waste produced in metropolitan areas was composed of plastic eating-ware, of which 80 percent ended up in landfills (USEPA, 2018).

Wheat straw is what remains after harvest. In 2019, United States (US) farmers produced 1,920 million bushels of wheat (USDA, 2020). Farmers burn wheat straw, use wheat straw to feed animals, or leave stubble on fields. Wheat straw can also be molded and then used to reinforce thermoplastic composites (Panthapulakkal and Sain, 2006). Single-use products made from molded wheat straw could be a substitute for SUEW made from petroleum-based plastics and reduce its landfill footprint. An alternative market for wheat straw could add value to agriculture.

CHAPTER II

OBJECTIVES

This dissertation includes three studies of consumer preferences for biobased products and specific product attributes. The product attributes are: 1) USDA Certified Biobased Product labeling; 2) the use of industrial crops versus food crops in the manufacture of biobased products; 3) product biodegradability; 4) raw materials grown in the U.S., such as wheat straw; and 5) product price.

Results of this dissertation contribute to the general understanding of WTP for emerging bio-product markets. The research also extents econometric methods commonly used for choice modeling by introducing Bayesian estimators of rank ordered logit and hybrid mixed logit models.

Study I Objectives

- to control for attention bias and availability bias during estimation of WTP for biobased products using a split sample choice experiment and generalized multinomial logit (GMNL) regression.
- to estimate WTP for each SUEW attribute.
- to determine the optimal price for the wheat SUEW product and change inconsumer surplus.
-

Study II Objectives

- to extend the rank ordered logit (ROL) model to the generalized rank ordered logit (GROL) model.to estimate the GROL using Bayesian procedures.
- to determine the optimal price for the wheat SUEW product and consumer surplus change.

Study III Objectives

- to reformulate a hybrid mixed choice model as a hybrid generalized multinomial logit (HGMNL) model, where the attributes coefficients and latent variables are estimated simultaneously.
- to estimate the HGMNL using Bayesian procedures to determine the WTP for the SUEW products.

CHAPTER III

STUDY I: CONTROLLING FOR INATTENTION AND AVAILABILITY BIAS IN ATTRIBUTE PREMIUM ESTIMATION OF A BIOBASED PRODUCT

Background and Previous Research

The USDA has supported expansion of the biobased economy through the BioPreferred program since 2002.[1] The program's goal is to encourage companies to use biobased inputs in the manufacturing of goods and to inform and educate consumers about the composition of products made from biobased materials. Companies may voluntarily display a 'USDA Certified Biobased Product' on products following a third-party content analysis. The certification label indicates what percent a product's composition is biobased, but labels do not indicate other attributes that consumers might prefer such as degradability or attributes related to the source, production process, or origin of inputs used to make biobased products.

Demand for Biobased Products

Duncan et al. (2009) examined US consumer preferences for labeling programs supporting the promotion of biobased products. Duncan et al.'s study focused on the environmental footprint of biobased products. Their research developed metrics to support industry leaders in the production and marketing of bioproducts. Duncan et al. concluded that biobased products would

[1] https://www.biopreferred.gov/BioPreferred/

likely need to meet the same performance standards as fossil energy products if these products were to gain broad consumer appeal.

Several studies focused on consumer knowledge about and perceptions of biobased products. Kainz et al. (2013) found that German consumers favorably viewed products made from bioplastics. Consumers most commonly associated bioplastics with resource renewability and degradability. However, consumers were skeptical that bioplastics were environmentally sustainable. Sijtsema et al. (2016) examined consumer attitudes toward biobased products across the Czech Republic, Denmark, Italy, Germany, and the Netherlands. Respondents were generally unfamiliar with bioproducts, but they associated ‘biobased’ with natural or environmentally friendly products and preferred them to products made with petroleum-based materials. Sijtsema et al. also reported that consumers were skeptical of bioproduct functionality, aesthetics, and degradability. Arjunan et al. (2010) found that consumers were enthusiastic about bioplastic products and their relationship with renewable feedstock sources, recyclability, and degradability. Choi et al. (2020) found that consumers preferred bioproducts made from agricultural or wood waste by-products but were averse to biobased products made from renewable fuel co-products.

Reinders et al. (2017) found that European consumers were more likely to purchase 100 percent biobased products rather than partly biobased products. Carus et al. (2014) found that consumers attributed positive premiums to biobased inputs used to make chemicals, plastics, and polymers. Carus et al. also concluded that consumers were willing to pay an additional 10 percent above the market price for food packaged in biobased containers. Gill et al. (2020) estimated consumer WTP for dinnerware plates molded from wheat straw using contingent valuation methods. Gill et al. found that Tennessee consumers would pay an additional $1.35 for a 25-count package of SUEW made with molded wheat straw. Consumers expressed distaste for petroleum-based plastic products. Other product attributes valued by consumers included recyclability and certification labeling.

Brenna, Barrett, and Atual (2015) found that consumers were willing to pay a $0.67 to $1.12 premium for bioplastic plant containers compared to petroleum-based plastic pots. Consumers valued most bioplastic pots that improved plant health and degraded quickly. Gender, household income, frequency of plant purchases, use of reusable bags, and composting were demographic characteristics that influenced the premium.

Scherer, Emberger-Klein, and Menrad (2017) estimated German consumer WTP for children's toys made with bioplastics. Attributes examined included the number of pieces the toys set included, the percent composition of bioplastic, the origin of precursor biomaterials (e.g., castor oil, palm oil, or sunflower oil), and other product attributes including fair trade, sustainable cultivation, and organic cultivation. The most important attribute was product price, followed by feedstock procured by 'environmentally friendly' methods and if the toys were produced in the European Union. Scherer, Emberger-Klein, and Menrad (2018) estimated consumer WTP for bioplastic bottles and running shoes made with biobased soles. Attributes valued most by these consumers were the product's potential to reduce CO_2 emissions and the use of organic input materials made in Europe.

Kainz et al. (2016) found that consumers expressed higher WTP for biopolymer products when they were provided detailed information on the product's composition and materials. Kainz et al. also concluded that premiums for biopolymer products differed by gender, with lower premium for males. Barnes et al. (2011) reported similar findings in their study of consumer preferences for plant-based food containers. Their analysis concluded that most respondents preferred takeout containers made from locally produced sugarcane bagasse, suggesting that consumer preferences oriented towards locally sourced products.

These studies are important contributions for understanding consumer WTP for biobased products. We extend the previous research by analyzing a choice experiment conducted with a nationally representative survey of US consumers. We focus on the effects information respondents receive on the product considered and respondent attentiveness on WTP.

Inattention Bias

Survey respondents unfamiliar with a product may lose interest in completing choice tasks, which leads to survey fatigue or incorrect responses caused by inattention bias (Malone and Lusk, 2019). The psychology literature generally finds that incorrect responses to obvious yes/no questions signal participant inattention (Berinsky et al., 2014). Inattentive respondents have a higher probability of violating revealed preference axioms (Jones et al., 2015). Inattention bias also lowers statistical power (Oppenheimer et al., 2009). Some studies controlled for respondent inattention with the time spent to complete a survey task (Börger, 2016; Li et al., 2016). However, time-to-completion only identifies how fast participants complete a survey, and not if the respondent attentively answered questions (Malone and Lusk, 2018b).

One approach to minimize inattention bias is to exclude respondents caught not paying attention. This work-around comes at the cost of losing data. Surveys can include trap questions to detect and control for inattention bias rather than eliminating observations. Respondent failure to answer correctly trap questions is common (Berinsky et al., 2014). Trap questions identify inattentive respondents with indicators, which can serve as instruments to control for inattention bias. Malone and Lusk (2018b) used trap questions in a split-sample survey to control for inattention bias. They found that individuals who incorrectly answered trap questions responded differently. Malone and Lusk (2019) used double trap questions to identify inattentive respondents. They concluded that individuals who answered incorrectly on both trap questions exhibited significantly different preferences. We included two double trap questions in the survey in addition to monitoring the time respondents spent answering questions.

Information Effects and Availability Bias

The amount of information respondents receive about a product during a choice experiment may affect WTP estimates (Roosen et al., 2011). Limited information about a product may also inadvertently introduce availability bias (Kahneman, 2011). Availability bias occurs when respondents evaluate choice tasks based only on the most recent information screen. When this happens, respondents anchor their choices to the latest information received about a product, issue, or context. In the case of bioproducts, consumers are likely unfamiliar with the terminology, concepts, or novel product cycles characterizing the attributes associated with biobased products (Reinders et al., 2017).

The effects of information content on WTP have been analyzed using split-sample surveys. Researchers typically compare responses from an information treatment group with a control group who receive minimal or no information about a product or issue (Malone and Lusk, 2018a). Some studies find no differences in WTP between information treatments. In their study of information effects on consumer preferences for organic and natural chicken, Gifford and Bernard (2011) withheld information on definitions of ‘organic’ and ‘natural’ from participants. They found no significant differences in WTP between the split-sample groups. Likewise, Czajkowski et al. (2014) found that respondent WTP for a good remained unchanged when respondents were provided additional information about the product.

Other studies find that WTP estimates differ between groups exposed to different information sets. Syrengelas et al. (2018) found that consumers who were given the USDA definition of "natural" were unwilling to pay more for natural beef, but participants who were not given this definition were willing to pay more. Lusk et al. (2008) found that respondents who received information on the health benefits of grass-fed beef were more likely to select grass-fed beef products. Risius and Hamm (2017) found that when extensive background information on suckler cow husbandry was provided, the labeled product carried with it a higher premium. Consumers placed the highest premium on an 'organic' label when there was no information about the attribute (Risius and Hamm, 2017). LaRiviere et al. (2014) found that consumers were willing to pay more for a good after reviewing information about the product. Roosen et al. (2011) found that the amount of information respondents received about the product's effects on health unambiguously affected WTP estimates, but different levels of information pertaining to societal and environmental situations did not.

This study varies the amount of information respondents receive about biobased products and the processes used to make SUEW with bioplastics prior to the choice experiment. Development of the information sets follows.

Survey and Data

Data were collected with an online survey launched October 2019. Qualtrics hosted the survey. Qualtrics survey administrators randomly sampled individuals 18 years or older from a nationally representative frame of US households. Qualtrics stratifies their frame by census regions[2], income levels, gender, and age. Households with a computer and internet were invited

[2] The four census divisions of the lower 48 US states are the Northeast (ME, NH, VT, NY, PA, MA, RI, CT, NJ, DE, MD, and DC), South (DE, MA, VA, WV, KY, NC, SC, TN, GA, FL, AL,

to participate. Households without a computer or internet completed surveys on a cell phone. Respondents were compensated with coupons for completing surveys. The university's Institutional Review Board approved the survey[3].

The survey began with a consent question, followed by a series of screening questions. The purpose of the screening process was to identify a subgroup of consumers that most likely define the SUEW market. Consenting respondents were asked if they (1) were primarily responsible for preparing and serving food in the household; (2) shopped for groceries; (3) planned and organized home entertainment events; and (4) if their household used SUEW, they were the person that purchased the product. There were 1,000 completed surveys. The sample corresponded with a margin of error of three percent with a 95 percent confidence interval.

The survey elicited information on respondent gender, age, educational attainment, residential location, household income, and household size. Around half (49 percent) of respondents were male (Table 1) (49 percent in the 2010 US Census). The average age of respondents was 46 (2010 median age from the 2010 US Census is 37). Forty-five percent of the respondents had a college degree. On average, there were 2.9 persons living in a household (2.6 in the 2010 US Census). Thirty-two percent of respondents lived in rural areas according to the US Census Bureau's definition (McGeeney et al., 2019). Eighteen percent of the respondents lived in the northeast region, twenty-one percent in the Midwest region, and thirty-seven in the south, with the remainder in the western states. Respondents reported their 2018 household income before taxes in eight ranges (Table 1).

MI, AR, LO, TX, and OK), Midwest (including ND, SD, NE, KS, MH, IA, MO, WI, IL, IN, MI, and OH), and West (all other states).

[3] XXXXX University IRB Application AG-19-9.

Table 1. Variable Names and Summary Statistics

Variable Name	Description	Mean	Standard Deviation	Min	Max
Demographics:					
Age	Respondents age (years)	45.68	16.44	18	84
Male	1 if male, otherwise 0	0.49		0	1
Mw	1 if in Midwest, otherwise 0	0.21		0	1
Ne	1 if in Northeast, otherwise 0	0.18		0	1
So	1 if in South, otherwise 0	0.37		0	1
Recycle	1 if recycles on a regular basis, otherwise 0	0.78		0	1
Envir	1 if member of any environmental organization, otherwise 0	0.18		0	1
College	1 = had college or higher, otherwise 0	0.45		0	1
Famil	1 = unfamiliar, 8 = very familiar	3.36		1	8
Rural	1 if rural, otherwise 0	0.32	0.47	0	1
Seconds	Time to finish the survey (seconds)	829	905	205	23632
Hhi	1 if less than $25,000	0.20		0	1
	2 if $25,000 to $49,999	0.22		0	1
	3 if $50,000 to $74,999	0.17		0	1
	4 if $75,000 to $99,999	0.11		0	1
	5 if $100,000 to $149,999	0.13		0	1
	6 if $150,000 to $200,000	0.09		0	1
	7 if $200,000 or more	0.06		0	1
Factor Scores:					
Technology Solution	Factor score: attitudes toward technology solution	0	0.79	-2.26	1.60
Market	Factor score: attitudes toward market	0	0.72	-3.01	1.17
Stewardship	Factor score: attitudes toward stewardship	0	0.92	-4.14	0.90
Recalcitrant	Factor score: attitudes toward recalcitrant	0	0.91	-1.45	1.69
N = 1,000					

Information Screens

Respondents were provided information about: (1) single-use products and definitions of ‘biobased’; (2) biobased product degradability (Figure 1); (3) the economic contribution of biobased products to the US economy (Figure 2); (4) product content certification (Figure 3), and; (5) transforming wheat straw to a biobased material input (Figure 4). All respondents received the same definition of ‘single-use eating-ware products’ and ‘bio-based’. The first information screen included the text;

> *We consume single-use products every day when we shop for food, eat at restaurants, and entertain. For example:*
>
> - *We use disposable bags to carry groceries.*
> - *Leftover food we take home after eating-out is placed in a bag or box.*
> - *If food is delivered to our home or eaten at a restaurant, it might be packaged in a container or wrapping.*
> - *We might use disposable utensils, bowls, plates, or cups when we entertain.*
> - *We might use disposable utensils, bowl, or plates for everyday use.*
>
> *These single-use products can be made from materials such as petroleum-based plastics, recycled products, paper made from trees, or plant fibers from agricultural crops.*

A definition of ‘bio-based’ followed this screen, informing respondents about the potential use of bio-based inputs in the manufacture of products:

> *All of the single-use items previously mentioned can also be made partly or entirely from* ***bio-based materials****. Products made from bio-based materials are called ‘****bio-based products****’.*

This first set of information screen concluded with examples of products made with bio-based inputs, including shopping bags (which can be made from corn starch); drinking straws (which can be made from bamboo or wheat straw); bowls, cartons, containers, and plates (which can be made from sugar cane, paper, or molded wheat straw). All respondents were asked to indicate how familiar they were with bio-based products by answering a Likert question (1 = not at all familiar,…, 5 = extremely familiar).

Bio-based Material Characteristics: Biodegradability

Biodegradability is the time it takes for packaging or a product to degrade. Biodegradable items include those whose degradation occurs by microorganisms, over a defined period.

Source "www.BigGreensmile.com"

Figure 1. Biobased products and degradability information screen.

Bio-based Materials and The U.S. Economy

In 2013, bio-based industries directly employed 1.5 million jobs.

In 2015, bio-based industries contributed 369 billion dollars to the U.S. Economy.

Federal agencies are required to purchase bio-based products with the highest bio-based content when purchases exceed $10,000 per year.

In 2014, bio-based products displaced **300 million** gallons of petroleum, around 4 percent of petroleum products consumption per year, in the U.S.

Figure 2. Economic contribution of biobased products to the US economy information screen.

Bio-based Content Labeling

The United States Department of Agriculture (USDA) defines "the Percent Bio-based Content" as the ratio of new organic carbon to total organic carbon in a product. The USDA certifies bio-based products under the Certified Bio-based labeling program.

Packaging, wrappings, linings, and bags must be a minimum of 45 percent bio-based content to be labeled "Certified Bio-based".

A tree is 100% biobased

Coal is 0% biobased

The **USDA Certified Biobased Product label** indicates *the ratio of new to total organic carbon*. To determine the ratio, the products must undergo testing by a third party using government-approved standards and testing methods. This is a voluntary labeling program.

Figure 3. Product content certification information screen

What is Wheat Straw?

Wheat straw is a byproduct of producing wheat. Wheat straw is what remains after the wheat kernel is removed to make flour and cereal products. Wheat straw can also be used to make biobased products.

Figure 4. Wheat straw as a biobased input information screen

Next, respondents were randomly assigned to three groups. The first group (n = 332, 'Limited-information') only viewed the previous information pertaining to the bio-based definition and single-use products. The second group (n = 335, 'full-information') was exposed to all four information screens in random order, including (a) biobased product degradability, (b) the economic contribution of biobased products to the economy, (c) product content certification, and (d) recycling wheat straw as a biobased composite input. The third group (n = 333, 'half-information') received additional information about bio-based products, but were randomly presented only two of the four product attributes: (a, b), (a, c) (a, d), (b, c), (b, d), or (c, d).

Budget Reminder and Trap Question I

Two traps questions were included in the surveys to detect respondent attentiveness prior to the choice experiment screens. The budget reminder followed the information screens, reminding respondents to reflect on their usual budget allocated for this type of expense (Cummings and Taylor, 1999; List, 2006; Loomis, 2014). The first trap question was embedded in the budget reminder, where instructions directed participants to select "None of the above" in response to a question unrelated to their budget. For example,

> *In surveys like this, people often do not pay much attention to the actual prices shown because they don't really have to pay the cost of the plate they prefer. Instead, they simply notice that one price is higher than another. When answering the survey questions on the next screen, please closely examine the prices and consider these in comparison to your household's budget before choosing a particular plate attribute.* ***To show that you have read the instructions, please answer the question below about "What color is the sky according to the above paragraph?" by checking "none of the above" as your answer****.* [Bold emphasis added.]

Respondents who correctly answered the trap question advanced to the choice experiment. Respondents who incorrectly answered the trap question were given a second chance re-read the budget reminder and to answer the question again. If the respondent failed on the second try, they advanced to the choice experiment section and their incorrect response recorded ('1' = inattentive, '0' otherwise). The second trap question appeared later in the survey, embedded in a set of debriefing equations that followed the choice experiment (discussed below).

Choice Experiment Details

Respondents were presented five product choices from which they could select one product or "none of the above." The opt-out choice enables measurement of the effects on consumer choice of factors beyond the attributes offered in the choice sets (Adamowicz et al., 1998). The opt-out choice is coded as an alternative specific constant (*Asc*).

The following attributes differentiated the five choices: (a) product degradability (three levels: not degradable, degradable in six months (*Degrade6*), degradable in 24 months (*Degrade24*); (b) origin (two levels: made in the US (*Origin*), or made elsewhere); (c) product content certification (*Label*, two levels: no or yes), material source (three levels; plastic, paper (*Paper*), or wheat straw (*Wheat*)), and a price per 25-count of 10-inch size SUEW food plates (six levels: $2.27, $3.82, $5.36, $6.91, $8.45, or $10.00) (Design matrix, Table 2.)[4] Among 20 SUEW products reviewed, the highest price for a 25-count package of 10-inch plates was $10.00, while the lowest price for the same quantity was $2.27. The other three prices used in the choice experiment were uniformly spaced intervals between the minimum ($2.27/25 count) and maximum ($10/25 count) prices. These price points were evaluated in a pre-survey of 100 respondents. The focus of the analysis was on extrinsic attributes, so respondents were asked to assume the eating-ware products were identical in all ways (including product functionality) except for the attributes they were asked to evaluate.

[4] Prices were collected from Amazon, June 2019. The link to the $10.00 package of 25 single use food plates is: https://www.amazon.com/10/25counts. The link to the $2.27 package of single use food plate is: https://www.amazon.com/2.27/25counts.

Choice tasks were structured as a balanced fractional factorial design where the main effect design is orthogonal. This design minimizes correlation between product alternatives (Lentner and Bishop, 1986). There were $6 \times 3^2 \times 2^2 = 216$ possible combinations in the choice experiment's design space. The SAS macro %*mktex* (SAS, 9.4) was used to determine a 100 percent efficient design, which resulted in 12 tasks per respondent. The order of the choice tasks was randomized across individuals. The number of observations available for choice modeling was 72,000 (12 tasks × 6 choices × 1,000 respondents).

Table 2. Choice experiment levels and attributes

Attribute	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6
Degradability	Not degradable	6 months	24 months			
Ccontent certification	No	Yes				
Material	Plastic	Paper	Wheat straw			
Origin	Made in the US	Made elsewhere				
Price ($/25 count)	$2.27	$3.82	$5.63	$6.91	$8.45	$10.00

Debriefing Questions and Trap Question II

Respondents answered a set of debriefing questions after completing the choice experiment. Debriefing questions included where respondents most likely purchased disposable plates (choices; big box stores, warehouse clubs, convenience stores, online); how much they spent on disposable plates over the last six months; the importance of each attribute on their purchasing decision; self-ascribed political viewpoints (strong conservative, moderate conservative, lean towards conservative, independent, lean toward liberal…); a description of their residential status (single home owner, rent, apartment, mobile home); and the respondent's rural/urban status (lived in rural/urban area) (Table 3).

Table 3. Respondent Perceptions and Viewpoints on Product Attributes and Shopping Habit

Statements (1)	Mean	Std. Dev.	Min	Max
How important were each of the following attributes to you in making your choices?				
The plate was made from wheat straw	3.02	1.40	1	5
The plate was USDA certified biobased	3.41	1.32	1	5
The plate was made in the United States	3.41	1.40	1	5
The plate's biodegradability	3.87	1.19	1	5
The plate's price	3.91	1.13	1	5
Compared to a low price, please rate the importance of the following attributes for disposable plates or utensils:				
Recyclable	3.87	1.20	1	5
Made from renewable source	3.66	1.19	1	5
Sturdy	4.18	0.95	1	5
Biodegradable	4.31	0.89	1	5
Appealing appearance	3.91	1.14	1	5
Safe to use	3.38	1.29	1	5
In the past 6 months, about how much did you spend on disposable plate?				
$0.00	0.08		0	1
$1.00-$1.99	0.04		0	1
$2.00-$2.99	0.06		0	1
$3.00-$3.99	0.06		0	1
$4.00-$4.99	0.05		0	1
$5.00-$5.99	0.09		0	1
$6.00-$6.99	0.06		0	1

Table 3. Respondent Perceptions and Viewpoints on Product Attributes and Shopping Habit (Continued)

$7.00-$9.99	0.08	0	1
$10.00-$19.99	0.21	0	1
$20.00-$29.99	0.12	0	1
$30.00 or more	0.16	0	1
Where do you most often purchase disposable plates?			
Big Box Stores	0.43	0	1
Retail Grocery Stores	0.20	0	1
Warehouse Clubs	0.14	0	1
Discount Store	0.15	0	1
Online	0.05	0	1
Convenience Stores	0.01	0	1
Other	0.02	0	1
N = 1000			

Notes:

(1) Likert scale: 1 = 'strongly disagree', 2 = 'somewhat disagree', 3 = 'neither agree or disagree', 4 = 'somewhat agree', 5 = 'strongly agree'.

Attitudinal views on respondents' assessment of environmental statements, themes, and issues were collected using a series of Likert questions. Respondents were asked if they 'strongly agreed' or 'strongly disagreed' on a five-interval scale regarding their outlook on environmental issues, causes, and solutions to problems (Table 4).

Table 4. Respondent Perceptions and Viewpoints on Environmental Issues

Statements (1)	Mean	Std. Dev.	Min	Max
This survey could encourage producers of single-use food containers to use bio-based materials.	4.12	1.02	1	5
Consumers affect the environment with their product choices.	4.30	0.94	1	5
My personal actions have no impact on environmental problems.	2.60	1.47	1	5
Science and technology will find ways to solve environmental problems.	3.81	1.03	1	5
Most people are unwilling to make sacrifices to address environmental problems.	3.84	1.03	1	5
Government policy is needed to solve environmental problems.	3.89	1.10	1	5

Table 4. Respondent Perceptions and Viewpoints on Environmental Issues (Continued)

Private industry will develop ways to minimize environmental problems.	3.66	1.11	1	5
Protecting the world's forests is critical to maintaining healthy environment.	4.41	0.93	1	5
Protecting the world's oceans is critical to maintaining healthy environment.	4.42	0.88	1	5
There is no urgent need to slow climate change.	2.58	1.50	1	5
Reducing the amount of single-use plastic pollution is important.	4.24	0.97	1	5
There is no urgent need to reduce greenhouse gas emissions.	2.61	1.50	1	5
We have a responsibility to protect the environment for future generations.	4.35	0.89	1	5
I do not have enough knowledge to make well-informed decisions on environmental issues.	2.88	1.32	1	5
N = 1000				

Notes: (1) Likert scale: 1 = 'strongly disagree', 2 = 'somewhat disagree', 3 = 'either agree or disagree', 4 = 'somewhat agree', 5 = 'strongly agree'.

The second trap question appeared in the Likert questions covering respondent views on the environment. Respondents were asked, "*Do you live in the United States?*" with a correct answer of 'strongly agree'. Respondents who answered 'strongly agree' continued to the last section of the survey. Respondents failing to answer correctly were given a second chance to answer the question. Thereafter respondents continued to the last section of the survey regardless of the answer provided. Incorrect answers were coded with a "1" ("0" otherwise).

Of the 1,000 respondents who completed the survey, 83 percent answered the first trap question correctly (Table 5). Of those respondents who incorrectly answered the first trap question, 30 percent changed their answer to the correct response. For the second trap question, 81 percent of the respondents provided correct answers on their first try. On the second try, 28 percent revised their answer to the correct response during their second try. Enumerated, 22 percent (224) of the respondents were identified as 'inattentive'. These individuals were coded with a “1” (“0” otherwise) with an inattentive dummy variable. The inattentive dummy variable was interacted with each of the product attributes, price, and the alternative-specific constant to determine the effect of respondent attention on extrinsic attribute premiums.

Table 5. Trap Question Summary

Trap Question	Answer	Number of respondents	Percent
First trap question, first attempt	correct	832	83.2%
	incorrect	168	16.8%
First trap question, second attempt	correct	50	5.0%
	incorrect	118	11.8%
Second trap question, first attempt	correct	814	81.4%
	incorrect	186	18.6%
Second trap question, second attempt	correct	52	5.2%
	incorrect	134	13.4%
Inattentive respondents		224	22.4%
N		1000	

Methods and Procedures

Factor Analysis: Environmental Themes and Issues

Factor analysis was used to reduce the dimensionality of the attitudinal variables gauging consumer awareness of and concern for environmental issues (Table 6). Factors scores are artificial variables made by combining strongly correlated variables (here, responses to Likert questions) into a composite index. The resulting factor scores are orthogonal with the other factor score vectors, yet the information originally contained in the question block is reduced to a smaller set of covariates that can be used as regression instruments (Johnson and Wichern, 2018). Thus, the dimensionality of the Likert question block is reduced to a subset of artificial variables (factors) that retain the information contained in the original variables. Principle component analysis was used to estimate the factor scores.

Table 6 Factor Analysis: Attitudinal Variables and the Environment

Statement	Market	Technology Solution	Stewardship	Recalcitrance	Uniqueness
This survey could encourage producers of single-use food containers to use bio-based materials.	0.67	0.22			0.51
Consumers impact the environment with their product choices.	0.75	0.01			0.44
My personal actions have no impact on the environmental problems.	-0.13	0.61			0.61
Science and technology will find ways to solve environmental problems.	0.29	0.56			0.60
Most people are unwilling to make sacrifices to protect the environmental problems.	0.32	0.39			0.75
Government policy needed to solve environmental problems.	0.46	0.25			0.72
Private industry will develop ways to minimize environmental problems.	0.23	0.63			0.55
Protecting the world’s forests is critical to maintaining healthy environment.			0.77	0.38	0.26
Protecting the world’s oceans is critical to maintaining healthy.			0.78	0.32	0.29
There is no urgent need to slow climate change.			-0.55	0.66	0.26
Reducing the amount of single-use plastic pollution is important.			0.62	0.28	0.54
There is no urgent need to reduce greenhouse gas emissions.			-0.53	0.66	0.28
We have a responsibility to protect the environment for future generations.			0.66	0.24	0.51
I do not have enough knowledge to make well-informed decisions on environmental issues.			-0.29	0.53	0.64
N = 1000					

The number of factors to include in the data reduction step was determined by observing the cumulative sum of the variables' covariance principle eigenvalues. The cut-off was 50 percent or higher (Johnson and Wichern, 2018). Standardized factor loadings are interpreted as correlation coefficients. Factor membership was determined by inspecting the factor loadings. Four artificial variables resulted from the factor analysis of the Likert scale questions on environmental issues (Table 6). The first factor was termed "Market", with the factor loadings of 0.67 and 0.75 for two questions. Both questions corresponded with biobased market themes. Three questions' factor loadings were 0.61, 0.56, and 0.63. This factor was termed "Technology Solutions". These questions address potential solutions for environmental problems. Four variables loaded onto a third factor we labeled "Stewardship". The Likert questions for this group were related to actions or policies oriented towards environmental protection or repair. Three Likert questions' loadings were 0.66, 0.66, and 0.53 contributed to the factor we named "Complacent". These questions generally corresponded with a perceived lack of urgency to address environmental concerns. The resulting factor score vectors were included as covariates in the statistical model.

Generalized Multinomial Logit Model and Estimation

A generalized multinomial logit (GMNL) model is used to estimate the effects of respondent demographics, expenditures, and environmental attitudes on the choices made during the choice experiment tasks (Fiebig et al., 2010). The GMNL model accommodates scale and taste (or preference) heterogeneity. Previous applications using the GMNL include Greene and Hensher (2010), Knox et al. (2013), and Gu et al. (2013). The GMNL is "generalized" because it nests a family of multinomial logistic models commonly used in applied choice analyses. First, utility is linear in arguments with systematic and random components:

$$v_{ijt} = \mathbf{x}_{ijt}\boldsymbol{\beta}_i + \varepsilon_{ijt} \quad (1)$$

where v_{ijt} is the indirect utility respondent i receives from alternative j on choice occasion t. The vector $\mathbf{x}_{ijt}$ is a $1 \times J$ vector of attributes including the per-unit price of alternative j (Table 7); $\boldsymbol{\beta}_i = \left(\beta_{i,price}, \cdots, \beta_{iJ}\right)'$ are individual-specific price and attribute coefficients; and ε_{ijt} is an idiosyncratic random error term.

Second, the GMNL parameterizes individual-specific attribute coefficients as random effects:

$$\boldsymbol{\beta}_i = \sigma_i \cdot \overline{\boldsymbol{\beta}} + \gamma \cdot \boldsymbol{\eta}_i + (1 - \gamma) \cdot \sigma_i \cdot \boldsymbol{\eta}_i \quad (2)$$

which includes a population average attribute effect ($\overline{\boldsymbol{\beta}}$), a scaling parameter σ_i that varies across individuals, and preference heterogeneity denoted by $\boldsymbol{\eta}_i$. The parameter $\gamma \in [0,1]$ measures the trade-off between the scale effects and differences in taste with an individual's choice (Fiebig et al., 2010). The choice model is a multinomial logit model (MNL) when the independence of irrelevant alternative assumption is valid (IIA, Cameron and Trivedi, 2005). This occurs when σ_i = 1 (i.e., the ε_{ijt} share a common variance), $\gamma = 0$, and $\boldsymbol{\eta}_i = \mathbf{0}$. Allowing taste to vary across individuals ($\boldsymbol{\eta}_i \neq \mathbf{0}$) with scale held constant and $\gamma = 0$ results in the mixed (or random parameter) logit model. A scaled MNL (SMNL) obtains when $\gamma = 0$, $\sigma_i > 1$, and preferences are shared across the population. The mixed MNL (MIXL) is nested in Eq. (2) when scale heterogeneity is absent and $\gamma = 0$. When preferences and scaling effects are heterogeneous and $\gamma = 1$, then the utility weights are $\boldsymbol{\beta}_i = \sigma_i \cdot \overline{\boldsymbol{\beta}} + \boldsymbol{\eta}_i$, which Fiebig et al. call the GMNL-I. Alternatively, the GMNL-II estimator, $\boldsymbol{\beta}_i = \sigma_i \cdot \left(\overline{\boldsymbol{\beta}} + \boldsymbol{\eta}_i\right)$ obtains when $\gamma = 0$ and tastes and scale effects are individual-specific. The γ parameter is estimable. Feibig et al. (2010) parameterize γ using the logistic distribution.

Third, scale heterogeneity is parametrized as a function of individual characteristics or tastes:

$$\sigma_i = \exp(\,\overline{\sigma} + \mathbf{z}_i\boldsymbol{\theta} + \tau \cdot \varepsilon_{0i}) \tag{3}$$

where the constant $\overline{\sigma}$ is parameterized as $-0.5 \cdot \tau^2$ such that $\mathrm{E}(\sigma_i) = 1$ when $\boldsymbol{\theta} = \mathbf{0}$ (Fiebig et al., 2010). The parameter vector $\boldsymbol{\theta}$ weights the importance of individual-specific characteristics in the determination of heterogeneous scale effects. Individual-specific characteristics are included in the 1 by g vector $\mathbf{z}_i$. The parameter τ is estimable and governs the degree of scale heterogeneity. Scale heterogeneity increases as τ increases. The error term ε_{0i} is a standardized normal random variable with an expected value of zero and a variance of one.

Age, gender, and residential patterns have been used in previous studies to control for the level effects on WTP attributable to individual-specific scaling effects (Phanikumar and Maitra, 2007; Yoo and Ready, 2014). Variables included in **z** hypothesized to determine scale heterogeneity are respondent age (*age*); gender (*male* = 1); census region (*mw* = midwest, *ne* = northeast, *so* = south, with the remaining western states the reference group); if the respondent recycled (*recycle*); if the respondent belonged to an environmental organization (*envir*); if the respondent had college degree (*college*); how familiar respondents are with biobased products before the survey (*famil*); and household income (*hhi*).

Factor analysis was used to reduce the dimensionality of the attitudinal variables gauging consumer awareness of and concern for environmental issues (Table 8). Factors scores are artificial variables made by combining strongly correlated variables (here, responses to Likert questions) into a composite index. The resulting factor scores are orthogonal with the other factor score vectors, yet the information originally contained in the question block is reduced to a smaller set of covariates that can be used as regression instruments (Johnson and Wichern, 2018). Thus, the dimensionality of the Likert question block is reduced to a subset of artificial variables (factors) that retain the information contained in the original variables.

Principle component analysis was used to estimate the factor scores. The factor scores that proxy individual attitudes towards different environmental themes were also included in the scale heterogeneity function, assuming that differences in respondent views and attitudes on environmental themes and issues level-shift WTP estimates by some random scalar across the population.

Table 7 Variable Names and Summary Statistics

Variable Name	Description	Mean	Standard Deviation	Min	Max
Demographics:					
Age	Respondents age (years)	45.68	16.44	18	84
Male	1 if male, otherwise 0	0.49		0	1
Mw	1 if in Midwest, otherwise 0	0.21		0	1
Ne	1 if in Northeast, otherwise 0	0.18		0	1
So	1 if in South, otherwise 0	0.37		0	1
Recycle	1 if recycles on a regular basis, otherwise 0	0.78		0	1
Envir	1 if member of any environmental organization, otherwise 0	0.18		0	1
College	1 = had college or higher, otherwise 0	0.45		0	1
Famil	1 = unfamiliar, 8 = very familiar	3.36		1	8
Rural	1 if rural, otherwise 0	0.32	0.47	0	1
Seconds	Time to finish the survey (seconds)	829	905	205	23632
	1 if less than $25,000	0.20		0	1
	2 if $25,000 to $49,999	0.22		0	1
	3 if $50,000 to $74,999	0.17		0	1
Hhi	4 if $75,000 to $99,999	0.11		0	1
	5 if $100,000 to $149,999	0.13		0	1
	6 if $150,000 to $200,000	0.09		0	1
	7 if $200,000 or more	0.06		0	1

Table 7 Variable Names and Summary Statistics (Continued)

Variable Name	Description	Mean	Standard Deviation	Min	Max
Factor Scores:					
Technology Solution	Factor score: attitudes toward technology solution	0	0.79	-2.26	1.60
Market	Factor score: attitudes toward market	0	0.72	-3.01	1.17
Stewardship	Factor score: attitudes toward stewardship	0	0.92	-4.14	0.90
Recalcitrant	Factor score: attitudes toward recalcitrant	0	0.91	-1.45	1.69

N = 1,000

Table 8 Factor Analysis: Attitudinal Variables and the Environment

Statement	Market	Technology Solution	Stewardship	Recalcitrance	Uniqueness
This survey could encourage producers of single-use food containers to use bio-based materials.	0.67	0.22			0.51
Consumers impact the environment with their product choices.	0.75	0.01			0.44
My personal actions have no impact on the environmental problems.	-0.13	0.61			0.61
Science and technology will find ways to solve environmental problems.	0.29	0.56			0.60
Most people are unwilling to make sacrifices to protect the environmental problems.	0.32	0.39			0.75
Government policy needed to solve environmental problems.	0.46	0.25			0.72
Private industry will develop ways to minimize environmental problems.	0.23	0.63			0.55
Protecting the world's forests is critical to maintaining healthy environment.			0.77	0.38	0.26
Protecting the world's oceans is critical to maintaining healthy.			0.78	0.32	0.29
There is no urgent need to slow climate change.			-0.55	0.66	0.26
Reducing the amount of single-use plastic pollution is important.			0.62	0.28	0.54
There is no urgent need to reduce greenhouse gas emissions.			-0.53	0.66	0.28
We have a responsibility to protect the environment for future generations.			0.66	0.24	0.51
I do not have enough knowledge to make well-informed decisions on environmental issues.			-0.29	0.53	0.64

N = 1000

Optimal Price and Consumer Surplus

The optimal make-up price for wheat SUEW products is determined by using Kohli and Mahajan (1991)'s method. The firm's expected profit of selling the wheat SUEW products at P_W is:

$$\max_{P_W}(\pi) = m * \Pr(\mathrm{W} = 1) * (P_W - C_a) \tag{4}$$

where π is the firm's profit, P_W is the optimal price as the choice variable, m indicates the population who would purchase wheat SUEW products, Pr is the probability of purchasing wheat SUEW products, C_a is the marginal cost at a level (the six survey price points: $2.27, $3.82, $5.36, $6.91, $8.45, and $10.00). These marginal costs assume the market is competitive and price equals the marginal cost of production.

In this study, two scenarios are examined. Scenarios one is where option one is the paper SUEW product, option two is the degradable paper SUEW product, and option three is the wheat SUEW product. Scenario two is where option one is the paper SUEW product, option two is the degradable paper SUEW product, and option three is the degradable wheat SUEW product. The retail prices for paper SUEW product and degradable paper SUEW product are $2.25 and $3 for 25 counts on Amazon [5]. At each marginal cost point the optimal price, profit margin, and market share are calculated.

If option three is omitted in each scenario, then it will cause a change in consumer surplus. The change of consumer surplus is calculated following Train (2005)'s method:

$$\Delta CS = -\frac{1}{\hat{\beta}_p}[\ln\left(\sum_{j_0=1}^{J_0}\exp(\hat{V}_{oj_0})\right) - \ln\left(\sum_{j_1=1}^{J_1}\exp(\hat{V}_{1j_0})\right)] \tag{5}$$

[5] Prices were collected from Amazon, June 2021. The link to the $10.00 package of 25 single use food plates is: https://www.amazon.com/paperThe link to the $3 degradable paper package of single use food plate is: https://www.amazon.com/paper+degradable

Model Specification

This study follows Hendry (2006)'s general-to-simple approach to select the statistical model. Model specification begins with the full sample of N = 1,000 respondents and the GMNL parameterization of Eq. 2. First, we conduct joint hypotheses on the scale, preference heterogeneity, and the GMNL parameter γ to identify a preferred model.

Next, we further specify the model by testing if WTP is different between attentive and inattentive respondents. Using the resulting specification, we determine if the information treatment groups can be pooled. Table 9 summarizes the null hypotheses and corresponding degrees of freedom for each specification.

Inattention and Information Treatment Effects

Given the preferred choice model identified above, a Wald statistic tests the null hypothesis that WTP estimates were not different between attentive and inattentive respondents. The null hypothesis is H_0: $\delta_{price} = \delta_{source} = \delta_{degrade} = \delta_{label} = \delta_{origin} = \delta_{asc} = 0$, with $\boldsymbol{\delta}$ a vector containing the interaction variables' parameters. This is a joint test with six degrees of freedom. At the five percent level of significance, the critical value of the Wald statistic is $\chi^2(6)$ = 12.59. Rejection of the null hypothesis suggests that WTP is different between attentive and inattentive respondents.

A likelihood ratio statistic is used to test the null hypothesis is that the information treatments had no effect on WTP. Failure to reject this hypothesis suggests that responses from the three information treatments can be pooled and the choice model estimated using the full sample. Rejection of the null hypothesis suggests that WTP should be estimated separately for each information group. This test has $p \times (m-1)$ degrees of freedom (Zellner, 1962), with p

the number of parameters appearing in the preferred model and m = 3 information treatment groups. At the five percent level of significance, the critical value for this test statistic is 67.50.

Estimation

The GMNL was estimated with Stata's *gmnl* command (Stata 15.1, StataCorp LLC, College Station, TX). The *gmnl* routine uses simulated maximum likelihood to estimate the model parameters (Gu et al., 2013). A burn-in sequence of 25 was used, followed by $2 \times \sqrt{N}$ Halton draws (Roodman, 2010) (63 draws for the N = 1,000 full sample, and 37 draws for each split sample). The log-likelihood function was maximized by iterating between a Newton-Raphson routine (five iterations) followed by the Davidson-Fletcher-Powell algorithm (five iterations) until convergence. A Huber-White heteroskedastic robust covariance estimator was used to calculate the parameters' covariance matrix (Huber, 1967).

Equation (1) was estimated in willingness-to-pay space (Train and Weeks, 2005). This means the parameter on price is restricted to be -1. Normalized this way, coefficients on the attributes are directly interpreted as WTP premium. Interaction effects are the difference between attentive respondents and the inattentive group.

Results

The GMNL estimates based on the full sample were used to calculate the percent of choice responses correctly classified (84 percent). The GMNL log likelihood for the full sample was -16,316, and the log likelihood of the model excluding covariates was -35,168. These numbers correspond with a McFadden pseudo R^2 of 0.54 (McFadden, 1973). The joint test that all parameters were not different from zero was rejected at the five percent level of significance (Wald statistics (W) = 391).

The log-likelihoods of the unrestricted GMNL model estimated separately for the three information treatment groups were -5,543 (limited information group), -5,418 (half information group), and -5,375 for the full information group. Summed together, the restricted log-likelihood is - 5,543 - 5,418 - 5,375 = -16,336. The log-likelihood of the unrestricted GMNL estimated with the pooled data was -16,316. The likelihood ratio statistic is 40, which is less than the critical value of 67.5 at the five percent level of significance. We conclude that extrinsic attribute premiums were not different between the respondents assigned to the information treatments. The three information groups were pooled for further statistical analysis.

One explanation for this result could be that the information treatments did not provide participants with information they did not already know or find surprising. For example, in Syrengelas (2018), the information treatment containing the USDA definition of "natural" likely provided participants with information they were surprised to discover and did not previously consider. That is what plausibly caused participants in the information treatment to exhibit different preferences for natural beef than those who did not receive the information. The information treatments in this study were possibly not surprising or unknown to participants and that is why they did not alter participant preferences. Future research could investigate how prior knowledge about the information provided in the treatment alters how the treatment affects preferences.

Model Specification

The null hypothesis of the joint test H0: $\boldsymbol{\theta} = \mathbf{0}$, $\tau = 0$, $\boldsymbol{\eta} = \mathbf{0}$, $\gamma = 0$ (Wald statistic, $W =$ 1,557) was rejected at the five percent level of significance. This finding suggests violation of the IIA assumption and that the MNL specification is inappropriate (Table 9).

The third column of Table 9 reports the hypothesis for the scaled MNL model. The null hypotheses of the joint test H0: $\boldsymbol{\theta} = \mathbf{0}$, $\tau = 0$ ($W = 1{,}166$) was rejected at the five percent level of significance. We conclude that the SMNL is an inappropriate specification.

The fourth column of Table 9 reports the test results for the MIXL specification. The null hypotheses of the joint test H0: $\boldsymbol{\theta} = \mathbf{0}$, $\tau = 0$ ($W = 3{,}203$) were rejected, suggesting that the MIXL is an inappropriate specification.

The last two columns of Table 9 test the appropriateness of the GMNL-I and GMNL-II specifications. The null hypotheses H0: $\gamma = 0$ ($W = 38$) and H0: $\gamma = 1$ ($W = 1{,}996$) were rejected at the five percent level of significance, suggesting neither GMNL-I nor GMNL-II are preferred specifications. Together, these results are evidence in favor of the unrestricted GMNL. We use this specification to examine the effects of information and respondent attentiveness on WTP for SUEW extrinsic attributes. The GMNL estimates for the full sample were used to calculate the percent of choice responses correctly classified (84 percent). The GMNL log likelihood for the full sample was -16,316, and the log likelihood of the model excluding covariates was -35,168. These numbers correspond with a McFadden pseudo R^2 of 0.54 (McFadden, 1973). The joint test that all parameters were not different from zero was rejected at the five percent level of significance ($W = 391$).

Table 9. Wald Tests and Chi-square critical values for Preference Heterogeneity, Scaled Heterogeneity, and GMNL-type models

Hypothesis	MNL(2)	SMNL	MIXL	GMNL-I	GMNL-II
$\boldsymbol{\theta} = \mathbf{0}, \tau = 0$	✓		✓		
$\boldsymbol{\eta} = \mathbf{0}$	✓	✓			
$\gamma = 0$	✓	✓			✓
$\gamma = 1$			✓	✓	
d.f.	33	16	17	1	1
Test Statistic	1557(3)	1166	3203	1966	38
Critical Value	49	26	28	4	4

Notes:

(1) d.f., degrees of freedom for individual tests or for joint tests.

(2) Model acronyms are: MNL= 'Multinomial Logit Model', SMNL= 'Scaled Multinomial Logit Model', MIXL= 'Mixed Multinomial Logit Model', GMNL-I= 'Generalized Multinomial Logit Type I Model', GMNL-II= 'Generalized Multinomial Logit Type I Model'.

(3) Table entries are Wald statistics for the individual tests.

Extrinsic Attributes

For attentive respondents, the extrinsic attribute with the highest premium is *Degrade6* ($4.35) followed by *Degrade24* ($2.94) (Table 10). For inattentive respondents, the premium of *Degrade6* and *Degrade24* are $0.66 and $0.28. This result suggests that, compared to the reference attribute 'not degradable', consumers are willing to pay more for SUEW products that degrade quickly. The finding is similar to what Arjunan et al. (2010) concluded, indicating that product biodegradability is an important attribute for consumers.

For attentive respondents, the third highest WTP premium is the material source wheat straw ($2.10 premium), followed by *Paper* ($2.06). For inattentive respondents, the premium for wheat straw and paper SUEW are $1.20 and $1.70 (not significant). This result suggests that consumers prefer SUEW products made with renewable biobased materials to plastics. Kainz et al. (2013) also concluded that consumers generally preferred degradable bioplastics made with renewable materials.

The attribute *Origin* ($1.98 premium) has the third highest premium for attentive respondents while the premium for inattentive respondents is $1.42 (not significant). Consumers value more SUEW products made in the U.S. This result is similar to Barnes et al. (2011)'s finding that consumers prefer locally sourced products.

The attribute exhibiting the lowest premium for inattentive respondents is *Label* ($1.77), suggesting that respondents ranked the biobased certification label lowest in terms of product features. The certification premium for inattentive respondents is $1.20 (not significant). However, the positive sign of *Label* indicates that consumers prefer SUEW products with certification labeling. This finding is similar to Gill et al. (2020)'s conclusions.

Table 10 Generalized Multinomial Logit Model Estimates of Single Use Plate, with Inattention-Attribute Interactions, Random Effect and Heterogeneity

Variable	Estimate	Standard Error	
Attributes:			
Price	-1		
Asc	-9.1580	0.9022	***
Paper	2.0614	0.2288	***
Wheat	2.1003	0.2485	***
Degrade6	4.3451	0.3950	***
Degrade24	2.9442	0.3001	***
Label (Certified biobased)	1.7715	0.2183	***
Origin (Made in US)	1.9757	0.1977	***
Inattention:			
d×Price	0.2096	0.1088	*
d×Asc	-9.8660	1.7354	***
d×Paper	-0.3562	0.4600	
d×Wheat	-0.9009	0.5367	*
d×Degrade6	-3.6922	0.5707	***
d×Degrade24	-2.6570	0.4708	***
d×Label	-0.5661	0.3721	
d×Origin	-0.5608	0.4415	
Scale Heterogeneity:			
Age	0.0181	0.0024	***

Table 7 Generalized Multinomial Logit Model Estimates of Single Use Plate, with Inattention-Attribute Interactions, Random Effect and Heterogeneity (Continued)

Variable	Estimate	Standard Error	
Male	0.0932	0.0955	
Mw	-0.2140	0.1250	*
Ne	-0.0598	0.1277	
So	-0.1707	0.1055	
Recycle	-0.0239	0.1049	
Envir	-0.5231	0.1424	***
College	0.0684	0.0836	
Famil	-0.0256	0.0203	
Hhi	0.0098	0.0199	
Seconds	0.0001	1.04×10^{-5}	***
Technology solution	-0.2442	0.0775	***
Market	0.2085	0.0787	***
Stewardship	0.1400	0.0708	**
Recalcitrant	-0.0181	0.0707	
constant	-1.9454	0.2013	***
τ	0.8638	0.0673	***
γ	0.1221	0.0196	***
Preference Heterogeneity:			
Price	0.8954	0.0595	***
Asc	8.4504	0.6662	***
Paper	1.0535	0.3893	***
Wheat	0.7859	0.6759	
Degrade6	1.5690	0.1984	***
Degrade24	0.1965	0.2004	
Label	1.0670	0.1928	***
Origin	1.0780	0.1985	***
d×Price	0.1567	0.0676	**
d×Asc	8.8597	0.9405	***
d×Paper	1.0884	0.3180	***
d×Wheat	1.4131	0.4403	***
d×Degrade6	0.6405	1.0717	
d×Degrade24	0.5089	0.2888	
d×Label	0.2241	0.3071	
d×Origin	-0.8247	0.2930	***
N	72,000		
Log likelihood	-16,316		

Notes: Asterisks (***, **, and *) indicate the level of statistical significance (99%, 95%, and 90%, respectively).

Overall, the results suggest that respondents are willing to pay for attributes linked with positive environmental outcomes including degradability and renewable biobased materials. Around 70 percent of the respondents rated degradability as an important product feature, while 60 percent rated renewable materials as an input source an important attribute (Table 11). These two findings are consistent with the WTP results that degradability has the highest premium, followed by input source.

Table 11. Respondent Perceptions and Viewpoints on Product Attributes and Shopping Habit

Statements (1)	Mean	Std. Dev.	Min	Max
How important were each of the following attributes to you in making your choices?				
The plate was made from wheat straw	3.02	1.40	1	5
The plate was USDA certified biobased	3.41	1.32	1	5
The plate was made in the United States	3.41	1.40	1	5
The plate's biodegradability	3.87	1.19	1	5
The plate's price	3.91	1.13	1	5
Compared to a low price, please rate the importance of the following attributes for disposable plates or utensils:				
Recyclable	3.87	1.20	1	5
Made from renewable source	3.66	1.19	1	5
Sturdy	4.18	0.95	1	5
Biodegradable	4.31	0.89	1	5
Appealing appearance	3.91	1.14	1	5
Safe to use	3.38	1.29	1	5
In the past 6 months, about how much did you spend on disposable plate?				
$0.00	0.08		0	1
$1.00-$1.99	0.04		0	1
$2.00-$2.99	0.06		0	1
$3.00-$3.99	0.06		0	1
$4.00-$4.99	0.05		0	1
$5.00-$5.99	0.09		0	1
$6.00-$6.99	0.06		0	1
$7.00-$9.99	0.08		0	1
$10.00-$19.99	0.21		0	1
$20.00-$29.99	0.12		0	1
$30.00 or more	0.16		0	1

Table 11. Respondent Perceptions and Viewpoints on Product Attributes and Shopping Habit (Continued)

Statements	Mean	Std. Dev.	Min	Max
Where do you most often purchase disposable plates?				
Big Box Stores	0.43		0	1
Retail Grocery Stores	0.20		0	1
Warehouse Clubs	0.14		0	1
Discount Store	0.15		0	1
Online	0.05		0	1
Convenience Stores	0.01		0	1
Other	0.02		0	1
N = 1000				

Notes:
(1) Likert scale: 1 = 'strongly disagree', 2 = 'somewhat disagree', 3 = 'neither agree or disagree', 4 = 'somewhat agree', 5 = 'strongly agree'.

Optimal Prices and Consumer Surplus

Using the methods described in equations 4 and 5, the optimal prices for wheat SUEW products and wheat SUEW products with 24 months degradability and changes of consumer surplus are provided in table 12 For wheat SUEW products the consumer surplus increases from \$0.00 to \$0.03 per person and the optimal price is from \$3.30 to \$11.00 when the marginal cost increases from \$2.27 to \$10.00. For wheat SUEW products with 24 months degradability the consumer surplus increases form \$0.00 to \$0.42 per person and the optimal price is from \$3.69 to \$11.00 when the marginal cost increases from \$2.27 to \$10.00.

Table 12. Optimal Price For Wheat-Molded Single-Use Eating Ware (SUEW) Product And Change In Consumer Surplus

Marginal cost[3]	Optimal Price[1]	Change in consumer surplus [2]
Wheat SUEW		
2.27	3.30	0.03
3.82	4.83	0.01
5.36	6.36	0.00
6.91	7.91	0.00
8.45	9.45	0.00
10.00	11.00	0.00

Wheat SUEW + 24 month degradability

Marginal cost	Optimal Price	Change in consumer surplus
2.27	3.69	0.42
3.82	4.94	0.12
5.36	6.39	0.03
6.91	7.92	0.01
8.45	9.45	0.00
10.00	11.00	0.00

Notes: [1] optimal price for a molded wheat SUEW product determined using Kohli and Mahajan (1991)'s method; [2] change in consumer surplus determined using Train (2005)'s method; [3] Per-unit marginal costs of production for a molded wheat SUEW product are the survey price points.

Interestingly, 66 percent of respondents believed that most people are unwilling to make sacrifices to address environmental concerns, even though the extrinsic attributes had positive premiums (Table 13). In addition, only 38 percent of respondents believed that utensils and eating ware made form wheat straw is an important attribute to them to make their choices of SUEW product, while 82 percent of the respondents believed that reducing the environmental footprint of plastic SUEW is an important issue to address. As for the survey potentially affecting industry direction in their product lines, 78 percent of the respondents believed the survey would encourage SUEW manufacturers to use biobased materials.

Table 13. Respondent Perceptions and Viewpoints on Environmental Issues

Statements (1)	Mean	Std. Dev.	Min	Max
This survey could encourage producers of single-use food containers to use bio-based materials.	4.12	1.02	1	5
Consumers affect the environment with their product choices.	4.30	0.94	1	5
My personal actions have no impact on environmental problems.	2.60	1.47	1	5
Science and technology will find ways to solve environmental problems.	3.81	1.03	1	5
Most people are unwilling to make sacrifices to address environmental problems.	3.84	1.03	1	5
Government policy is needed to solve environmental problems.	3.89	1.10	1	5
Private industry will develop ways to minimize environmental problems.	3.66	1.11	1	5
Protecting the world's forests is critical to maintaining healthy environment.	4.41	0.93	1	5
Protecting the world's oceans is critical to maintaining healthy environment.	4.42	0.88	1	5
There is no urgent need to slow climate change.	2.58	1.50	1	5
Reducing the amount of single-use plastic pollution is important.	4.24	0.97	1	5
There is no urgent need to reduce greenhouse gas emissions.	2.61	1.50	1	5
We have a responsibility to protect the environment for future generations.	4.35	0.89	1	5
I do not have enough knowledge to make well-informed decisions on environmental issues.	2.88	1.32	1	5
N = 1000				

Notes: (1) Likert scale: 1 = 'strongly disagree', 2 = 'somewhat disagree', 3 = 'either agree or disagree', 4 = 'somewhat agree', 5 = 'strongly agree'.

Conclusion and Discussion

This study controlled for inattention and availability bias while estimating consumer WTP for extrinsic attributes of single-use eating ware. The attributes were biomaterial source, manufacture origin, biobased certification, and product degradability. The study finds significant preference heterogeneity for the eating-ware product made with renewable biomaterials.

Consumers also attributed a relatively high premium to biomaterial origin, followed by biobased certification labeling. Premiums associated with these attributes were lower for inattendant respondents. The amount of information respondents received about the SUEW product before the choice experiment did not affect WTP estimates. The impact of availability bias (the order of information provided to participants) did not affect attribute premiums.

Attribute premium estimates were found for attributes consumers may value when purchasing SUEW products.Consumers were willing to pay nearly $2 more per plate package if they were made from paper or wheat as opposed to being made from plastic. Consumers were willing to pay approximately $4 and $3 more per plate package if the product was degradable in 6 months and 24 months, respectively, compared to not being degradable at all. Consumers were also willing to pay nearly $2 more per plate package if they were made in the US compared to being made elsewhere, and nearly $2 more per plate package if they contained the biobased label. For most attributes, inattention bias decreases consumer WTP for SUEW plate packages by $0.36 to $3.69.

Availability bias was not evident in this study, but findings did support the presence of inattention bias having an effect on consumer preferences. Using a Wald test, we found that attribute WTP estimates were different between attentive and inattentive respondents. This is an important result, especially considering that many WTP studies do not include a check for inattentive participants in their studies. The study found that attribute premiums were generally lower for inattentive respondents.

CHAPTER IV

STUDY II: BAYESIAN ESTIMATION OF A GENERALIZED RANK ORDERED LOGIT MODEL: AN APPLICATION ESTIMATING CONSUMER PREFERENCES FOR A BIOBASED PRODUCT

Previous Research

Finn and Louviere (1992) extended Richardson's (1938) max-diff preference ranking method to best-worst scaling (BWS). There are three versions of BWS. In version 1, respondents evaluate the degree of importance for a set of objects ranked by a rating scale (Finn and Louviere 1992). The profile case of BWS (version 2) is used when the choices are profiles arranged in combinations and respondents indicate their 'best' and 'worst' choices that correspond with an attribute (Flynn, 2010; Cheung et al., 2016; Mühlbacher et al., 2015; Aizaki and Fogarty 2019). The third version of BWS pertains to discrete choice experiments where respondents are offered a sequence of choice sets, with each set including at least three profiles (Louviere, Hensher, and Swait 2000). Respondents select the best and worst profiles of item in each set. Previous studies that used version 3 include Mühlbacher et al. (2020) and Adamsen, Rundle-Thiele, and Whitty (2013).

There were 2,612 studies that used BWS since 1998 (Scopus, key word search of best-worst-scaling). Ninety-six percent of the studies were published between 2010 to 2021. The most prominent fields using BWS were medicine (30 percent) and the social sciences (18 percent). The agricultural and biological sciences (16 percent), business, management and accounting (15 percent), economics, econometrics and finance (11 percent), and environmental science (9 percent) followed (Scopus, 2021).

BWS generates information about respondent preferences by collecting data about a good's most and least preferred qualities (Scarpa et al., 2011; Ryan, Watson, and Amaya-Amaya, 2003; Auger, Devinney, and Louviere, 2006). An advantage of BWS elicit is that it normally reduces the cognitive burden respondents may experience as they complete tasks in a conjoint analysis (Potoglou et al, 2011). BWS also minimizes response bias arising from inaccurate answers and improves discrimination between options (Jones, Jones, and Gross, 2013; Finn and Louviere, 1992). Like max-diff, BWS forces respondents to make choices among options instead of providing respondents a 'prefer not to select' option as is typically done in conjoint analyses (Louviere and Flynn, 2012).

Lockshin et al. (2015) used BWS to measure segmented wine markets. They concluded that BWS generated more information about behavior compared with conventional choice experimental methods. Petrolia, Interis, and Hwang (2018) compared single-choice and BWS elicitation methods. They concluded that BWS yielded more precise welfare estimates. Weernik et al. (2016) used BWS, time trade-off, and visual analogue scales to compare treatment profiles for Parkinson disease. They concluded that among these three methods, BWS was the best among three methods, especially when they were closely related. Lagerkvist (2013) used BWS to estimate consumer preferences for food labelling attributes. They concluded that BWS improved prediction of respondent choices compared with scale ranking methods. Shoji et al. (2021) used BWS to estimate individual preferences for pricing policies. Their study concluded that, compared with Likert scale ranking methods, BWS minimized response bias and provided accurate results.

BWS preference data is usually analyzed using ROL (Scarpa et al. 2011). The number of annual articles using ROL increased from nine during 1987 to 1999, to 135 during 2000 to 2021 (Scopus search: key words of rank-ordered-logit). ROL regression has been used in many fields, including marketing (Dagsvik and Liu, 2006; Ahn et al., 2006), horse race betting studies (Ali, 1998; Lo and Bacon-Shone, 1994), school choice (Mark et al., 2004; Drewes and Michael, 2006), auto racing (Graves et al., 2003; Guiver and Snelson, 2009), labor economics (van Beek et al., 1997), and consumer behavior economics (Wirthgen, 2005; Resano et al., 2012). Beggs et al. (1981) introduced ROL to estimate consumer preferences from choice rankings. Rank ordered logistic (ROL) regression is typically used to estimate willingness to pay (WTP) derived from BWS surveys (Scarpa et al. 2011; Choi et al., 2020).

Like its multinomial logistic (MNL) cousin, ROL maintains the Independence of Irrelevant Alternatives (IIA) property and does not consider preference or scale heterogeneity. Violation of the IIA could bias ROL estimates when attributes are correlated (Fork, Paap, and Van Dijk, 2012). Calfee, Winston and Stempski (2001) proposed a mixed rank ordered logit model (MROL). This paper extends the MROL to simultaneously address scale and preference heterogeneity effects as a generalize ROL.

The generalized ROL is an extension of Fiebig et al. (2010)'s generalized multinomial logit (GMNL) to Calfee et al.'s MROL. The GMNL has been used in previous studies including Balogh et al. (2016), Knox et al. (2013), and Li et al. (2017). The GMNL's parameterization relaxes IIA requirements by simultaneously modeling scale and taste (or preference) heterogeneity. The GMNL nests a family of multinomial logistic model specifications, including the scaled multinomial logit, mixed logit, and GMNL models I and II. Scale heterogeneity is independent of preference heterogeneity when the model is GMNL-I. For the GMNL-II, preference heterogeneity is proportional to scale heterogeneity in GMNL-II (Fiebig et al., 2010). GMNL parameters are typically estimated using simulated maximum likelihood (Gu et al., 2013).

Survey Data

Data were collected with an online BWS survey December, 2019.[6] Qualtrics hosted the survey. Qualtrics randomly sampled individuals that were at least 18 years old from a nationally representative list frame of United States (US) households. Qualtrics stratified the survey by US Census regions, income levels, gender, and age.[7] The sample corresponded with a margin of error of 3 percent with a 95 percent confidence interval. Households were invited to participate in the survey on their computer or by cellphone. Respondents who completed the survey were compensated with coupons.

Following a survey consent question, respondents were asked to answer a series of screening questions. The purpose of the screening questions was to identify the subgroup of consumers who would most likely define the SUEW market. The series of screening questions included 1) if the respondent was primarily responsible for preparing and serving food in the household; 2) if they shopped for groceries; 3) if they planned and organized home entertainment events; and (4) if their household used SUEW, were they the person making the purchase decision. Non-consenting respondents and respondents answering ‘no’ to screening questions 1 – 4 did not continue the survey. There were 1,010 completed surveys.

[6] XXXXX University IRB Application AG-19-9.
[7] The four census divisions of the lower 48 US states are the Northeast (ME, NH, VT, NY, PA, MA, RI, CT, NJ, DE, MD, and DC), South (DE, MA, VA, WV, KY, NC, SC, TN, GA, FL, AL, MI, AR, LO, TX, and OK), Midwest (including ND, SD, NE, KS, MH, IA, MO, WI, IL, IN, MI, and OH), and West (all other states).

Information collected by the survey included respondent gender, age, educational attainment, residential location, household income, and household size. Fifty-one percent of the respondents were male (49 percent in 2010 US Census) (Table 14). The average age of respondents was 46 (2010 median age from the 2010 US Census is 37). Forty-three percent of the respondents had a college degree. On average, there were 2.8 persons living in a household (2.6 in 2010 U.S. Census). Thirty-three percent of respondents lived in rural areas according to the US Census Bureau's definition (McGeeney et al., 2019). Eighteen percent of the persons surveyed lived in the northeast region (18 percent in 2010 US Census), twenty-one percent in the Midwest region (22 percent in 2010 US Census), and thirty-seven in the south (37 percent in 2010 US Census), with the remainder living in western states. Respondents reported their 2018 household income before taxes in eight brackets. The $25,000 to $49,999 range had the most respondents (23 percent), followed by $50,000 to $74,999 range (18 percent). Respondents were asked about their political viewpoints (strong conservative, moderate conservative, lean towards conservative, independent, lean toward liberal, strong liberal). Respondents were also asked to indicate their residential status (single homeowner, rent, apartment, mobile home) and if they lived in a urban or rural location.

Table 14. Variable Names and Summary Statistics

Variable Name	Description	Mean	Standard Deviation	Min	Max
Demographics:					
Age	Respondents age (years)	46.40	16.31	19	90
Male	1 if male, otherwise 0	0.51		0	1
Mw	1 if in Midwest, otherwise 0	0.21		0	1
Ne	1 if in Northeast, otherwise 0	0.18		0	1
So	1 if in South, otherwise 0	0.37		0	1
Recycle	1 if recycles on a regular basis, otherwise 0	0.82		0	1

Table 14. Variable Names and Summary Statistics (Continued)

Variable Name	Description	Mean	Standard Deviation	Min	Max
Envir	1 if member of any environmental organization, otherwise 0	0.12		0	1
College	1 = had college or higher, otherwise 0	0.43		0	1
Famil	1 = unfamiliar, 8 = very familiar	5.00		1	8
Rural	1 if rural, otherwise 0	0.32	0.47	0	1
Seconds	Time to finish the survey (seconds)	1411	1878	390	44864
Hhi	1 if less than $25,000	0.19		0	1
	2 if $25,000 to $49,999	0.23		0	1
	3 if $50,000 to $74,999	0.18		0	1
	4 if $75,000 to $99,999	0.12		0	1
	5 if $100,000 to $149,999	0.16		0	1
	6 if $150,000 to $200,000	0.05		0	1
	7 if $200,000 or more	0.03		0	1

N = 1,010

Information Screens

Respondents received general information about SUEW products and the term ‘biobased’ before they completed BWS tasks. There were five information screens pertaining to: (1) definitions of single-use products and ‘biobased’; (2) biobased product degradability (Figure 5); (3) the contribution of biobased products to the US economy (Figure 6); (4) product content certification (Figure 7); and (5) the use of wheat straw (the biobased material) for fabricating bioplastic molds (Figure 8). All respondents viewed the first screen, which included definitions of ‘single-use eating-ware products’ and ‘biobased’. On the first information screen, respondents were provided with examples of products made with biobased inputs, including shopping bags (which can be made from corn starch); drinking straws (which can be made from bamboo or wheat straw); bowls, cartons, containers, and plates (which can be made from sugar cane, paper, or molded wheat straw). The first information screen included the text:

We consume single-use products every day when we shop for food, eat at restaurants, and entertain. For example:

- *We use disposable bags to carry groceries.*
- *Leftover food we take home after eating-out is placed in a bag or box.*
- *If food is delivered to our home or eaten at a restaurant, it might be packaged in a container or wrapping.*
- *We might use disposable utensils, bowls, plates, or cups when we entertain.*
- *We might use disposable utensils, bowl, or plates for everyday use.*

These single-use products can be made from materials such as petroleum-based plastics, recycled products, paper made from trees, or plant fibers from agricultural crops.

A definition of 'biobased' followed, informing all respondents about the potential use of biobased inputs in the manufacture of products:

All of the single-use items previously mentioned can also be made partly or entirely from ***biobased materials****. Products made from bio-based materials are called '****biobased products****'.*

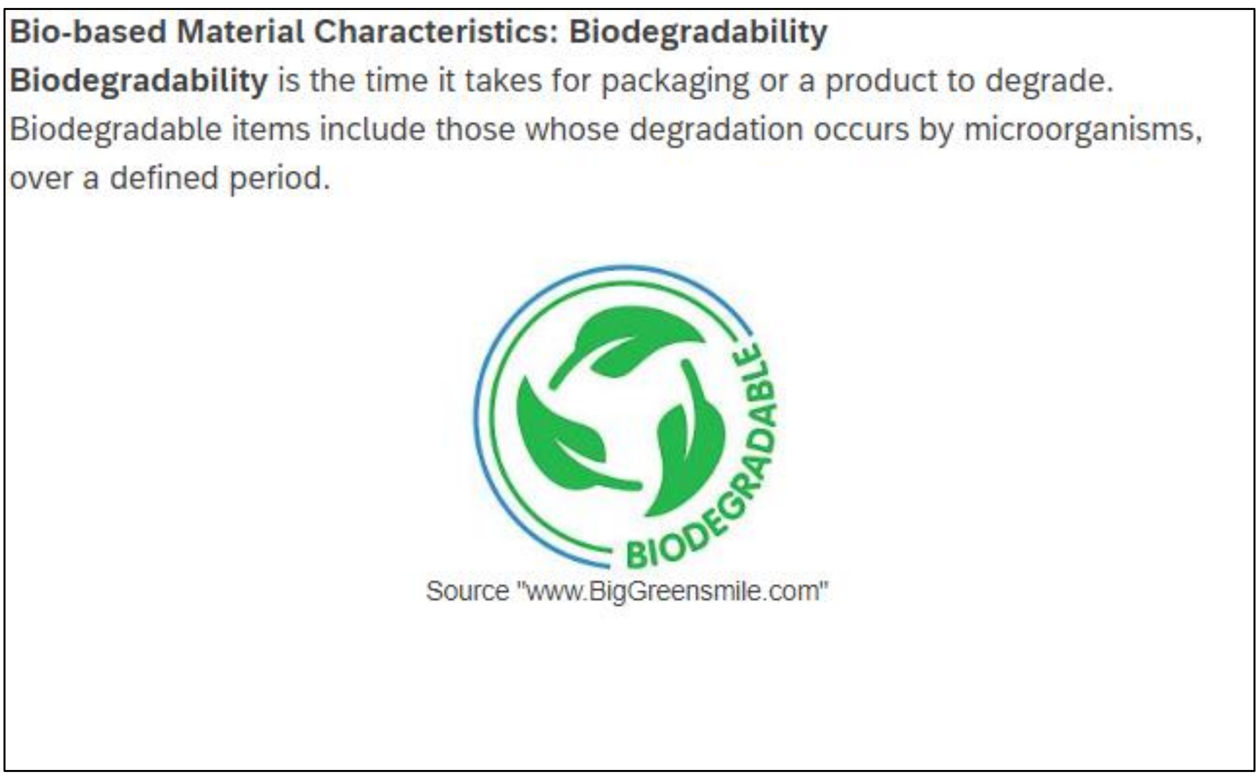

Figure 5. Biobased products and degradability information screen.

Bio-based Materials and The U.S. Economy

In 2013, bio-based industries directly employed 1.5 million jobs.
In 2015, bio-based industries contributed 369 billion dollars to the U.S. Economy.
Federal agencies are required to purchase bio-based products with the highest bio-based content when purchases exceed $10,000 per year.
In 2014, bio-based products displaced **300 million** gallons of petroleum, around 4 percent of petroleum products consumption per year, in the U.S.

Figure 6. Economic contribution of biobased products to the US economy information screen.

Bio-based Content Labeling

The United States Department of Agriculture (USDA) defines “the Percent Bio-based Content” as the ratio of new organic carbon to total organic carbon in a product.
The USDA certifies bio-based products under the Certified Bio-based labeling program.
Packaging, wrappings, linings, and bags must be a minimum of 45 percent bio-based content to be labeled “Certified Bio-based”.

A tree is 100% biobased

Coal is 0% biobased

USDA CERTIFIED BIOBASED PRODUCT
PRODUCT 100%

The **USDA Certified Biobased Product label** indicates *the ratio of new to total organic carbon*. To determine the ratio, the products must undergo testing by a third party using government-approved standards and testing methods. This is a voluntary labeling program.

Figure 7. Product content certification information screen

What is Wheat Straw?

Wheat straw is a byproduct of producing wheat. Wheat straw is what remains after the wheat kernel is removed to make flour and cereal products. Wheat straw can also be used to make biobased products.

Figure 8. Wheat straw as a biobased input information screen

All respondents viewed the above information. Next, respondents were randomly and uniformly sorted into three groups. Group A (limited information) did not receive any additional information about SUEW products or biobased materials (n=332). Group B (all information) viewed information screens 2 to 4 (n=345). Group C (half information) was exposed to the first screen, information about single used product and biobased product, plus (randomly) two of the four product attributes (2, 3), (2, 4) (2, 5), (3, 4), (3, 5), or (4, 5) (n=333).

Cheap Talk and Trap Question I

A cheap talk screen followed the information screens, asking respondents to reflect on their usual budget allocated for this type of expense as they completed choice tasks (Cummings and Taylor, 1999; List et al., 2006; Loomis, 2014). A trap question (Malone and Lusk, 2018) was included in the cheap talk paragraph to gauge respondent attentiveness to the survey.

The budget reminder with the trap question was:

> *In surveys like this, people often do not pay much attention to the actual prices shown because they don't really have to pay the cost of the plate they prefer. Instead, they simply notice that one price is higher than another. When answering the survey questions on the next screen, please closely examine the prices and consider these in comparison to your household's budget before choosing a particular plate attribute.* ***To show that you have read the instructions, please answer the question below about "What color is the sky according to the above paragraph?" by checking "none of the above" as your answer***. [Bold emphasis added.]

Respondents correctly answering the question continued to the next section of the survey. Respondents who incorrectly answered the trap question were asked to re-read the paragraph and revise their answer. Respondents who incorrectly answered the question on the second try were coded as inattentive (= '1', '0' otherwise).

Best-Worst Choice Experiment

The following attributes differentiated the choices: (a) product degradability (3 levels; not degradable, degradable in 6 months (*degrade6*), degradable in 24 months (*degrade24*)); (b) origin (2 levels; made in the US, or made elsewhere (*origin*)); (c) product content certification (2 levels; no or yes, (*label*)); (d) material source (3 levels; plastic, paper (*paper*), or wheat straw (*wheat*)); and (e) a price for a 25-count of 10-inch size SUEW plates (6 levels; $2.27, $3.82, $5.36, $6.91, $8.45, or $10.00) (Table 15)[8]. Price points were determined from a review of 20 SUEW products. The highest price was $10.00 for a 25-count package of 10-inch plates. The lowest price for the same quantity and plate size was $2.27. These lower and upper bound prices were used to determine the other three price levels. The prices were uniformly distributed between the lower and upper price bounds.

[8] Prices were collected from Amazon, June 2019. The link to the $10.00 package of 25 single use food plates is: https://www.amazon.com/10/25counts. The link to the $2.27 package of single use food plate is: https://www.amazon.com/2.27/25counts.

The choice experiment's design space included $6 \times 3 \times 3 \times 2 \times 2 = 216$ combinations. The SAS macro %*mktex* was used to generate a balanced fractional factorial orthogonal design was used to structure choice tasks (SAS, 9.4; Lentner and Bishop, 1986). The total number of observations available for analysis was 60,600 (12 tasks × 5 products × 1,010 respondents). The optimal design resulted in 12 choice tasks for each respondent.

Table 15. Choice experiment levels and attributes

Attribute	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6
Degradability	Not degradable	6 months	24 months			
Content certification	No	Yes				
Material	Plastic	Paper	Wheat straw			
Origin	Made in the US	Made elsewhere				
Price ($/25 count)	$2.27	$3.82	$5.63	$6.91	$8.45	$10.00

Respondents were asked to assume the SUEW products were identical in all ways (including product functionality) except for the attributes they were asked to evaluate. Respondents viewed a screen with the five attributes from which they selected the most and least attractive product attribute in the set (Figure 9). The most and least attractive attributes were removed from the set, leaving three attributes from which to rank most or least preferred in a second round. Completion of the second round resulted in an attribute ranking for a task.

	Plate A	Plate B	Plate C	Plate D	Plate E
Made in the U.S.	No	Yes	Yes	Yes	No
Source	Wheat straw	Paper	Plastic	Wheat straw	Plastic
Biodegradable	No	Yes, 2 years	No	Yes, 2 years	Yes, 6 months
USDA Certificated Bio-based	Yes	No	Yes	No	Yes
Price for 25 plates	$5.36	$3.82	$2.27	$10.00	$8.45

Which plate do you prefer most?		Which plate do you least prefer?
○	Plate A	○
○	Plate B	○
○	Plate C	○
○	Plate D	○
○	Plate E	○

Figure 9. Best Worst Question Example

Debriefing Questions and Trap Question II

Debriefing questions followed the BWS choice experiment. Debriefing questions included where respondents would most likely purchase SUEW plates (big box stores, warehouse clubs, convenience stores, online); how much they spent on disposable plates in the last six months; and the importance of each attribute on their purchasing decision (Table 16).

Table 16. Respondent Perceptions and Viewpoints on Product Attributes and Shopping Habit

Statements (1)	Mean	Std. Dev.	Min	Max
How important were each of the following attributes to you in making your choices?				
The plate was made from wheat straw	2.71	1.34	1	5
The plate was USDA certified biobased	3.14	1.29	1	5
The plate was made in the United States	3.11	1.39	1	5
The plate's biodegradability	3.76	1.24	1	5
The plate's price	3.91	1..15	1	5
Compared to a low price, please rate the importance of the following attributes for disposable plates or utensils:				
Recyclable	3.69	1.31	1	5
Made from renewable source	3.47	1.29	1	5
Sturdy	4.08	1.01	1	5
Biodegradable	4.24	0.93	1	5
Appealing appearance	3.78	1.21	1	5
Safe to use	3.18	1.35	1	5
In the past 6 months, about how much did you spend on disposable plate?				
$0.00	0.08		0	1
$1.00-$1.99	0.03		0	1
$2.00-$2.99	0.05		0	1
$3.00-$3.99	0.08		0	1
$4.00-$4.99	0.07		0	1
$5.00-$5.99	0.10		0	1
$6.00-$6.99	0.06		0	1
$7.00-$9.99	0.10		0	1
$10.00-$19.99	0.18		0	1
$20.00-$29.99	0.11		0	1
$30.00 or more	0.13		0	1
Where do you most often purchase disposable plates?				
Big Box Stores	0.44		0	1
Retail Grocery Stores	0.21		0	1
Warehouse Clubs	0.15		0	1
Discount Store	0.15		0	1
Online	0.03		0	1
Convenience Stores	0.01		0	1
Other	0.01		0	1
N = 1010				

Notes:
(1) Likert scale: 1 = 'strongly disagree', 2 = 'somewhat disagree', 3 = 'neither agree or disagree', 4 = 'somewhat agree', 5 = 'strongly agree'.

Respondent views on environmental issues were also collected with a series of Likert questions. Respondents were asked if they 'strongly disagree' or 'strongly agree' on a five-interval scale regarding their outlook on causes of environmental problems or issues and potential solutions to these problems (Table 17).

Table 17. Respondent Perceptions and Viewpoints on Environmental Issues

Statements (1)	Mean	Std. Dev.	Min	Max
This survey could encourage producers of single-use food containers to use bio-based materials.	4.01	0.99	1	5
Consumers affect the environment with their product choices.	4.30	0.89	1	5
My personal actions have no impact on environmental problems.	2.50	1.43	1	5
Science and technology will find ways to solve environmental problems.	3.71	1.03	1	5
Most people are unwilling to make sacrifices to address environmental problems.	3.70	1.03	1	5
Government policy is needed to solve environmental problems.	3.79	1.12	1	5
Private industry will develop ways to minimize environmental problems.	3.60	1.09	1	5
Protecting the world's forests is critical to maintaining healthy environment.	4.38	0.91	1	5
Protecting the world's oceans is critical to maintaining healthy environment.	4.40	0.88	1	5
There is no urgent need to slow climate change.	2.42	1.44	1	5
Reducing the amount of single-use plastic pollution is important.	4.01	0.99	1	5
There is no urgent need to reduce greenhouse gas emissions.	4.30	0.89	1	5
We have a responsibility to protect the environment for future generations.	2.50	1.43	1	5
I do not have enough knowledge to make well-informed decisions on environmental issues.	3.71	1.03	1	5
N = 1010				

Notes: (1) Likert scale: 1 = 'strongly disagree', 2 = 'somewhat disagree', 3 = 'either agree or disagree', 4 = 'somewhat agree', 5 = 'strongly agree'.

The second trap question was embedded in the Likert questions covering respondent views on the environment. Respondents were asked, "*Do you live in the United States?*" with a correct answer of 'strongly agree'. Respondents answering correctly advanced to the survey's next section. Respondents who incorrectly answered the question were given a second chance to revise their answer. If they incorrectly answered the question on the second try, they were coded as inattentive (='1', '0' otherwise). Of the 1,010 completed respondents, 90 percent answered the first trap question correctly (Table 18). Of those respondents who incorrectly answered the first trap question, 34 percent revised their answer to the correct response. For the second trap question, 83 percent of the respondents responded the correct answer on their first try. On the second try, 38 percent revised their answer to the correct response. Thus, 16 percent of the respondents were coded as 'inattentive' with a "1" ("0" otherwise). The inattentive dummy variable was interacted with each of the product attributes and price to control for respondent inattention in the regression analysis.

Table 18. Trap Question Summary

Trap Question	Answer	Number of respondents	Percent
First trap question, first attempt	correct	913	90.0%
	incorrect	97	10.0%
First trap question, second attempt	correct	33	3.3%
	incorrect	64	6.3%
Second trap question, first attempt	correct	840	83.0%
	incorrect	170	17.0%
Second trap question, second attempt	correct	52	5.1%
	incorrect	118	11.8%
Inattentive respondents		164	16.2%
N		1,010	

Generalized Rank Ordered Logit Model and Formulation

Notation for deriving the generalized ROL follows Beggs, Cardell, and Hausman (1981) and Allison and Christakas (1994) exposition of the ROL and Calfee, Winston, and Stempski (2001)'s derivation of the mixed ROL (MROL). These studies begin with a linear, random indirect utility specification with the stochastic terms of the function following the type I extreme value distribution. Utility is composed of deterministic and random components as $v_{ijt} = \mathbf{x}_{ijt}\boldsymbol{\beta} + \epsilon_{ijt}$, where for individual i, v_{ij} is the utility derived from the jth choice on occasion t, $\mathbf{x}_{ijt}\boldsymbol{\beta}$ is the deterministic component, $\mathbf{x}_{ijt}$ includes $j = 1,\ldots,J$ attributes of the good, $\boldsymbol{\beta}$ a J by 1 vector of attribute coefficients, and ϵ_{ijt} an unobserved random disturbance term with an expected value of zero and a variance of $\sigma^2_{\epsilon_{ijt}}$.

It is assumed that individuals can rank the choice alternatives in order of most to least preferred. Let $r_{it} = (r_{i1t}, \ldots, r_{iJt})$ indicate an individual's choice ranking in descending order of preference. The probability an individual orders $\mathbf{r}$ in any particular sequence is $\Pr\left[v_{it}(r_{i1t}) > v_{it}(r_{i2t}) > \cdots v_{it}(r_{iJt})\right]$. Calfee, Winston, and Stempski show how the J-dimensional vector of ordered preferences can be decomposed into J – 1 (0,1) variables that indicate which alternative the individual prefers, subject to the censoring of choice set elements that are least preferred. A closed-form expression for the ROL probability is (Calfee, Winston, and Stempski, 2001):

$$\Pr\left[v_{it}(r_{i1t}) > v_{it}(r_{i2t}) > \cdots v_{it}(r_{iJt})\right] = \prod_{t=1}\prod_{i=1}\prod_{h=1}^{J-1}\frac{\exp(\mathbf{x}_{ijt}(r_h)\boldsymbol{\beta})}{\sum_{m=h}^{J}\exp(\mathbf{x}_{ijt}(r_m)\boldsymbol{\beta})} \qquad (6)$$

where $\mathbf{x}_{ijt}(r_h)$ contains the alternative's attributes receiving rank h in the ordered set. The ROL log likelihood follows by taking the natural log of this probability.

Generalized Rank Ordered Logit

Parameterization of the ROL to a generalized ROL (GROL) follows Feibig et al. (2010)'s treatment of scale and preference heterogeneity for the multinomial logistic choice model. The GROL re-parameterizes coefficients as individual-specific random parameters for the choice attributes:

$$\boldsymbol{\beta}_i = \sigma_i \cdot \bar{\boldsymbol{\beta}} + \gamma \cdot \boldsymbol{\eta}_i + (1-\gamma) \cdot \sigma_i \cdot \boldsymbol{\eta}_i \tag{7}$$

where $\bar{\boldsymbol{\beta}}$ is a population average attribute effect, σ_i is a scaling parameter that varies across individuals, and $\boldsymbol{\eta}_i$ denotes preference heterogeneity. The parameter $\gamma \in [0,1]$ is estimable and measures the trade-off between scale effects and differences in taste (Fiebig et al., 2010).

The choice model is ROL when the independence of irrelevant alternative assumption is maintained (IIA, Cameron and Trivedi, 2005). This occurs when $\sigma_i = 1$, $\gamma = 0$, and $\boldsymbol{\eta}_i = \mathbf{0}$. A scaled ROL (RMNL) results when $\gamma = 0$, $\sigma_i > 1$, and preferences are shared across the population. Calfee et al.'s MROL is nested in Eq. (2) when scale heterogeneity is absent and $\gamma = 0$. When preferences and scaling effects are heterogeneous and $\gamma = 1$, then the utility weights are $\boldsymbol{\beta}_i = \sigma_i \cdot \bar{\boldsymbol{\beta}} + \boldsymbol{\eta}_i$. This form is the GROL version of what Fiebig et al. call the GMNL-I. Alternatively, the attribute parameter $\boldsymbol{\beta}_i = \sigma_i \cdot (\bar{\boldsymbol{\beta}} + \boldsymbol{\eta}_i)$ results when $\gamma = 0$ and tastes and scale effects are individual-specific. This form is the GROL version of Fiebig et al.'s GMNL-II.

Scale heterogeneity is parameterized as a function of individual characteristics included in matrix $\mathbf{z}$:

$$\sigma_i = \exp(\bar{\sigma} + \mathbf{z}_i\boldsymbol{\theta} + \tau \cdot \varepsilon_{0i}) \tag{8}$$

where the constant $\bar{\sigma}$ is parameterized as $-0.5 \cdot \tau^2$ such that $\mathrm{E}(\sigma_i) = 1$ when $\boldsymbol{\theta} = \mathbf{0}$ (Gu et al., 2015). The parameter vector $\boldsymbol{\theta}$ weights the importance of individual characteristics in determining heterogeneous scale effects. The parameter τ is estimable and controls the magnitude of scale heterogeneity. Scale heterogeneity increases as τ increases. The term ε_{0i} is a standardized normal random variable.

Bayesian Estimation of the GROL

The GROL model is estimated using Bayesian procedures. The posterior distributions of the model's parameters were recovered using R-Stan's Hamiltonian Monte Carlo No U-turn Sampler (HMC-NUTS). The HMC-NUTS performance is superior to Gibbs Metropolis-Hastings algorithms in terms of the number of iterations typically required for convergence (Hoffman and Gelman 2014). The prior distributions for the GROL parameters are:

$$\boldsymbol{\beta}_{i,price} \sim N_{-\infty}^{0}(0, 10),\ \boldsymbol{\beta}_{i,nonprice} \sim N(0, 10)$$

$$\boldsymbol{\theta} \sim N(0, 10)$$

$$\boldsymbol{\eta}_i \sim N(0, 1)$$

$$\gamma \sim\ Beta(2, 2)$$

$$\tau \sim \exp(1)$$

$$\varepsilon_{0i} \sim N(0, 1)$$

The prior for the price parameter ($\boldsymbol{\beta}_{i,price}$) is normal and truncated below zero. As price increase, demand for the product decreases. The prior for the γ parameter is Beta (2,2) because the parameter lies in the (0, 1) interval. The exponential distribution with a decay rate of one is the prior for τ. Set this way, the exponential scale prior carries no more information than an average deviation around zero (McElreath, 2020).

Gelman and Rubin (1992)'s $\hat{R}$ statistic was used to verify convergence. $\hat{R}$ diagnostics approaching one indicate a parameter chain is stationary. The leave-one-out (LOO) and was used to measure estimations predictive accuracy (Vehtari, 2017). The warmup series included 4,000 iterations, followed by an additional 4,000 iterations. The $\hat{R}$ statistic is used to confirm chain convergence.

Optimal Price and Consumer Surplus

The optimal make-up price for wheat SUEW products is determined by using Kohli and Mahajan (1991)'s method. The firms expected profit of selling the wheat SUEW products at P_W is:

$$\max_{P_W}(\pi) = m * \Pr(\mathrm{W} = 1) * (P_W - C_a) \quad (9)$$

where π is the firm's profit, P_W is the optimal price as the choice variable, m indicates the population who would purchase wheat SUEW products, Pr is the probability of purchasing wheat SUEW products which relates to the price of wheat SUEW products, C_a is the marginal cost at a level (the six survey price points: \$2.27, \$3.82, \$5.36, \$6.91, \$8.45, and \$10.00. In the free market, the price equals to the marginal cost).

The scenario is estimated in this study where option one is the paper SUEW product, option two is the degradable paper SUEW product, and option three is the wheat SUEW product. The retail prices for paper SUEW product and degradable paper SUEW product are \$2.25 and \$3 for 25 counts on Amazon. At each marginal cost point the optimal price, profit margin, and market share are calculated.

If the option three is omitted in the scenario, then it will cause the change of consumer surplus. The change of consumer surplus is calculated following Train (2005)'s method:

$$\Delta CS = -\frac{1}{\hat{\beta}_p}[\ln\left(\sum_{j_0=1}^{J_0}\exp(\hat{V}_{o j_0})\right) - \ln\left(\sum_{j_1=1}^{J_1}\exp(\hat{V}_{1 j_0})\right)] \quad (10)$$

where ΔCS indicates the change of consumer surplus, $\hat{\beta}_p$ is the estimated coefficient of price, the log-sum is the expected maximum utility, $J_0, J_1 \in J$, are the number of choices.

Inattention Effects

An interval joint test was used to test if WTP estimates difference between attentive and inattentive respondents (Huber, 2016). The null hypothesis is H_0: $\delta_{price} = \delta_{source} = \delta_{degrade} = \delta_{label} = \delta_{origin} = 0$, with $\boldsymbol{\delta}$ a vector containing the interaction variables' parameters. The probability equation of the null hypothesis is:

$$\mathrm{P}(H_0) = \frac{1}{T}\sum_{t=1}^{T} 1_{(\delta_{price_t} = \delta_{source_t} = \delta_{degrade_t} = \delta_{label_t} = \delta_{origin_t} = 0)} \tag{11}$$

where $\mathrm{P}(H_0)$ is the probability equation of the null hypothesis, T is the number of Monte Carlo iterations, δ estimates from their respective posterior distributions. In each iteration, if $\delta_{price_t} = \delta_{source_t} = \delta_{degrade_t} = \delta_{label_t} = \delta_{origin_t} = 0$, then this iteration is marked as 1, otherwise 0. The null hypothesis is rejected, if $\mathrm{P}(H_0)$ is less than 0.10. Rejection of the null hypothesis suggests that WTP is different between attentive and inattentive respondents jointly.

Results

For the Bayesian estimation, all $\hat{R}$ are 1 in the three information treatments, indicating that the estimation is reliable. The LOO for the pooling sample is 879, which is larger than the LOO of each information treatment. The LOO is 388 for the 'limited information' group, 396 for the 'half information' group, and 269 for the all 'information group'. This result suggests that the model should be estimated by separately instead of with the pooled sample.

For the 'all information' group, the probability of the interval joint test for the null hypothesis, H_0: $\delta_{price} = \delta_{paper} = \delta_{wheat} = \delta_{degrade6} = \delta_{degrade24} = \delta_{label} = \delta_{origin} = 0$ is 0.53. Thus, failure to reject the null hypothesis indicates conclude that the attribute premiums are not jointly different between attentive and inattentive respondents in the 'all information' group.

For the 'half information' group, the probability of the interval joint test for the null hypothesis, H_0: $\delta_{price} = \delta_{paper} = \delta_{wheat} = \delta_{degrade6} = \delta_{degrade24} = \delta_{label} = \delta_{origin} = 0$ is

0.52. This result suggests that attribute premiums are not different between attentive and inattentive respondents in the ‘half information’ group.

For the ‘limited information’ group, the probability of the interval joint test for the null hypothesis, H_0: $\delta_{price} = \delta_{paper} = \delta_{wheat} = \delta_{degrade6} = \delta_{degrade24} = \delta_{label} = \delta_{origin} = 0$ is 0.56. This result suggests that the attribute premiums are not different between attentive and inattentive respondents in the ‘limited information’ group. Based on the three the interval joint tests in three information group, the conclusion is that there is no attention effect jointly.

The scale heterogeneity variables, *envir*, *mw*, *ne* and *s* are significant at the five percent level in the ‘all information’ group, *envir* is significant at the five percent level in the ‘half information’ group, and *male* is significant at the five percent level in the limited information group (Table 19). These findings suggest that scale effect exists in the all three groups.

The estimated coefficient γ, a weighting parameter common to all respondents, is also significant at the five percent level for all three information groups. The parameter τ is significant at the five percent level, suggesting scale heterogeneity is operative across the set of respondent preferences for all three groups.

In the ‘all information’ group, and focusing on attentive respondents, the extrinsic attribute with the highest premium is ‘*source*’ (*paper*, \$5.44 and *wheat*, \$3.93) followed by ‘*degradability*’ (*degrade6,* \$4.71 and *degrade24,* \$2.79) (Table 20). For inattentive respondents, the premium of *paper* and *wheat* are \$6.67 and \$4.19 (respectively), while the premium of *degrade6* and *degrade24* are \$2.12 and - \$0.25 (respectively). This result suggests that, relative to SUEW made plastic with non-degradable material, consumers in the ‘all information group’ are willing to pay more for SUEW products made with biobased materials that degrade quickly.

The attribute *origin* ($2.10) has the third highest premium for attentive respondents in the 'all information' group while the premium for inattentive respondents is $2.09 (not significant). The SUEW products made in the US are more highly valued for consumers in the 'all information' group. The attribute *label* ($1.23) exhibits the lowest premium for attentive respondents in the group, suggesting that respondents ranked the biobased certification label lowest in terms of product features. The premium for inattentive respondents is $1.09, and not significant.

For attentive respondents in the 'half information' group, the extrinsic attribute with the highest premium is '*degradability*' (*degrade6*, $5.26, and *degrade24*, $3.01), followed by '*source*' (*paper*, $4.29, and *wheat*, $3.14). For inattentive respondents, the premium of *degrade6* and *degrade24* are $1.30 and $0.92, while the premium for wheat straw and paper SUEW are $6.77 and $4.55 (not significant). This result suggests that, compared to SUEW made with plastic material and non-degradable materials, consumers in the 'half information' group are willing to pay more for SUEW products made with degradable biobased materials.

The attribute *origin* ($2.06) has the third highest premium for attentive respondents in the 'half information' group. The premium is $1.81 (not significant) for inattentive respondents. This result suggests that consumers in the 'half information' group prefer SUEW products made with renewable biobased materials to plastics. The attribute *label* ($1.67) exhibits the lowest premium for attentive respondents in the group while the premium is $1.15 for inattentive respondents, suggesting that respondents rank biobased certification label lowest in terms of product features. However, the positive sign of *label* indicates that consumers in the half information group prefer SUEW products with certification labeling.

For attentive respondents in the 'limited information' group, the extrinsic attribute with the highest premium is '*degradability*' (*degrade6*, \$5.16, and *degrade24*, \$2.96), followed by '*source*' (*paper*, \$4.09, and *wheat*, \$3.13). The attribute *origin* (\$2.21) has the third highest premium for attentive respondents in the 'limited information' group. The attribute *label* (\$1.60) exhibits the lowest premium for attentive respondents in the 'limited information' group, suggesting that respondents rank biobased certification label lowest in terms of product features.

Table 19. Generalized Rank Ordered Logit Model Estimates of Single Use Plate, Random Effect and Heterogeneity

	All Information Group		Half Information Group		Limited Information Group	
Variable	Estimate		Estimate		Estimate	
Scale Heterogeneity:						
Age	-0.0009		-0.0013		0.0001	
Hhi	-0.0065		-0.0107		0.0400	
Recycle	-0.1667		-0.0088		-0.1329	
Envir	-0.5196	*	-0.3519	*	-0.0802	*
Male	-0.0596		-0.0984		-0.2509	
MW	-0.4432	*	-0.1075		-0.0698	
NE	-0.2921	*	-0.1125		-0.0261	
S	-0.3490	*	-0.1755		-0.0835	
College	-0.1344		0.0578		-0.1434	
Rural	-0.1054		-0.0736		0.0096	
Familiar	-0.0306		-0.0076		-0.0077	
τ	0.3481	*	0.1735	*	0.1735	*
γ	0.1727	*	0.4370	*	0.2816	*
Preference Heterogeneity:						
Price	-0.0003		0.0012		-0.0001	
Paper	0.0041		0.0166		0.0869	
Wheat	0.0063		-0.0004		-0.0011	
Degrade6	-0.0166		0.0015		0.0043	
Degrade24	0.0002		0.0021		-0.0019	
Label	0.0040		-0.0059		-0.0015	
Origin (Made in US)	-0.0006		-0.0008		-0.0013	

Table 19. Generalized Rank Ordered Logit Model Estimates of Single Use Plate, Random Effect and Heterogeneity (Continued)

Variable	Estimate	Estimate	Estimate
d×Price	-0.0024	-0.0001	0.0022
d×Paper	-0.0017	0.0091	0.0325
d×Wheat	0.0053	-0.0117	0.5675
d×Degrade6	-0.0051	-0.1344	0.0086
d×Degrade24	0.0027	0.4345	-0.0020
d×Label	-0.0067	-0.0003	-0.0598
d×Origin	0.0010	-0.0534	-0.0121
LOO (Leave-one-out)	268	399	389
WAIC (Widely Applicable Information Criterion)	265	396	385
Likelihood	-21,896	-20,974	-21,036
N	345	332	333

Notes: Asterisks (*) indicate the level of statistical significance (95%, respectively).

Table 20. WTP Results of Three Information Groups

Variable	All Information Group WTP		Half Information Group WTP		Limited Information Group WTP	
Attributes (average beta):						
Paper	5.44	*	4.29	*	4.09	*
Wheat	3.93	*	3.14	*	3.13	*
Degrade6	4.71	*	5.26	*	5.16	*
Degrade24	2.79	*	3.01	*	2.96	*
Label(Certified biobased)	1.23	*	1.67	*	1.60	*
Origin (Made in US)	2.10	*	2.06	*	2.21	*
Inattention:						
d×Price	0.37	*	0.26		0.49	*
d×Paper	1.23	*	2.48	*	-0.37	
d×Wheat	0.26		1.41		0.78	
d×Degrade6	-2.59	*	-3.96	*	-2.88	*
d×Degrade24	-3.04	*	-2.09	*	-1.91	
d×Label	-1.01		-0.52		-0.24	
d×Origin	-0.01		-0.25		-0.24	
Likelihood	-21,896		-20,974		-21,036	
N	345		332		333	

Notes: Asterisks (*) indicate the level of statistical significance (95%, respectively).

Information Treatments

Overall, the results of the three information treatments indicate that the attributes '*source*' and '*degradability*' are what the respondents rank highest in term of SUEW product features. The results are similar to Arjunan et al. (2010)'s conclusions. They found that product biodegradability is an important concern for consumers, Kainz et al. (2013) also concluded that consumers generally preferred degradable bioplastics made with renewable materials. That the attribute *origin* has the third highest premium in the three information group results is similar to Barnes et al. (2011)'s conclusion that consumers prefer locally sourced products. The positive signs of *label* in the three information group results is similar to Gill et al. (2020)'s conclusions that consumers prefer SUEW products with certification labeling.

The GROL posterior distributions of each attribute in the three information groups are reported in figure 5. For each attribute, the posterior distribution of the all information group is closer to the right side than the distributions of the half and limited information groups. This result suggests that consumers WTP is different when they were provided different amount of information, and is consistent with the availability hypothesis test result.

Optimal Price and Change of Consumer Surplus

The optimal prices for wheat SUEW products among three information treatments are similar (Table 21). When the marginal cost increases from \$2.27 to \$10.00, the optimal price increases from \$3.28 (\$3.30 in the limited information group) to \$11.00. The change of consumer surplus increases in all three information groups, with marginal cost decreasing. The biggest change of consumer surplus is in the limited information group, followed by the half information group, then the least change is in the all information group.

About 55 percent of the respondents rated renewable materials as an important attribute while 63 percent of the respondents rated degradability as an important product feature. These two findings are consistent with the WTP results that '*source*' and '*degradability*' have the highest premiums.

Even if all of the extrinsic attributes premiums are positive, 64 percent of respondents believed that most people are unwilling to make sacrifices to address environmental concerns. Moreover, only 28 percent of respondents believed that utensils and eating ware made form wheat straw is an important attribute to them to make their choices of SUEW product. However, 79 percent of respondents thought reducing the amount of single-use plastic pollution is important and 74 percent of respondents believed that the survey would encourage SUEW manufacturers to use biobased materials.

Table 21. Optimal Price For Wheat-Molded Single-Use Eating Ware (SUEW) Product and Change in Consumer Surplus among Three Information Treatments

	All Information Group		Half Information Group		Limited Information Group	
Marginal Cost	Optimal Price	Change in Consumer Surplus	Optimal Price	Change in Consumer Surplus	Optimal Price	Change in Consumer Surplus
\$2.27	\$3.28	0.01	\$3.28	0.01	\$3.30	0.03
\$3.82	\$4.82	2.00×10^{-3}	\$4.82	2.25×10^{-3}	\$4.83	0.01
\$5.36	\$6.36	4.15×10^{-4}	\$6.36	4.85×10^{-4}	\$6.36	1.58×10^{-3}
\$6.91	\$7.91	8.81×10^{-4}	\$7.91	1.03×10^{-4}	\$7.91	3.35×10^{-4}
\$8.45	\$9.45	1.89×10^{-5}	\$9.45	2.21×10^{-5}	\$9.45	7.19×10^{-5}
\$10.00	\$11.00	4.01×10^{-6}	\$11.00	4.68×10^{-6}	\$11.00	1.53×10^{-5}

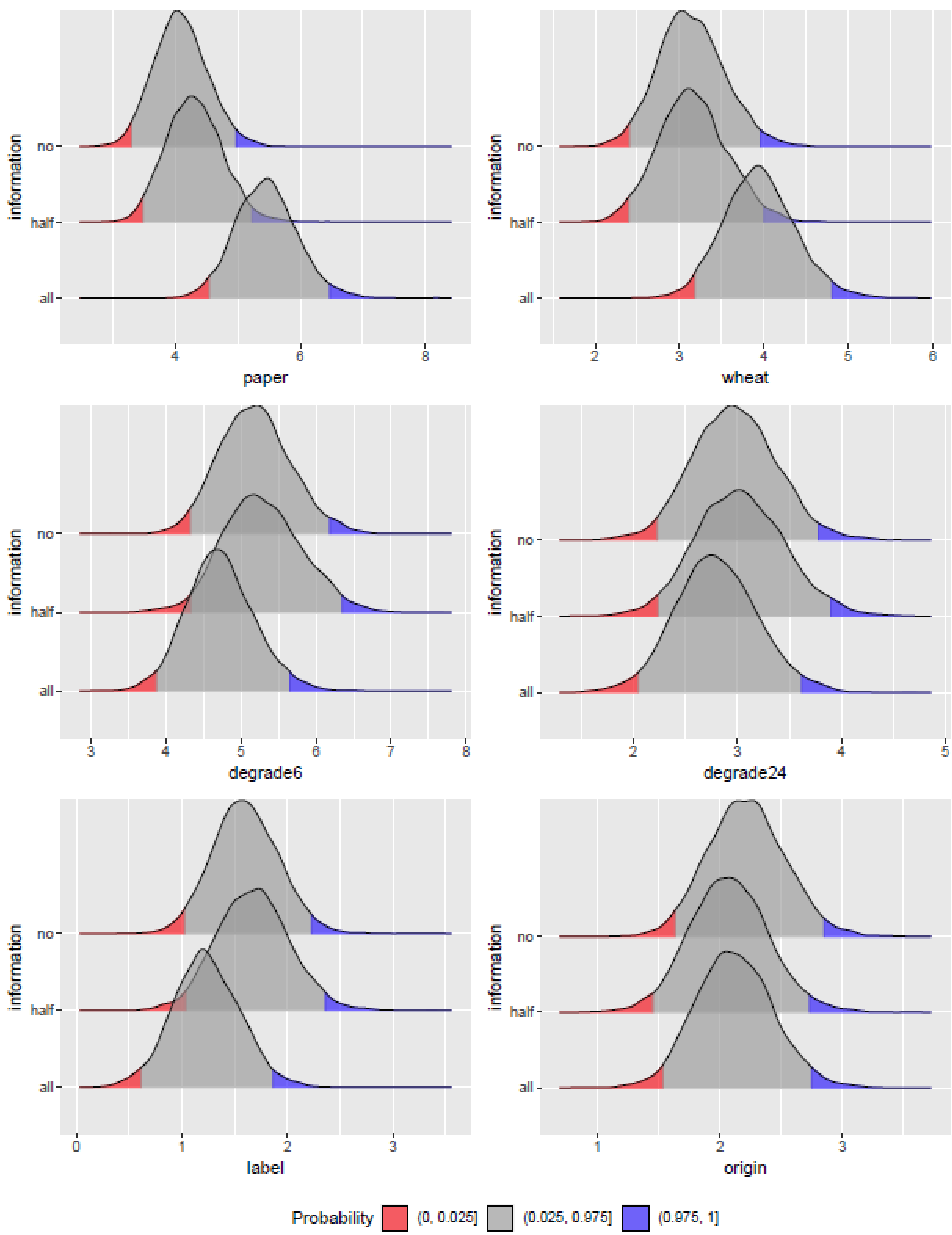
information
no
half
all
paper
wheat
degrade6
degrade24
label
origin
Probability
(0, 0.025]
(0.025, 0.975]
(0.975, 1]

Figure 10. Attributes Posterior Distributions of Every Information Group

Conclusions

This study extended the ROL model to the GROL model in estimating consumer WTP for extrinsic attributes controlling inattention bias. The attributes include biobased source, product degradability, USDA biobased certification, and manufacture origin. Consumers rated biobased source and product degradability highest, followed by USDA biobased certification, and manufacture origin. Premiums associated with biobased sources were higher for inattentive respondents while they were lower for other attributes. The amount of information respondents received about the SUEW product before the choice experiment affected WTP estimates. This study did not find significant attention effect jointly while there were significant differences between few variables and their attention interactions.

The use of the example profiles where there were three options illustrated the differences in probabilities of selecting different SUEW products. The optimal price across differing marginal cost of production indicated that how higher marginal costs affected on market share and firms' profits.

This study supplied another option to estimate best-worst data, which SMNL and MIXL were nested. However, one limitation was in this study. This study did not test whether the GROL was better than any other competing models. Thus, an important avenue for future research could be to compare GROL with alternative models, which were commonly used in best-worst case.

CHAPTER V

STUDY III: BAYESIAN ANALYSIS OF A HYBRID GENERALIZED MULTINOMIAL LOGIT MODEL

Latent variables have been widely used in consumer preference choice and behavior research because they can control for unobserved respondent beliefs. Latent variable analysis dates back to Spearman (1904). In consumer preference and behavior research, latent variables are used to link an individual's psychological profile with their preferences (Bouscasse, 2017). Unobserved psychological states relate to general opinions that influence the utility that individuals derive from their choices (Kim, Rasouli, and Timmermans, 2014). There are various ways to incorporate latent variables into consumer choice models and behavior. Some research uses latent variables, that are estimated by using predictive models (Wold, 1974; Wold, 1975; Muthen, 2004). Dimension reduction techniques like factor analysis are an alternative method to introduce latent variables into choice models. Dimensionality reduction results in a handful of vectors called factor scores which group similar responses into distinct categories based on their correlation (Wedel and Kamakura, 2001; Borsboom, Mellenbergh, and van Heerden, 2003). Factor scores are subsequently included as covariates in choice models to proxy the influence of beliefs, sentiments, and attitudes on preference formation (Harman, 1976; Coffman and MacCallum, 2005).

Ben-Akiva et al. (2002) introduced the hybrid choice model (HCM). This discrete choice model subsumes a latent variable model, both of which are estimated simultaneously. The HCM provides a framework to account for individual heterogeneity that may arise as latent, unobservable attitudes (Kim, Rasouli, and Timmermans, 2016). Some studies recently used HCM to analyze individual choice and behavior and to calculate consumer willingness to pay (WTP) (Daziano and Bolduc, 2013; Ferguson et al., 2018). Like the standard multinomial logit and its allies, the standard HCM maintains the Independence of Irrelevant Alternatives (IIA) assumptions and does not consider preference or scale heterogeneity. In practice, the IIA assumption is oftentimes violated (Schechter, 2010).

This study extends Czajkowski, Hanley, and Nyborg (2017)'s hybrid mixed logit (HMXL) model to Fiebig et al. (2010)'s generalized multinomial logit (GMNL). The modified model is used to estimate consumer preferences for a single use eating ware (SUEW) product fabricated with biobased materials. The reformulated model can accommodate latent attitudes, preference heterogeneity, and scale heterogeneity, with parameters estimated jointly. Preference heterogeneity is parameterized by random individual-specific coefficients on product attributes, and scale heterogeneity is parameterized as an exponential function of respondent characteristics. Thus, the extension is called a hybrid generalized multinomial logit (HGMNL) model. The HGMNL is estimated using Bayesian methods implemented with a Hamiltonian Monte Carlo sampling algorithm.

Literature Review

Ben-Akiva et al. (2002) proposed HCM models to simultaneously estimate latent factors scores that proxy psychosocial beliefs simultaneously with determinants of consumer preferences. There were 143 studies that used HCM since 2002 (Scopus, key word search of ‘hybrid-choice-model’). Ninety-seven percent of the studies were published between 2010 to 2021. The most prominent field using HCM was social sciences (69 percent). Economics, econometrics and finance (10 percent), business, management and accounting (10 percent), and computer science (9 percent) followed.

Czajkowski, Hanley, and Nyborg (2017) extended HCM to the mixed logit (MIXL) model to relax IIA assumptions. Since the introduction of HMXL model, 6 studies have used it in consumer preference studies (Scopus, key word search of ‘hybrid-mixed-logit’). Half of the studies were published in 2021, with three in the economics, econometrics and finance category (Czajkowski et al., 2017; Giansoldati et al., 2020; Bartczak, Budziński, Gołębiowska, 2021). The HMXL model was used to directly estimate latent variables in McFadden’s (1974) random utility maximization framework (RUM) (Czajkowski, Hanley, and Nyborg, 2017). The HMXL permits preferences to vary across individuals as a function of a population average effect and a random, idiosyncratic term. However, like the MIXL, the HMXL does not allow scale heterogeneity to vary across respondents.

Fiebig et al., (2010) introduced the GMNL extended from MIXL, which the GMNL’s parameterization relaxes IIA requirements by simultaneously modeling scale and taste (or preference) heterogeneity. The GMNL nests a family of multinomial logistic model specifications, including the scaled multinomial logit, mixed logit, and GMNL models I and II. Scale heterogeneity is independent of preference heterogeneity when the model is GMNL-I. For the GMNL-II model, preference heterogeneity is proportional to scale heterogeneity (Fiebig et al., 2010). When latent variables are considered in the GMNL regression, some studies used a two-step factor analysis approach (Ding, Abdulai, Jiang, 2020; Baek et al., 2013). In the first step, latent factors group questions were divided into different categories based on their correlation. In a second step, factor scores were included as covariates in a choice model to proxy the effects of beliefs, sentiments, and attitudes on preferences (Harman, 1976; Coffman and MacCallum, 2005).

There were 75 studies that used GMNL since Fiebig et al. (2010) (Scopus, key word search of 'generalized-multinomial-logit'). The GMNL has been used in many disciplines including the agricultural and biological sciences (Zhang and Sohngen, 2018; Balogh et al., 2016), economics, econometrics and finance (Keane and Wasi, 2013; Ahmed, Tefera, and Kassie, 2020), environmental science (Li et al., 2014; Kunwar, Bohara, and Thacher, 2020), decision science (Czajkowski and Budziński, 2019; Hess and Train, 2017), and business, management, and accounting (Lenk, 2011; Zeleke et al., 2020).

The HGMNL extends the GMNL to HMXL to estimate scale heterogeneity, preference heterogeneity and factor score simultaneous. GMNL parameters are typically estimated using simulated maximum likelihood (Gu et al., 2013). This study uses Bayesian methods to estimate the proposed HGMNL model for analyzing consumer preferences for SUEW fabricated with biobased materials.

Survey and Data

Our application focuses on consumer preference of the biobased SUEW products. An online survey[9] that it was approved by the university's Institutional Review Board was launched October 2019 by Qualtrics. Individuals 18 years old or older from a nationally representative frame of US households were sampled randomly through Qualtrics survey administrators. Qualtrics frame stratification includes census regions[10], gender, age, and income level.

[9] XXXXX University IRB Application AG-19-9.

[10] The four census divisions of the lower 48 US states are the Northeast (ME, NH, VT, NY, PA, MA, RI, CT, NJ, DE, MD, and DC), South (DE, MA, VA, WV, KY, NC, SC, TN, GA, FL, AL,

Individuals were invited to response the survey through computer or cellphone. The survey completing respondents were compensated with coupons by Qualtrics.

There were 335 completed survey respondents. The sample corresponded with a margin of error of five percent with a ninety-five percent confidence interval. The survey started with a consent question. A series of screening questions that they were used to identify a subgroup of consumers that most likely define the SUEW market followed the consent question. The screening questions included if the respondent (1) was primarily responsible for preparing and serving food in the household; (2) shopped for groceries; (3) planned and organized home entertainment events; and (4) if the respondent household used SUEW, the respondent the person that purchased the product.

Individuals' eliciting information by the survey includes gender, age, residential location, educational attainment, and household income. Male percent was forty-nine percent (Table 22) (49 percent in the 2010 US Census). The average age of respondents was 45 (2010 median age from the 2010 US Census is 37). Eighteen percent of the respondents lived in northeast region, twenty-one percent in Midwest region, and thirty-eight in the south, with the remainder in western states. The respondents had a college degree was forty-four percent. Respondents reported their 2018 household income before taxes in seven ranges.

Table 22. Variable Names and Summary Statistics

Variable Name	Description	Mean	Standard Deviation	Min	Max
Demographics:					
Age	Respondents age (years)	45.22	17.19	18	84
Male	1 if male, otherwise 0	0.49		0	1
Mw	1 if in Midwest, otherwise 0	0.21		0	1
Ne	1 if in Northeast, otherwise 0	0.18		0	1

MI, AR, LO, TX, and OK), Midwest (including ND, SD, NE, KS, MH, IA, MO, WI, IL, IN, MI, and OH), and West (all other states).

Table 22. Variable Names and Summary Statistics (Continued)

Variable Name	Description	Mean	Standard Deviation	Min	Max
So	1 if in South, otherwise 0	0.38		0	1
Recycle	1 if recycles on a regular basis, otherwise 0	0.75		0	1
Envir	1 if member of any environmental organization, otherwise 0	0.19		0	1
College	1 = had college or higher, otherwise 0	0.44		0	1
Famil	1 = unfamiliar, 8 = very familiar	3.47		1	8
Hhi	1 if less than $25,000 2 if $25,000 to $49,999 3 if $50,000 to $74,999 4 if $75,000 to $99,999 5 if $100,000 to $149,999 6 if $150,000 to $200,000 7 if $200,000 or more	3.39		1	7
N = 335					

Information Screens

Information screens following a series of screening questions including: (1) definitions of single-use products and ‘biobased’; (2) degradability of biobased product (Appendix, Figure 1); (3) the economic contribution of biobased products to the US economy (Appendix, Figure 2); (4) product ‘biobased’ content certification (Appendix, Figure 3), and; (5) transforming wheat straw into a bioplastic molding (Appendix, Figure 4). All respondents received the same definition of ‘single-use eating-ware products’ and ‘bio-based’. The first information screen included the text;

We consume single-use products every day when we shop for food, eat at restaurants, and entertain. For example:

- *We use disposable bags to carry groceries.*
- *Leftover food we take home after eating-out is placed in a bag or box.*
- *If food is delivered to our home or eaten at a restaurant, it might be packaged in a container or wrapping.*
- *We might use disposable utensils, bowls, plates, or cups when we entertain.*
- *We might use disposable utensils, bowl, or plates for everyday use.*

These single-use products can be made from materials such as petroleum-based plastics, recycled products, paper made from trees, or plant fibers from agricultural crops.

A definition of 'bio-based' followed, informing all respondents about the potential use of bio-based inputs in the manufacture of products:

*All of the single-use items previously mentioned can also be made partly or entirely from **biobased materials**. Products made from bio-based materials are called '**biobased products**'.*

Some examples of products made or containing with biobased inputs like drinking straws (which can be made from bamboo or wheat straw); shopping bags (which can be made from corn starch); bowls, cartons, containers, and plates (which can be made from sugar cane, paper, or molded wheat straw) were included in the first information screen.

Respondents were exposed to all information screens in random order, including (a) biobased product degradability, (b) the economic contribution of biobased products to the economy, (c) product content certification, and (d) recycling wheat straw as a biobased composite input.

Budget Reminder

The budget reminder followed the information screens and asked respondents to reflect on their usual budget allocated for this type of expense (Cummings and Taylor, 1999; List et al., 2006; Loomis, 2014).

The budget reminder with the trap question was:

*In surveys like this, people often do not pay much attention to the actual prices shown because they don't really have to pay the cost of the plate they prefer. Instead, they simply notice that one price is higher than another. When answering the survey questions on the next screen, please closely examine the prices and consider these in comparison to your household's budget before choosing a particular plate attribute. **To show that you have read the instructions, please answer the question below about "What color is the sky according to the above paragraph?" by checking "none of the above" as your answer**.* [Bold emphasis added.]

Choice Experiment

There were five products choices from which respondents could select one of them or "none of them" for respondents in each task. The opt-out choice coded as an alternative specific constant (*Asc*) enables measurement of the effects on consumer choice of factors beyond the attributes offered in the choice sets (Adamowicz et al., 1998).

The five attributes differentiated the five choices are: (a) product degradability (three levels: not degradable, degradable in six months (*Degrade6*), degradable in 24 months (*Degrade24*); (b) material source (three levels; plastic, paper (*Paper*), or wheat straw (*Wheat*)); (c) origin (two levels: made in the US (*Origin*), or made elsewhere); (d) product content certification (*Label*, two levels: no or yes), and (e) a price per 25-count of 10-inch size SUEW food plates (six levels: \$2.27, \$3.82, \$5.36, \$6.91, \$8.45, or \$10.00) (Design matrix, Table 23.)[11]. Among 20 SUEW products reviewed on Amazon, the lowest price for a 25-count package of 10-inch plates was \$2.27, while the highest price for the same quantity was \$10.00. The other three prices in the choice experiment were determined by uniformly spaced intervals between the minimum (\$2.27/25 count) and maximum (\$10/25 count) prices. A pre-survey with 100 sample was used to evaluate these price points. Respondents were asked to assume the SUEW products were identical in all ways (including product functionality) except for the attributes they were asked to evaluate.

A balanced factional design where the main effect design is orthogonal to minimize correlation between product alternatives (Lentner and Bishop, 1986) was used to determine the number of choice tasks. The possible combinations were $6 \times 3^2 \times 2^2 = 216$ in the choice

[11] Prices were collected from Amazon, June 2019. The link to the \$10.00 package of 25 single use food plates is: https://www.amazon.com/10/25counts. The link to the \$2.27 package of single use food plate is: https://www.amazon.com/2.27/25counts.

experiment’s design space. The number of choice tasks was determined as 12 task per respondent that the order of choice tasks was randomized across respondents by a 100 percent efficient design through The SAS macro %*mktex* (SAS, 9.4).

Thus, the number of observations available for choice modeling was 24,120 (12 tasks × 6 choices × 335 respondents).

Table 23. Choice experiment levels and attributes

Attribute	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6
Degradability	Not degradable	6 months	24 months			
Content certification	No	Yes				
Material	Plastic	Paper	Wheat straw			
Origin	Made in the US	Made elsewhere				
Price ($/25 count)	$2.27	$3.82	$5.63	$6.91	$8.45	$10.00

Debriefing Questions

Following the choice experiment, there were banks of debriefing questions including included where respondents most likely purchased disposable plates (big box stores, warehouse clubs, convenience stores, online); how much they spent on disposable plates in the last six months; the importance of each attribute on their purchasing decision; self-ascribed political viewpoints (strong conservative, moderate conservative, lean towards conservative, independent, lean toward liberal, strong liberal); a description of their residential status (single home owner, rent, apartment, mobile home); and rural/urban status (lived in a rural or urban area).

A series of Likert questions were used to collect respondent attitudinal views on assessment of environmental statements and issues. The answers on a five-interval scale from 'strongly agreed' to 'strongly disagreed' to regard respondents outlook on environmental issues, causes, and solutions to problems (Table 24).

Table 24. Respondent Perceptions and Viewpoints on Environmental Issues

Statements (1)	Mean	Std. Dev.	Min	Max
This survey could encourage producers of single-use food containers to use bio-based materials.	4.11	1.01	1	5
Consumers affect the environment with their product choices.	4.28	0.91	1	5
My personal actions have no impact on environmental problems.	2.68	1.48	1	5
Science and technology will find ways to solve environmental problems.	3.82	1.04	1	5
Most people are unwilling to make sacrifices to address environmental problems.	3.88	0.99	1	5
Government policy is needed to solve environmental problems.	3.94	1.05	1	5
Private industry will develop ways to minimize environmental problems.	3.72	1.05	1	5
Protecting the world's forests is critical to maintaining healthy environment.	4.42	0.90	1	5

Table 24 Respondent Perceptions and Viewpoints on Environmental Issues

Statements (1)	Mean	Std. Dev.	Min	Max
Protecting the world's oceans is critical to maintaining healthy environment.	4.43	0.86	1	5
There is no urgent need to slow climate change.	2.73	1.50	1	5
Reducing the amount of single-use plastic pollution is important.	4.22	1.04	1	5
There is no urgent need to reduce greenhouse gas emissions.	2.69	1.50	1	5
We have a responsibility to protect the environment for future generations.	4.32	0.91	1	5
I do not have enough knowledge to make well-informed decisions on environmental issues.	3.00	1.32	1	5
N = 335				

Notes: (1) Likert scale: 1 = 'strongly disagree', 2 = 'somewhat disagree', 3 = 'either agree or disagree', 4 = 'somewhat agree', 5 = 'strongly agree'.

Choice Model and Estimation

Utility is linear utility in arguments with systematic and random components is defined as (McFadden, 1974):

$$v_{ijt} = \mathbf{x}_{ijt}\boldsymbol{\beta}_i + \varepsilon_{ijt} \tag{9}$$

where v_{ijt} is the indirect utility respondent i receives from selecting alternative j on choice occasion t. The matrix $\mathbf{x}_{ijt}$ is a $1 \times K$ vector of product attributes including the per-unit price of choice j; $\boldsymbol{\beta}_i = (\beta_{i,price}, \cdots, \beta_{iK})'$ are individual-specific price and attribute effects; and ε_{ijt} is an independent and identically distributed random error term with an expected value of zero and a constant variance.

The HGMNL model builds on Fiebig et al. (2010)'s GMNL. Individual-specific preferences for alternatives are stated as function of random parameters:

$$\boldsymbol{\beta}_i = \sigma_i \cdot \overline{\boldsymbol{\beta}} + \gamma \cdot \boldsymbol{\eta}_i + (1-\gamma) \cdot \sigma_i \cdot \boldsymbol{\eta}_i \tag{10}$$

where $\overline{\boldsymbol{\beta}}$ is the population average attribute effect; σ_i is a scaling parameter varying across individuals, and preference heterogeneity $\boldsymbol{\eta}_i$; The trade-off between scale effects and differences in taste $\gamma \in [0,1]$ (Fiebig et al., 2010).

Scale heterogeneity is parametrized as a function of the latent factors $(\mathbf{f}^{1*}, \mathbf{f}^{2*}, \mathbf{f}^{3*})$:

$$\sigma_i = \exp(\,\overline{\sigma} + \theta_1 \cdot \mathbf{f}_\mathbf{i}^{\mathbf{1}*} + \theta_2 \cdot \mathbf{f}_\mathbf{i}^{\mathbf{2}*} + \theta_3 \cdot \mathbf{f}_\mathbf{i}^{\mathbf{3}*} + \tau \cdot \varepsilon_{0i}) \tag{11}$$

where the constant $\overline{\sigma}$ is parameterized as $-0.5 \cdot \tau^2$ (Fiebig et al., 2010). The parameter τ is estimable and governs scale heterogeneity magnitude. Scale heterogeneity increases as τ increases. The term ε_{0i} is a standardized normal random variable with an expected value of zero and a variance of one. Demographic latent factors are included in $\mathbf{f}^{1*}$. Likert scale question related to respondent sentiments and beliefs on technology, political viewpoints, and environmental issues are included in the latent factors $\mathbf{f}^{2*}$ and $\mathbf{f}^{3*}$. The parameters $(\theta_1, \theta_2, \theta_3)$ weight the importance of the factors in determination of scale heterogeneity effects.

The latent factors $(\mathbf{f}^{1*}, \mathbf{f}^{2*}, \mathbf{f}^{3*})$ are parametrized as functions of demographic and attitudinal variables. Attitudinal variables were measured using a series of Likert scale questions. The factors are parameterized as:

$$\mathbf{f}_\mathbf{i}^{\mathbf{1}*} = \textstyle\sum_g \lambda_g^1 \cdot v_{ig}^1 \tag{12}$$

$$\mathbf{f}_\mathbf{i}^{\mathbf{2}*} = \textstyle\sum_k \lambda_k^2 \cdot v_{ik}^2 \tag{13}$$

$$\mathbf{f}_\mathbf{i}^{\mathbf{3}*} = \textstyle\sum_k \lambda_k^3 \cdot v_{ik}^3 \tag{14}$$

where $\mathbf{v}^1$ is the matrix of demographic variables including age, gender, region, if the respondent recycled, if the respondent belonged to an environmental organization, if the respondent had college degree, how familiar the respondent was with biobased products before the survey, and household income (table 25). The variables $\mathbf{v}^2$and $\mathbf{v}^3$ are the Likert scale question banks pertaining to respondent familiarity and attitudes towards technology, politics and the environment. The parameters ($\boldsymbol{\lambda}^1, \boldsymbol{\lambda}^2, \boldsymbol{\lambda}^3$) are coefficients for each score vector.

Table 25 Factor Loading Names and Summary Statistics

Variable Name	Description	Mean	Standard Deviation	Min	Max
Demographics (λ^1):					
Age	Respondents age (years)	45.68	16.44	18	84
Male	1 if male, otherwise 0	0.49	0.5	0	1
Mw	1 if in Midwest, otherwise 0	0.21	0.41	0	1
Ne	1 if in Northeast, otherwise 0	0.18	0.38	0	1
So	1 if in South, otherwise 0	0.37	0.48	0	1
Recycle	1 if recycles on a regular basis, otherwise 0	0.78	0.42	0	1
Envir	1 if member of any environmental organization, otherwise 0	0.18	0.38	0	1
College	1 = had college or higher, otherwise 0	0.45	0.5	0	1
Famil	1 = unfamiliar, 8 = very familiar	3.47		1	8
	1 if less than $25,000	0.2	0.4	0	1
	2 if $25,000 to $49,999	0.22	0.41	0	1
	3 if $50,000 to $74,999	0.17	0.38	0	1
Hhi	4 if $75,000 to $99,999	0.11	0.31	0	1
	5 if $100,000 to $149,999	0.13	0.33	0	1
	6 if $150,000 to $200,000	0.09	0.28	0	1
	7 if $200,000 or more	0.06		0	1
Attitudes Towards Technology, Politics And The Environment (λ^2):					
This survey could encourage producers of single-use food containers to use bio-based materials.	1 = strongly disagree, 5 = strongly agree	4.11	1.01	1	5
Consumers impact the environment with their product choices.	1 = strongly disagree, 5 = strongly agree	4.28	.091	1	5
My personal actions have no impact on the environmental problems.	1 = strongly disagree, 5 = strongly agree	2.68	1.48	1	5

Table 25 Factor Loading Names and Summary Statistics (Continued)

Variable Name	Description	Mean	Standard Deviation	Min	Max
Science and technology will find ways to solve environmental problems.	1 = strongly disagree, 5 = strongly agree	3.83	1.04	1	5
Most people are unwilling to make sacrifices to protect the environmental problems.	1 = strongly disagree, 5 = strongly agree	3.88	0.99	1	5
Government policy needed to solve environmental problems.	1 = strongly disagree, 5 = strongly agree	3.94	1.05	1	5
Private industry will develop ways to minimize environmental problems.	1 = strongly disagree, 5 = strongly agree	3.72	1.06	1	5
Attitudes Towards Technology, Politics And The Environment (λ^3):					
Protecting the world's forests is critical to maintaining healthy environment.	1 = strongly disagree, 5 = strongly agree	4.42	0.90	1	5
Protecting the world's oceans is critical to maintaining healthy.	1 = strongly disagree, 5 = strongly agree	4.43	0.86	1	5
There is no urgent need to slow climate change.	1 = strongly disagree, 5 = strongly agree	2.73	1.50	1	5
Reducing the amount of single-use plastic pollution is important.	1 = strongly disagree, 5 = strongly agree	4,22	1.04	1	5
There is no urgent need to reduce greenhouse gas emissions.	1 = strongly disagree, 5 = strongly agree	2.69	1.50	1	5
We have a responsibility to protect the environment for future generations.	1 = strongly disagree, 5 = strongly agree	4.32	0.91	1	5
I do not have enough knowledge to make well-informed decisions on environmental issues.	1 = strongly disagree, 5 = strongly agree	3.00	1.32	1	5
N = 335					

Bayesian Estimation of HGMNL

The HGMNL was estimated with R Stan (Stan Development Team, 2020) Hamiltonian Monte Carlo No U-turn Sampler (HMC-NUTS). The HMC-NUTS procedure performance is superior to Gibbs of Metropolis-Hastings algorithms in terms of the number of iterations typically required for convergence. The number of iterations is 8,000, following warm up setting as 4,000. The maximum tree depth of 15 and adaptation rate of 0.95 was used. The prior density for all parameters is:

$$\overline{\boldsymbol{\beta}}_{price} \sim N_{-\infty}^{0}(0, 10), \overline{\boldsymbol{\beta}}_{nonprice} \sim N(0, 10)$$

$$\boldsymbol{\eta}_i \sim \text{Normal}(\mathbf{0}, \boldsymbol{\sigma}_{\overline{\boldsymbol{\beta}}})$$

$$\gamma \sim \text{Beta}(2, 2)$$

$$\tau \sim \text{Exponential}(1)$$

$$\boldsymbol{\sigma}_{\overline{\boldsymbol{\beta}}} \sim \text{Exponential}(1)$$

$$\varepsilon_{0i} \sim \text{Normal}(0,1)$$

$$(\boldsymbol{\lambda}^1, \boldsymbol{\lambda}^2, \boldsymbol{\lambda}^3) \sim \text{Normal}(0, 10)$$

$$(\theta_1, \theta_2, \theta_3) \sim \text{Normal}(0, 10)$$

The prior for the price parameter ($\boldsymbol{\beta}_{i,price}$) is normal and truncated below zero. The prior for the γ parameter is Beta because the parameter lies in the (0, 1) interval. The exponential distribution with a decay rate of one is the prior for τ. Set this way, the exponential scale prior carries no more information than an average deviation, which is the inverse of the rate (McElreath, 2020). $\overline{\boldsymbol{\beta}}_{nonprice}$, $\boldsymbol{\lambda}^1, \boldsymbol{\lambda}^2, \boldsymbol{\lambda}^3$, θ_1, θ_2 and θ_3 are assumed under the normal distribution.

Gelman and Rubin (1992)'s $\hat{R}$ statistic was used to verify convergence. Diagnostics approaching one indicate a parameter's chain is stationary. Leave-one-out (LOO) was used to measure estimations predictive accuracy. The warmup series included 4,000 iteration, which was followed by an additional 4,000 iterations.

Results

For the Bayesian estimation, there was 37 divergence after warmup but all $\widehat{\mathrm{R}}$ are 1 in the three information treatments, indicating that the estimation is reliable. All the scale heterogeneity parameters are significant at the five percent level (Table 26), suggesting not only the demographic latent factor, but also Likert scale latent factors exist in the model. To show the correct Bayesian estimation of HGMNL, the factor loading from Stata (Stata 15.1, StataCorp LLC, College Station, TX) is provided in the table 27. The factor loading of each variable from the HGMNL estimation through RSTAN and factor analysis through Stata are similar.

The estimated coefficient γ, a scaling parameter common to all respondents, and the parameter τ are significantly at the five percent level difference from zero, suggesting heterogeneity across the set of respondent preferences.

Table 26. Hybrid Generalized Multinomial Logit Model Estimates of Single Use Plate

Variable	Estimate	Standard Error	95 % Credible Interval	
Attributes (average beta):				
Price	-0.4360	0.0019	-0.5486	-0.3389
Asc	-3.3479	0.0251	-4.6458	-2.1898
Paper	0.9483	0.0056	0.6474	1.2756
Wheat	0.9805	0.0055	0.6603	1.3320
Degrade6	1.7652	0.0082	1.3969	2.2143
Degrade24	1.1569	0.0063	0.8433	1.5262
Label (Certified biobased)	0.7733	0.0036	0.5745	0.9979
Origin (Made in US)	0.8451	0.0040	0.6343	1.0929
Inattention:				
d×*Price*	0.3320	0.0035	0.1193	0.5552
d×*Paper*	-0.0707	0.0529	-2.7590	2.4895
d×*Wheat*	0.4762	0.0125	-0.2815	1.2742

Table 26. Hybrid Generalized Multinomial Logit Model Estimates of Single Use Plate (Continued)

Variable	Estimate	Standard Error	95 % Credible Interval	
d×Degrade6	0.0970	0.0115	-0.6721	0.9002
d×Degrade24	-1.5688	0.0123	-2.3203	-0.8978
d×Label	-1.4293	0.0113	-2.1738	-0.7807
d×Origin	-0.1127	0.0059	-0.5933	0.3941
Scale Heterogeneity:				
Z	-0.3935	0.0043	-0.5946	-0.1939
F1	-0.2162	0.0039	-0.3966	-0.0329
F2	-0.2682	0.0034	-0.4395	-0.1116
τ	0.9338	0.0035	0.7807	1.1002
γ	0.0643	0.0014	0.0115	0.1463
Preference Heterogeneity:				
Price	-0.1156	0.0487	-0.4340	0.3350
Asc	3.8725	0.0490	2.6828	5.0406
Paper	0.0135	0.0372	-0.5792	0.5912
Wheat	0.4394	0.3318	-1.6240	1.7327
Degrade6	0.3844	0.1616	-0.9731	1.1034
Degrade24	0.3429	0.1854	-0.9583	1.1760
Label	-0.0130	0.1823	-0.9089	0.8772
Origin (Made in US)	0.0745	0.1089	-0.7893	0.8381
Inattention:				
d×Price	0.0830	0.0466	-0.6489	0.7562
d×Paper	-3.9201	0.0755	-5.3353	-2.5169
d×Wheat	0.3419	0.1431	-1.4719	1.8316
d×Degrade6	-0.0515	0.1636	-1.5060	1.5484
d×Degrade24	-0.0088	0.1108	-1.2700	1.3658
d×Label	-0.0759	0.0823	-1.2532	1.2643
d×Origin	-0.1114	0.1138	-1.5384	1.0414
Loading:				
$\lambda1[1]$	-0.2737	0.0014	-0.3966	-0.1515
$\lambda1[2]$	0.5396	0.0014	0.4266	0.6535
$\lambda1[3]$	-0.0771	0.0013	-0.2032	0.0448
$\lambda1[4]$	0.3062	0.0013	0.1808	0.4311
$\lambda1[5]$	-0.1443	0.0012	-0.2649	-0.0236
$\lambda1[6]$	0.2455	0.0012	0.1253	0.3648
$\lambda1[7]$	0.4998	0.0013	0.3867	0.6140
$\lambda1[8]$	0.6015	0.0014	0.4929	0.7092
$\lambda1[9]$	0.7910	0.0020	0.6876	0.8963
$\lambda1[10]$	0.5611	0.0015	0.4460	0.6748
$\lambda2[1]$	-0.7289	0.0022	-0.8412	-0.6143
$\lambda2[2]$	-0.6155	0.0024	-0.7358	-0.4822

Table 26. Hybrid Generalized Multinomial Logit Model Estimates of Single Use Plate (Continued)

Variable	Estimate	Standard Error	95 % Credible Interval	
$\lambda2[3]$	-0.1420	0.0027	-0.2889	0.0034
$\lambda2[4]$	-0.4797	0.0022	-0.6082	-0.3552
$\lambda2[5]$	-0.4946	0.0016	-0.6176	-0.3768
$\lambda2[6]$	-0.5770	0.0015	-0.6938	-0.4622
$\lambda2[7]$	-0.4596	0.0026	-0.5983	-0.3270
$\lambda3[1]$	-0.2674	0.0012	-0.3819	-0.1560
$\lambda3[2]$	-0.3279	0.0012	-0.4418	-0.2207
$\lambda3[3]$	0.8989	0.0015	0.8213	0.9652
$\lambda3[4]$	-0.2070	0.0012	-0.3215	-0.0957
$\lambda3[5]$	0.8376	0.0014	0.7579	0.9211
$\lambda3[6]$	-0.3380	0.0013	-0.4498	-0.2253
$\lambda3[7]$	0.5213	0.0011	0.4228	0.6162
Likelihood	-10,266			
N	335			

Table 27 Factor Loading Score from Stata

Variable Name	Factor Loading
Age	-0.2426
Male	0.5411
Mw	-0.1020
Ne	0.3999
So	-0.1929
Recycle	0.2390
Envir	0.4605
College	0.6182
Famil	0.7288
Hhi	0.5944
This survey could encourage producers of single-use food containers to use bio-based materials.	-0.6575
Consumers impact the environment with their product choices.	-0.5553
My personal actions have no impact on the environmental problems.	-0.2672
Science and technology will find ways to solve environmental problems.	-0.5499
Most people are unwilling to make sacrifices to protect the environmental problems.	-0.5127
Government policy needed to solve environmental problems.	-0.5548

Table 19 Factor Loading Score from Stata (Continued)

Variable Name	Factor Loading
Private industry will develop ways to minimize environmental problems.	-0.5650
Protecting the world's forests is critical to maintaining healthy environment.	-0.7882
Protecting the world's oceans is critical to maintaining healthy.	-0.8213
There is no urgent need to slow climate change.	0.5625
Reducing the amount of single-use plastic pollution is important.	-0.6287
There is no urgent need to reduce greenhouse gas emissions.	0.4829
We have a responsibility to protect the environment for future generations.	-0.7423
I do not have enough knowledge to make well-informed decisions on environmental issues.	0.2388
N = 335	

Factor Loadings

All of loading parameters are significant at the five percent level, except 'region' ($\lambda^1[3]$) and 'my personal actions have no impact on the environment' ($\lambda^2[3]$). The factor loading, correlation between latent variables, is acceptable when it is above 0.5 in absolute value

For the demographic factor, the factor loading scores of gender ($\lambda^1[2]$), education($\lambda^1[8]$), 'how familiar the respondent was with biobased products before the survey' ($\lambda^1[9]$), and household income ($\lambda^1[10]$) are above 0.5 in absolute value, indicating that the demographic factor are mainly reflect by age, region, if the respondent recycled, if the respondent belonged to an environmental organization, if the respondent had college degree.

For the first Likert scale factor, 'this survey could encourage producers of single-use food containers to use biobased materials' ($\lambda^2[1]$), 'consumers impact the environment with their product choices'($\lambda^2[2]$), and 'government policy is needed to solve environmental problems' ($\lambda^2[6]$) are the variables that their loading scores are above 0.5 in absolute value.

There are three variables that their factor loading scores are above 0.5 in absolute value for the second Likert scale factor. They are 'there is urgent need to slow climate change' ($\lambda^3[3]$), 'there is no urgent need to reduce greenhouse gas emissions' ($\lambda^3[5]$), and 'I do not have enough knowledge to make well-informed decisions on environmental issues'($\lambda^3[7]$).

Extrinsic Attributes

The extrinsic attribute with the highest WTP premium is '*degradability*" where *degrade6* is $4.05 and *degrade24* is $2.65 (Table 28). This result suggests that compared to the reference attribute 'not degradable', consumers are willing to pay more for SUEW products that degrade quickly.

The attribute '*source*' has the second highest WTP premium where *wheat* is $2.25 and *paper* is $2.18. This result suggests that consumers prefer SUEW products made with renewable biobased materials to plastics (the reference attribute).

The attribute *origin* ($1.94 premium) has the third highest premium, suggesting Consumer value more SUEW products made in the US. The attribute exhibiting the lowest premium is *label* ($1.77), suggesting that respondents rank biobased certification label lowest in terms of product features while the positive sign of premium suggests that respondents still prefer biobased product with USDA biobased certification label.

Table 28. Each Attribute WTP Result

Variable	All Information Group WTP	
Attributes (average beta):		
ASC	-7.68	*(1)
Paper	2.17	*
Wheat	2.25	*
Degrade6	4.05	*
Degrade24	2.65	*
Label (Certified biobased)	1.77	*
Origin (Made in US)	1.94	*
Likelihood	-10,266	
N	335	

Notes:
(1) * is: at the five percent of significance

Conclusions

This study developed an HGMNL, which estimated factor analysis and consumer WTP for extrinsic attributes of SUEW simultaneously. The latent factors included respondent demographic variables and respondent familiarity with environmental issues. The attributes were biomaterial source, manufacture origin, biobased certification, and product degradability. We not only find significant factor scale heterogeneity affecting on consumer WTP, but also conclude that a relatively high premium attributed by consumers is degradability, followed by the eating-ware product made with renewable biomaterials.

This article found almost all latent variables and all factors were significant, affecting on attribute WTP estimation. This is an important result, especially considering that many WTP studies using GMNL did not count for latent variables or used factor analysis firstly and then plugged the factors in the regression. The HGMNL should increase the efficiency of estimation. One limitation in this study is that there is no comparison between HGMNL and other common used logit models, such as HMIL and GMNL, in the conjoint analysis. Thus, an interesting step for future study will be doing the comparison with other competing models.

CHAPTER VI

DISCUSSION AND CONCLUSION

This dissertation controlled for inattention and availability bias while estimating consumer WTP for extrinsic attributes of SUEW. Two models were extended based on the GMNL model in this dissertation. Attribute premium estimates were found for attributes consumers may value when purchasing SUEW products. The findings can be used to determine the optimal price for the wheat SUEW product and consumer surplus change.

In the study I, availability bias was found while no availability bias existed in the study two. This inconsistent result might be from the data, which were used in the two studies. BWS not only could generate more information about good's most and least preferred qualities, but also minimized response bias, compared with conjoint analysis. Another reason might be in the conjoint choice experiment, there was an Asc option, which did not enforce respondents to select one good. Thus, the model in the study I was used belonged to unconditional logit model. However, in the study II, there was no Asc option in the BWS choice experiment, where respondents were enforced to rank all goods in each set. Thus, the model, in the study II, belonged to conditional logit model.

In order to solve the above problem based on the current data, one interesting future research would be using the GMNL model to estimate BWS data to compare with the GROL result.

Another limitation of this dissertation was that for the two extended models, there was no comparison between these two and other potential competing models. Thus another interesting future research would be this comparison between the extended model and other potential competing models.

References

Abdelradi, F., & Adu, K. (2015, March). *Evaluation of consumers' lifestyles and willingness to pay for dates: A hybrid choice model approach*. Presentation presented at the 2015 Agricultural & Applied Economics Association, Naples, Italty.

Adamowicz, W., Boxall, P., Williams, M., & Louviere, J. (1998). Stated preference approaches for measuring passive use values: choice experiments and contingent valuation. *American Journal of Agricultural Economics*, *80*(1), 64–75. https://doi.org/10.2307/3180269

Adamsen, J. M., Rundle, S., & Whitty, J. A. (2013). Best-worst scaling. . . reflections on presentation, analysis, and lessons learnt from case 3 BWS experiments. *Market& Social Research*, *21*, 9–27. https://core.ac.uk/reader/143877740

Ahmed, J., Tefera, T., & Kassie, G. T. (2020). Consumers' preference and willingness to pay for enriched snack product traits in Shashamane and Hawassa cities, Ethiopia. *Agricultural and Food Economics*, *8*(1), 1–20. https://doi.org/10.1186/s40100-020-00157-1

Ahn, J., Lee, J., Lee, J. D., & Kim, T. Y. (2006). An Analysis of Consumer Preferences among Wireless LAN and Mobile Internet Services. *ETRI Journal*, *28*(2), 205–215. https://doi.org/10.4218/etrij.06.0105.0106

Aizaki, H., & Fogarty, J. (2019). An R package and tutorial for case 2 best–worst scaling. *Journal of Choice Modelling*, *32*, 100171. https://doi.org/10.1016/j.jocm.2019.100171

Ali, M. M. (1998). Probability models on horse-race outcomes. *Journal of Applied Statistics*, *25*(2), 221–229. https://doi.org/10.1080/02664769823205

Allison, P. D., & Christakis, N. A. (1994). Logit Models for Sets of Ranked Items. *Sociological Methodology*, *24*, 199. https://doi.org/10.2307/270983

Allenby, G. M., & Rossi, P. E. (1998). Marketing models of consumer heterogeneity. *Journal of Econometrics*, *89*(1–2), 57–78. https://doi.org/10.1016/s0304-4076(98)00055-4

Arjunan, S., C. Moir, K. Kirwan, and D. Pink (2010, June 16-18). The greening of 'green' technology: adoption of bio-plastic PLA [Conference presentation]. The fourteenth International Consortium on Applied Bioeconomy Research (ICABR), Ravello, Italy.

Auger, P., Devinney, T. M., & Louviere, J. J. (2006). Using Best–Worst Scaling Methodology to Investigate Consumer Ethical Beliefs Across Countries. *Journal of Business Ethics*, *70*(3), 299–326. https://doi.org/10.1007/s10551-006-9112-7

Baek, J. D., Xirasagar, S., Stoskopf, C. H., & Seidman, R. L. (2013). Physician-Targeted Financial Incentives and Primary Care Physicians' Self-Reported Ability to Provide High-Quality Primary Care. *Journal of Primary Care & Community Health*, *4*(3), 182–188. https://doi.org/10.1177/2150131912462036

Balogh, P., Békési, D., Gorton, M., Popp, J., & Lengyel, P. (2016). Consumer willingness to pay for traditional food products. *Food Policy*, *61*, 176–184. https://doi.org/10.1016/j.foodpol.2016.03.005

Barnes, M., Chan-Halbrendt, C., Zhang, Q., & Abejon, N. (2011). Consumer preference and willingness to pay for non-plastic food containers in Honolulu, USA. *Journal of Environmental Protection*, *02*(09), 1264–1273. https://doi.org/10.4236/jep.2011.29146

Bartczak, A., Budziński, W., & Gołębiowska, B. (2021). Impact of beliefs about negative effects of wind turbines on preference heterogeneity regarding renewable energy development in Poland. *Resources, Conservation and Recycling*, *169*, 105530. https://doi.org/10.1016/j.resconrec.2021.105530

Beggs, S., Cardell, S., & Hausman, J. (1981). Assessing the potential demand for electric cars. *Journal of Econometrics*, *17*(1), 1–19. https://doi.org/10.1016/0304-4076(81)90056-7

Ben-Akiva, M., Mcfadden, D., Train, K., Walker, J., Bhat, C., Bierlaire, M., … Munizaga, M. A. (2002). Hybrid Choice Models: Progress and Challenges. *Marketing Letters*, *13*(3), 163–175. https://doi.org/10.1023/a:1020254301302

Berinsky, A. J., Margolis, M. F., & Sances, M. W. (2014). Separating the shirkers from the workers? making sure respondents pay attention on self-administered surveys. *American Journal of Political Science*, *58*(3), 739–753. https://doi.org/10.1111/ajps.12081

Borsboom, D., Mellenbergh, G. J., & van Heerden, J. (2003). The theoretical status of latent variables. *Psychological Review*, *110*(2), 203–219. https://doi.org/10.1037/0033-295x.110.2.203

Bouscasse, H. (2017). *Essays on Travel Mode Choice Modeling - a Discrete Choice Approach to the Interactions Between Economic and Behavioral Theories*. Retrieved from https://tel.archives-ouvertes.fr/tel-01661687/document

Börger, T. (2016). Are Fast Responses More Random? Testing the effect of response time on scale in an online choice experiment. *Environmental and Resource Economics*, *65*(2), 389–413. https://doi.org/10.1007/s10640-015-9905-1

Brenna, E., Barrett, K., & Atul, N. (2015). *Consumers' willingness to pay for bioplastic plant containers: an experimental auction approach*. Presented at the 2015 AAEA & WAEA

Joint Annual Meeting, San Francisco, California: Agricultural and Applied Economics Association. https://doi.org/10.22004/ag.econ.205670

Calfee, J., Winston, C., & Stempski, R. (2001). Econometric Issues in Estimating Consumer Preferences from Stated Preference Data: A Case Study of the Value of Automobile Travel Time. *Review of Economics and Statistics*, *83*(4), 699–707. https://doi.org/10.1162/003465301753237777

Cameron, C. A., & Trivedi, P. K. (2005). *Microeconometrics: Methods and Applications* (unknown ed.). Boston, MA: Cambridge University Press.

Carus, M., Eder, A., & Beckmann, J. (2014). Green premium prices along the value chain of biobased products. *Industrial Biotechnology*, *10*(2), 83–88. https://doi.org/10.1089/ind.2014.1512

Cheung, K. L., Wijnen, B. F. M., Hollin, I. L., Janssen, E. M., Bridges, J. F., Evers, S. M. A. A., & Hiligsmann, M. (2016). Using Best–Worst Scaling to Investigate Preferences in Health Care. *PharmacoEconomics*, *34*(12), 1195–1209. https://doi.org/10.1007/s40273-016-0429-5

Chapman, R. G., & Staelin, R. (1982). Exploiting Rank Ordered Choice Set Data within the Stochastic Utility Model. *Journal of Marketing Research*, *19*(3), 288. https://doi.org/10.2307/3151563

Choi, Y., Lambert, D. M., Jensen, K. L., Clark, C. D., English, B. C., & Thomas, M. K. (2020). Rank-ordered analysis of consumer preferences for the attributes of a value-added biofuel co-product. *Sustainability*, *12*(6), 2363. https://doi.org/10.3390/su12062363

Coffman, D. L., & MacCallum, R. C. (2005). Using Parcels to Convert Path Analysis Models Into Latent Variable Models. *Multivariate Behavioral Research*, *40*(2), 235–259. https://doi.org/10.1207/s15327906mbr4002_4

Cummings, R. G., & Taylor, L. O. (1999). Unbiased value estimates for environmental goods: a cheap talk design for the contingent valuation method. *American Economic Review*, *89*(3), 649–665. https://doi.org/10.1257/aer.89.3.649

Czajkowski M., Hanley N., LaRiviere J., & Simpson K. 2014. What is the causal effect of information and learning about a public good on willingness to pay? No 2014-05, Stirling Economics Discussion Papers, University of Stirling, Division of Economics, https://EconPapers.repec.org/RePEc:stl:stledp:2014-05

Czajkowski, M. ł., Hanley, N., & Nyborg, K. (2017). Social Norms, Morals and Self-interest as Determinants of Pro-environment Behaviours: The Case of Household Recycling. *Environmental and Resource Economics*, *66*(4), 647–670. https://doi.org/10.1007/s10640-015-9964-3

Czajkowski, M. ł., Vossler, C. A., Budziński, W., Wiśniewska, A., & Zawojska, E. (2017). Addressing empirical challenges related to the incentive compatibility of stated preferences methods. *Journal of Economic Behavior & Organization*, *142*, 47–63. https://doi.org/10.1016/j.jebo.2017.07.023

Dagsvik, J. K., & Liu, G. (2006). A framework for analyzing rank-ordered data with application to automobile demand. *Transportation Research Part A: Policy and Practice*, *43*(1), 1–12. https://doi.org/10.1016/j.tra.2008.06.005

Daziano, R. A., & Bolduc, D. (2011). *Monte Carlo analysis of two simultaneous estimation methods for travel mode choice with qualitative attributes*. Presented at the International Choice Modelling Conference, Oulton Hall, England: International Choice Modelling Conference.

Ding, Z., Abdulai, A., & Jiang, Y. (2020). What can we learn from experience? An impact analysis of experience on households' preferences for microfinance. *China Agricultural Economic Review*, *12*(2), 215–239. https://doi.org/10.1108/caer-08-2019-0149

Drewes, T., & Michael, C. (2006). How do students choose a university?: an analysis of applications to universities in Ontario, Canada. *Research in Higher Education*, *47*(7), 781–800. https://doi.org/10.1007/s11162-006-9015-6

Duncan, M., B. Lippiatt, Z. Haq, M. Wang, and R. Conway (2009). Metrics to support informed decisionmaking for consumers of biobased products. OECD Report. Available at http://www.oecd.org/science/biotech/42400999.pdf

European Bioplastics. (2017). Bioplastics Market Data. Retrieved from http://www.european-bioplastics.org/market/

Federal Register. (2015, June). *Rules and Regulations*. Retrieved from https://www.govinfo.gov/content/pkg/FR-2015-06-15/pdf/FR-2015-06-15.pdf

Feng, X.-N., Wu, H.-T., & Song, X.-Y. (2017). Bayesian Regularized Multivariate Generalized Latent Variable Models. *Structural Equation Modeling: A Multidisciplinary Journal*, *24*(3), 341–358. https://doi.org/10.1080/10705511.2016.1257353

Ferguson, M., Mohamed, M., Higgins, C. D., Abotalebi, E., & Kanaroglou, P. (2018). How open are Canadian households to electric vehicles? A national latent class choice analysis with willingness-to-pay and metropolitan characterization. *Transportation Research Part D: Transport and Environment*, *58*, 208–224. https://doi.org/10.1016/j.trd.2017.12.006

Fiebig, D. G., Keane, M. P., Louviere, J., & Wasi, N. (2010). The generalized multinomial logit model: accounting for scale and coefficient heterogeneity. *Marketing Science*, *29*(3), 393–421. https://doi.org/10.1287/mksc.1090.0508

Finn, A., & Louviere, J. J. (1992). Determining the Appropriate Response to Evidence of Public Concern: The Case of Food Safety. *Journal of Public Policy & Marketing*, *11*(2), 12–25. https://doi.org/10.1177/074391569201100202

Flynn, T. N. (2010). Valuing citizen and patient preferences in health: recent developments in three types of best–worst scaling. *Expert Review of Pharmacoeconomics & Outcomes Research*, *10*(3), 259–267. https://doi.org/10.1586/erp.10.29

Fok, D., Paap, R., & Van Dijk, B. (2012). A rank-ordered logit model with unobserved heterogeneity in ranking capabilities. *Journal of Applied Econometrics*, *27*(5), 831–846. https://doi.org/10.1002/jae.1223

Giansoldati, M., Rotaris, L., Scorrano, M., & Danielis, R. (2020). Does electric car knowledge influence car choice? Evidence from a hybrid choice model. *Research in Transportation Economics, 80*, 100826. https://doi.org/10.1016/j.retrec.2020.100826

Gifford, K., & Bernard, J. C. (2010). The effect of information on consumers' willingness to pay for natural and organic chicken. *International Journal of Consumer Studies*, *35*(3), 282–289. https://doi.org/10.1111/j.1470-6431.2010.00929.x

Gill, M. K. B., Jensen, K. L., Lambert, D. M., Upendram, S., English, B. C., Labbé, N., Jackson, S. W., & Menard, R. J. (2020). Consumer preferences for eco-friendly attributes in disposable dinnerware. *Resources, Conservation and Recycling*, *161*, 104965. https://doi.org/10.1016/j.resconrec.2020.104965

Golden, J. S., Handfield, R. B., Daystar, J., & McConnell, T. E. (2015). An economic impact analysis of the us biobased products industry: a report to the congress of the United States of America. *Industrial Biotechnology*, *11*(4), 201–209. https://doi.org/10.1089/ind.2015.29002.jsg

Graves, T., Reese, C. S., & Fitzgerald, M. (2003). Hierarchical Models for Permutations. *Journal of the American Statistical Association*, *98*(462), 282–291. https://doi.org/10.1198/016214503000053

Gu, Y., Hole, A. R., & Knox, S. (2013). Fitting the generalized multinomial logit model in Stata. *The Stata Journal: Promoting Communications on Statistics and Stata*, *13*(2), 382–397. https://doi.org/10.1177/1536867x1301300213

Guiver, J., & Snelson, E. (2009). *Bayesian inference for Plackett–Luce ranking models*. The 26th Annual International Conference on Machine Learning, New York.

Harman, H. H. (1976). *Modern Factor Analysis* (Third Edition, Revised ed.). Chicago, United States: University of Chicago Press.

Harmsen, P. F. H., Hackmann, M. M., & Bos, H. L. (2014). Green building blocks for bio-based plastics. *Biofuels, Bioproducts and Biorefining*, *8*(3), 306–324. https://doi.org/10.1002/bbb.1468

Hendry, D. F. (2006). A comment on "Specification searches in spatial econometrics: The relevance of Hendry's methodology." *Regional Science and Urban Economics*, *36*(2), 309–312. https://doi.org/10.1016/j.regsciurbeco.2005.10.001

Hensher, D. A., & Green, W. H. (2011). Valuation of travel time savings in WTP and preference space in the presence of taste and scale heterogeneity. *Journal of Transport Economics and Policy*, *45*(3), 505–525. https://ideas.repec.org/a/tpe/jtecpo/v45y2011i3p505-525.html

Hess, S., & Train, K. (2017). Correlation and scale in mixed logit models. *Journal of Choice Modelling*, *23*, 1–8. https://doi.org/10.1016/j.jocm.2017.03.001

Huber, C. (2016, November 1). *Introduction to Bayesian statistics, part 1: The basic concepts*. The STATA Blog. https://blog.stata.com/2016/11/01/introduction-to-bayesian-statistics-part-1-the-basic-concepts/

Huber, P. J. (1967). He behavior of maximum likelihood estimates under nonstandard conditions. *Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability, 1*, 221–233. https://projecteuclid.org/euclid.bsmsp/1200512988

Jones, A., Jones, D., Edwards-Jones, G., & Cross, P. (2013). Informing decision making in agricultural greenhouse gas mitigation policy: A Best–Worst Scaling survey of expert and farmer opinion in the sheep industry. *Environmental Science & Policy*, *29*, 46–56. https://doi.org/10.1016/j.envsci.2013.02.003

Jones, M. S., House, L. A., & Gao, Z. (2015). Respondent screening and revealed preference axioms: testing quarantining methods for enhanced data quality in web panel surveys. *Public Opinion Quarterly*, *79*(3), 687–709. https://doi.org/10.1093/poq/nfv015

Johnson, R., & Wichern, D. (2018). *Applied Multivariate Statistical Analysis (Classic Version) (Pearson Modern Classics for Advanced Statistics Series)* (6th ed.). Prentice-Hall, Upper Saddle River, NJ.

Kahneman, D. (2011). *Thinking, Fast and Slow* (1st ed.). New York, U.S.A: Farrar, Straus and Giroux.

Kainz, U., Zapilko, M., Decker, T., & Menrad, K. (2013, November). Consumer-relevant information about bioplastics. *first international conference on resource efficiency in interorganizational networks*. Retrieved from https://d-nb.info

Kainz, U.W., (2016). Consumers' willingness to pay for durable biobased plastic products: findings from an experimental auction, (Dissertation) Technische Universität München.

Kamakura, W. A., & Russell, G. J. (1989). A Probabilistic Choice Model for Market Segmentation and Elasticity Structure. *Journal of Marketing Research*, *26*(4), 379. https://doi.org/10.2307/3172759

Keane, M. P. (1997). Modeling Heterogeneity and State Dependence in Consumer Choice Behavior. *Journal of Business & Economic Statistics*, *15*(3), 310. https://doi.org/10.2307/1392335

Kim, J., Rasouli, S., & Timmermans, H. (2014). Expanding scope of hybrid choice models allowing for mixture of social influences and latent attitudes: Application to intended purchase of electric cars. *Transportation Research Part A: Policy and Practice*, *69*, 71–85. https://doi.org/10.1016/j.tra.2014.08.016

Kim, J., Rasouli, S., & Timmermans, H. (2016). A hybrid choice model with a nonlinear utility function and bounded distribution for latent variables: application to purchase intention decisions of electric cars. *Transportmetrica A: Transport Science*, *12*(10), 909–932. https://doi.org/10.1080/23249935.2016.1193567

Knox, S. A., Viney, R. C., Gu, Y., Hole, A. R., Fiebig, D. G., Street, D. J., … Bateson, D. (2013). The effect of adverse information and positive promotion on women's preferences for prescribed contraceptive products. *Social Science & Medicine*, *83*, 70–80. https://doi.org/10.1016/j.socscimed.2012.12.025

Kunwar, S. B., Bohara, A. K., & Thacher, J. (2020). Public preference for river restoration in the Danda Basin, Nepal: A choice experiment study. *Ecological Economics*, *175*, 106690. https://doi.org/10.1016/j.ecolecon.2020.106690

Lagerkvist, C. J. (2013). Consumer preferences for food labelling attributes: Comparing direct ranking and best–worst scaling for measurement of attribute importance, preference intensity and attribute dominance. *Food Quality and Preference*, *29*(2), 77–88. https://doi.org/10.1016/j.foodqual.2013.02.005

Lambert, D. M., Clark, C. D., Wilcox, M. D., & Cho, S.-H. (2010). Distance, density, local amenities, and suburban development preferences in a rapidly growing east Tennessee county. *Agriculture and Human Values*, *28*(4), 519–532. https://doi.org/10.1007/s10460-010-9306-6

LaRiviere, J., Czajkowski, M. ł., Hanley, N., Aanesen, M., Falk-Petersen, J., & Tinch, D. (2014). The value of familiarity: effects of knowledge and objective signals on willingness to pay for a public good. *Journal of Environmental Economics and Management*, *68*(2), 376–389. https://doi.org/10.1016/j.jeem.2014.07.004

Leblanc, M., & Tibshirani, R. (1996). Combining Estimates in Regression and Classification. *Journal of the American Statistical Association*, *91*(436), 1641–1650. https://doi.org/10.1080/01621459.1996.10476733

Lenk, P. (2011). A comparison of generalized multinomial logit (GMNL) and latent class approaches to studying consumer heterogeneity with some extensions of the GMNL model by Peter J. Lenk. *Applied Stochastic Models in Business and Industry*, *27*(6), 580–583. https://doi.org/10.1002/asmb.941

Letner, M., & Bishop, T. (1986). *Experimental design and analysis*. Blacksburg, VA: Valley Book Co.

Li, X., Jensen, K. L., Lambert, D. M., & Clark, C. D. (2017). Consequentiality beliefs and consumer valuation of extrinsic attributes in beef. *Journal of Agricultural and Applied Economics*, *50*(1), 1–26. https://doi.org/10.1017/aae.2017.17

Li, X., Jensen, K. L., Clark, C. D., & Lambert, D. M. (2016). Consumer willingness to pay for beef grown using climate friendly production practices. *Food Policy*, *64*, 93–106. https://doi.org/10.1016/j.foodpol.2016.09.003

List, J. A., Sinha, P., & Taylor, M. H. (2006). Using choice experiments to value non-market goods and services: evidence from field experiments. *Advances in Economic Analysis & Policy*, *5*(2), 1–37. https://doi.org/10.2202/1538-0637.1132

Lo, V. S. Y., Bacon-Shone, J., & Busche, K. (1995). The Application of Ranking Probability Models to Racetrack Betting. *Management Science*, *41*(6), 1048–1059. https://doi.org/10.1287/mnsc.41.6.1048

Locksin. L. and E. Cohen (2015). How consumers choose wine: using best-worst scaling across countries. J.Louviere, T. Flynn, and A. Marley (Eds.), Best-Worst Scaling: Theory, Methods and Applications, Cambridge University Press, Cambridge (2015), 159-176.

Loomis, J. (2013). Strategies for overcoming hypothetical bias in stated preference surveys. *Journal of Agricultural and Resource Economics*, *39*(1), 34–46. https://doi.org/10.22004/ag.econ.168258

Louviere J, Engle T. Confound it! That pesky little scale constant messes up our convenient assumptions. 2006 Sawtooth Software Conference Proceedings; 2006 Mar 29–31; Delray Beach (FL). Sequim (WA): Sawtooth Software: 211-28

Louviere, J. J., Hensher, D. A., Swait, J. D., & Adamowicz, W. (2000). *Stated Choice Methods: Analysis and Applications* (Illustrated ed.). Cambridge, United Kingdom: Cambridge University Press.

Louviere, J. J., & Meyer, R. J. (2007). Formal choice models of informal choices. *Formal Choice Models of Informal Choices: What Choice Modeling Research Can (and Can't) Learn from Behavioural Theory*, *4*, 3–32. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.460.487&rep=rep1&type=pdf#page=24

Louvière, J., & Timmermans, H. (1990). Stated preference and choice models applied to recreation research: A review. *Leisure Sciences*, *12*(1), 9–32. https://doi.org/10.1080/01490409009513087

Lusk, J. L., Fields, D., & Prevatt, W. (2008). An incentive compatible conjoint ranking mechanism. *American Journal of Agricultural Economics*, *90*(2), 487–498. https://doi.org/10.1111/j.1467-8276.2007.01119.x

Malone, T., & Lusk, J. L. (2018a). A simple diagnostic measure of inattention bias in discrete choice models. *European Review of Agricultural Economics*, *45*(3), 455–462. https://doi.org/10.1093/erae/jby005

Malone, T., & Lusk, J. L. (2018b). Consequences of participant inattention with an application to carbon taxes for meat products. *Ecological Economics*, *145*, 218–230. https://doi.org/10.1016/j.ecolecon.2017.09.010

Malone, T., & Lusk, J. L. (2019). Releasing the trap: a method to reduce inattention bias in survey data with application to U.S. beer taxes. *Economic Inquiry*, *57*(1), 584–599. https://doi.org/10.1111/ecin.12706

McElreath, R. (2020). *Statistical Rethinking: A Bayesian Course with Examples in R and STAN (Chapman & Hall/CRC Texts in Statistical Science)* (2nd ed.). Chapman and Hall/CRC.

McFadden, D. (1973). Conditional logit analysis of qualitative choice behavior. *Frontiers in Econometrics*, 105–142. Retrieved from https://eml.berkeley.edu/reprints/mcfadden/zarembka.pdf

McFadden, D. (1974). The measurement of urban travel demand. *Journal of Public Economics*, *3*(4), 303–328. https://doi.org/10.1016/0047-2727(74)90003-6

McFadden, D., & Train, K. (2000). Mixed MNL models for discrete response. *Journal of Applied Econometrics*, *15*(5), 447–470. https://doi.org/10.1002/1099-1255(200009/10)

Merkle, E. C., & Wang, T. (2018). Bayesian latent variable models for the analysis of experimental psychology data. *Psychonomic Bulletin & Review*, *25*(1), 256–270. https://doi.org/10.3758/s13423-016-1016-7

McGeeney, K., Kriz, B., Mullenax, S., Kail, L., Waleiko, G., Vines, M., … Trejo, Y. (2019). *2020 census barries, attitudes, and motivators study survey report*. U.S. Department of Commerce Economics and Statistics Administration U.S. Census Bureau. Retrieved from https://www.census.gov/programs-surveys/decennial-census/2020-census/research-testing/communications-research/2020_cbams.html

Mühlbacher, A. C., Sadler, A., Lamprecht, B., & Juhnke, C. (2020). Patient Preferences in the Treatment of Hemophilia A: A Best–Worst Scaling Case 3 Analysis. *Value in Health*, *23*(7), 862–869. https://doi.org/10.1016/j.jval.2020.02.013

Mühlbacher, A. C., Zweifel, P., Kaczynski, A., & Johnson, F. R. (2016). Experimental measurement of preferences in health care using best-worst scaling (BWS): theoretical and statistical issues. *Health Economics Review*, *6*(1), 1. https://doi.org/10.1186/s13561-015-0077-z

Nair, H. S., Misra, S., Hornbuckle, W. J., Mishra, R., & Acharya, A. (2017). Big Data and Marketing Analytics in Gaming: Combining Empirical Models and Field Experimentation. *Marketing Science*, *36*(5), 699–725. https://doi.org/10.1287/mksc.2017.1039

Oppenheimer, D. M., Meyvis, T., & Davidenko, N. (2009). Instructional manipulation checks: Detecting satisficing to increase statistical power. *Journal of Experimental Social Psychology*, *45*(4), 867–872. https://doi.org/10.1016/j.jesp.2009.03.009

Panthapulakkal, S., & Sain, M. (2006). Injection molded wheat straw and corn stem filled polypropylene composites. *Journal of Polymers and the Environment*, *14*(3), 265–272. https://doi.org/10.1007/s10924-006-0021-8

Petrolia, D. R., Interis, M. G., & Hwang, J. (2018). Single-choice, repeated-choice, and best-worst elicitation formats: do results differ and by how much? *SSRN Electronic Journal*, 365–393. https://doi.org/10.2139/ssrn.2692171

Phanikumar, C. V., & Maitra, B. (2007). Willingness-to-pay and preference heterogeneity for rural bus attributes. *Journal of Transportation Engineering*, *133*(1), 62–69. https://doi.org/10.1061/(asce)0733-947x(2007)133:1(62)

Polydoropoulou, A., Pagoni, I., Tsirimpa, A., Roumboutsos, A., Kamargianni, M., & Tsouros, I. (2020). Prototype business models for Mobility-as-a-Service. *Transportation Research Part A: Policy and Practice*, *131*, 149–162. https://doi.org/10.1016/j.tra.2019.09.035

Potoglou, D., Burge, P., Flynn, T., Netten, A., Malley, J., Forder, J., & Brazier, J. E. (2011). Best–worst scaling vs. discrete choice experiments: An empirical comparison using social care data. *Social Science & Medicine*, *72*(10), 1717–1727. https://doi.org/10.1016/j.socscimed.2011.03.027

Reinders, M. J., Onwezen, M. C., & Meeusen, M. J. G. (2017). Can bio-based attributes upgrade a brand? How partial and full use of bio-based materials affects the purchase intention of brands. *Journal of Cleaner Production*, *162*, 1169–1179. https://doi.org/10.1016/j.jclepro.2017.06.126

Roosen, J., Bieberstein, A., Marette, S., Blanchemanche, S., & Vandermoere, F. (2011). The effect of information choice and discussion on consumers' willingness-to-pay for nanotechnologies in food. *Journal of Agricultural and Resource Economics*, *36*(2), 365–374. https://doi.org/10.22004/ag.econ.117398

Risius, A., & Hamm, U. (2017). The effect of information on beef husbandry systems on consumers' preferences and willingness to pay. *Meat Science*, *124*, 9–14. https://doi.org/10.1016/j.meatsci.2016.10.008

Roodman, D. (2011). Fitting fully observed recursive mixed-process models with CMP. *The Stata Journal: Promoting Communications on Statistics and Stata*, *11*(2), 159–206. https://doi.org/10.1177/1536867x1101100202

Ryan, M., Watson, V., & Amaya-Amaya, M. (2003). Methodological issues in the monetary valuation of benefits in healthcare. *Expert Review of Pharmacoeconomics & Outcomes Research*, *3*(6), 717–727. https://doi.org/10.1586/14737167.3.6.717

SAS (Version 9.4) [Software]. (2013). Cary, NV: SAS Institute Inc.

Scarpa, R., Notaro, S., Louviere, J., & Raffaelli, R. (2011). Exploring scale effects of best/worst rank ordered choice data to estimate benefits of tourism in alpine grazing commons. *American Journal of Agricultural Economics*, *93*(3), 813–828. https://doi.org/10.1093/ajae/aaq174

Scherer, C., Emberger-Klein, A., & Menrad, K. (2017). Biogenic product alternatives for children: Consumer preferences for a set of sand toys made of bio-based plastic. *Sustainable Production and Consumption*, *10*, 1–14. https://doi.org/10.1016/j.spc.2016.11.001

Scherer, C., Emberger-Klein, A., & Menrad, K. (2018). Consumer preferences for outdoor sporting equipment made of bio-based plastics: Results of a choice-based-conjoint experiment in Germany. *Journal of Cleaner Production*, *203*, 1085–1094. https://doi.org/10.1016/j.jclepro.2018.08.298

Schechter, L. (2010). The apple and your eye: Visual and taste rank-ordered probit analysis with correlated errors. *Food Quality and Preference*, *21*(1), 112–120. https://doi.org/10.1016

Scopus. (2021). [Software].

Shoji, Y., Kim, H., Kubo, T., Tsuge, T., Aikoh, T., & Kuriyama, K. (2021). Understanding preferences for pricing policies in Japan’s national parks using the best–worst scaling method. *Journal for Nature Conservation*, *60*, 125954. https://doi.org/10.1016/j.jnc.2021.125954

Sijtsema, S. J., Onwezen, M. C., Reinders, M. J., Dagevos, H., Partanen, A., & Meeusen, M. (2016). Consumer perception of bio-based products—An exploratory study in 5 European countries. *NJAS - Wageningen Journal of Life Sciences*, *77*, 61–69. https://doi.org/10.1016/j.njas.2016.03.007

Spearman, C. (1904). “General Intelligence,” Objectively determined and measured. *The American Journal of Psychology*, *15*(2), 201. https://doi.org/10.2307/1412107

Stata (Version 15) [Software]. (2017). College Station, TX: StataCorp LLC.

Syrengelas, K. G., DeLong, K. L., Grebitus, C., & Nayga, R. M. (2018). Is the natural label misleading? Examining consumer preferences for natural beef. *Applied Economic Perspectives and Policy*, *40*(3), 445–460. https://doi.org/10.1093/aepp/ppx042

Train, K.E., and M. Weeks. (2005). Discrete choice models in preference space and willingness-to-pay space [Unpublished manuscript]. Faculty of Economics, University of Cambridge

US EPA. (2018). *Facts and figures about materials, waste, and recycling. Nondurable goods: product-specific data.* Retrieved from https://www.epa.gov/facts-and-figures-about-materials-waste-and-recycling/nondurable-goods-product-specific-data#PaperandPaperboardProducts

USDA. (2020). *Wheat Outlook*. Retrieved from https://www.ers.usda.gov/webdocs/publications/95679/whs-20a.pdf?v=7026.8

van Beek, K. W., Koopmans, C. C., & van Praag, B. M. (1997). Shopping at the labour market: A real tale of fiction. *European Economic Review*, *41*(2), 295–317. https://doi.org/10.1016/s0014-2921(96)00037-2

van Ophem, H., Stam, P., & van Praag, B. (1999). Multichoice logit: modeling incomplete preference rankings of classical concerts. *Journal of Business & Economic Statistics*, *17*(1), 117. https://doi.org/10.2307/1392243

Wedel, M., & Kamakura, W. A. (2001). Factor analysis with (mixed) observed and latent variables in the exponential family. *Psychometrika*, *66*(4), 515–530. https://doi.org/10.1007/bf02296193

Weernink, M. G., Groothuis-Oudshoorn, C. G., IJzerman, M. J., & van Til, J. A. (2016). Valuing treatments for Parkinson disease incorporating process utility: performance of best-worst scaling, time trade-Off, and visual analogue scales. *Value in Health*, *19*(2), 226–232. https://doi.org/10.1016/j.jval.2015.11.011

Wirthgen, A. (2005). Consumer, retailer, and producer assessments of product differentiation according to regional origin and process quality. *Agribusiness*, *21*(2), 191–211. https://doi.org/10.1002/agr.20043

Wold, H. (1974). Causal flows with latent variables: partings of the ways in the light of NIPALS modelling. *European Economic Review*, *5*(1), 67–86. https://doi.org/10.1016/0014-2921(74)90008-7

Wold, H. (1975). Soft Modelling by Latent Variables: the non-linear iterative partial least squares (NIPALS) approach. *Journal of Applied Probability*, *12*(S1), 117–142. https://doi.org/10.1017/s0021900200047604

Wolpert, D. H. (1992). Stacked generalization. *Neural Networks*, *5*(2), 241–259. https://doi.org/10.1016/s0893-6080(05)80023-1

Wood, L. (2017). US Paper Cups and Paper Plates Market: Industry Trends, Share, Size, Growth, Opportunity and Forecast 2017-2022 – Research and Markets.com. Retrieved from https://www.businesswire.com/news/home/20180413005502/en/US-Paper-Cups-and-Paper-Plates-Market-Industry-Trends-Share-Size-Growth-Opportunity-and-Forecast-2017-2022---ResearchAndMarkets.com

Yao, Y., Vehtari, A., Simpson, D., & Gelman, A. (2018). Using Stacking to Average Bayesian Predictive Distributions (with Discussion). *Bayesian Analysis*, *13*(3), 917–1007. https://doi.org/10.1214/17-ba1091

Yoo, J., & Ready, R. C. (2014). Preference heterogeneity for renewable energy technology. *Energy Economics*, *42*, 101–114. https://doi.org/10.1016/j.eneco.2013.12.007

Zeleke, F., Kassie, G. T., Haji, J., & Legesse, B. (2020). Preference and Willingness to Pay for Small Ruminant Market Facilities in the Central Highlands of Ethiopia. *Journal of International Food & Agribusiness Marketing*, 1–23. https://doi.org/10.1080/08974438.2020.1838385

Zellner, A. (1962). An efficient method of estimating seemingly unrelated regressions and tests for aggregation bias. *Journal of the American Statistical Association*, *57*(298), 348–368. https://doi.org/10.1080/01621459.1962.10480664

Zhang, W., & Sohngen, B. (2018). Do U.S. Anglers Care about Harmful Algal Blooms? A Discrete Choice Experiment of Lake Erie Recreational Anglers. *American Journal of Agricultural Economics*, *100*(3), 868–888. https://doi.org/10.1093/ajae/aay006

VITA

Haotian Cheng

Candidate for the Degree of

Doctor of Philosophy

Thesis: Consumer Choice Models Applied On Biobased Product

Major Field: Agricultural Economics

Biographical:

Education:

Completed the requirements for the Doctor of Philosophy in Agricultural Economics at Oklahoma State University, Stillwater, Oklahoma in July, 2021.

Completed the requirements for the Master of Science in Agricultural Economics at Oklahoma State University, Stillwater, Oklahoma, in 2017.

Completed the requirements for the Bachelor of Science in Plant Protection at Hai-Nan University, Hai Kou, China in 2014.