Willingness to Pay for Climate Mitigation in Agricultural Production: Heterogeneity by Consumer Characteristics, Climate Change Knowledge and Risk Perception (Abstract ID: P13562)

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ABSTRACT

Consumers are increasingly concerned with the environmental, climate, and social impacts of their purchases, and some studies have found this also correlates with a willingness to pay more for sustainable attributes in food and beverage products. Prior research has found that willingness to pay for sustainable, climate friendly, and ethical attributes varies substantially across consumer characteristics and motivations. However, few studies have examined U.S. consumer willingness to pay (WTP) for more climate friendly foods or beverages or agricultural production practices that avert climate warming gases or consumer motivations to purchase such products and attributes. The objective of this study was to estimate consumer WTP for reduced greenhouse gas emissions (GHGs) in agricultural production and examine variability in WTP across consumer characteristics, climate change knowledge, and risk perception. A real choice experiment and a survey to assess climate change knowledge and risk perception were employed among a subpopulation of consumers in the Midwest and Northeastern U.S. Green tea was used as a case study product. Results indicate significant WTP for reduced GHGs in tea production and variability in WTP by income, gender, and geographic location, and unobservable consumer characteristics. Climate change knowledge and risk perception were not significantly associated with increased WTP for reduced GHGs in tea production. This result is concerning because it means knowledge and concern about climate change do not necessarily translate in interest or motivation to purchase climate friendly products. Results of this study have implications for tea producers and marketers and suggest that consumer demand could be a tool to drive reduced GHGs in agricultural production. Future research should focus on better understanding consumer motivations for purchasing climate friendly foods, beverage, and other consumer products.

KEYWORDS: Climate change, willingness to pay, climate change knowledge, climate change risks, green tea, carbon labelling, choice experiment, latent class analysis

INTRODUCTION

Consumers are increasingly concerned with the environmental and social impacts of their purchases, and companies are quickly responding to such demands (Banterle et al., 2012). Over the past decade there has been an explosion in consumer-facing product labels, especially those promoting sustainable and ethical credence attributes (Campbell-Arvai et al., 2014; Grunert et al., 2014). In 2010, approximately 7,000 products in the U.S. exhibited an environmental claim, including 89 products claiming to be carbon neutral (Cohen and Vandenbergh, 2012). These labels are increasingly found on foods and beverages. Such items can be labeled as organic, locally grown, genetically modified organism-free, fairly traded, and more. Certain consumers may even be willing to pay a premium for such qualities (Aoki and Akai, 2012; Breusted, 2014; Grunert et al., 2014; Shewmake et al., 2015; Peschel et al., 2016). With climate change a major threat to food production, and already impacting both the quantity and quality of crops, increasing such consumer behavior could help mitigate future climate impacts and shocks to agriculture (Auffhammer et al., 2012; Deschênes and Kolstad, 2011; IPCC, 2014; Jones et al., 2015; Rosenzweig et al., 2014; Wang and Frei, 2011).

Many studies have examined either consumer characteristics or motivations driving demand for such environmental and ethically-motivated attributes. These studies find that willingness to pay a premium for environmental or ethnical attributes is heterogeneous across consumer characteristics, including income, self-reported health, education, age, and food shopping preferences (Batte et al., 2007; Hughner et al., 2007; Loureiro, 2011; Loureiro and Hine, 2002; Loureiro and Lotade, 2005). Other studies have examined consumer motivations for purchasing products with environmentally or ethically oriented credence attributes. Surprisingly these studies do not consistently find that positive attitudes toward improving society or the environment are correlated with consumer willingness to pay more for such product attributes (Bray et al., 2011; Carrington et al., 2010; De Pelsmacker et al., 2005; Grunert et al., 2014). It is thus critical to delve further into understanding consumer motivations for purchasing products with such labels, as such consumer behavior has the potential to lower greenhouse gas emissions.

Consumer interest and motivation for food labels denoting the carbon intensity of products has not been studied extensively to date, especially in the U.S., due in part to the fact that these labels have not been widely available for consumers to purchase. However, in some global markets, food and beverage packages now have labels denoting the level of carbon dioxide emissions generated across the product's life cycle (Grunert et al., 2014; Shewmake et al., 2015). Most recent studies outside the U.S. have found that consumers were willing to pay a premium for low-carbon products (Aoki and Akai, 2012; Breustedt, 2014; Costanigro et al., 2014; Grebitus et al., 2016; Tait et al., 2011). Tait et al. found that United Kingdom and Japanese consumers were WTP only 1% more for fruit with a 21%-39% reduction in carbon emissions. Yet more recently, German consumers were found to be willing to pay over 30% more for carbon neutral milk and apple juice (Breustedt, 2014). Consumers in South Korea were also willing to pay premiums of 30% or higher for apples with carbon-emission reductions (Kim et al., 2014). A study of European consumers found 7%-20% higher willingness to pay than the average market price for milk with reduced carbon emissions (Feucht and Zander, 2018). However one study found that local label for apples, where it was made explicit that the local apples had lower greenhouse gas emissions than non-local due to fewer transportation miles, did not significantly influence WTP (Costanigro et al., 2014).

To date, no study has specifically focused on U.S. consumer WTP for foods or beverages with a reduced-carbon footprint or for agricultural practices that avert the production of climate warming gases. One study found that while some U.S. consumers will pay a premium for reducing their carbon footprint overall, many consumers do not have enough knowledge about carbon footprint measures on the products they purchase (Onozaka and Mcfadden, 2011). Continued research on U.S. consumer interest in carbon labels and low-carbon foods is particularly important since increasingly, foods and other products sold in the U.S. now carry voluntary labels denoting their carbon footprint (www.carbonfund.org/carbon-products). With companies such as Walmart, Nestlé, and Coca-Cola responding with large GHG reduction commitments, such consumer trends are being recognized by the industry, and carbon labels may soon be common in food and beverage markets (Nestle, 2017; The Coca-Cola Company, 2016; Walmart, Inc., 2017).

It is equally important to understand why consumers want to buy low carbon foods or other products. There are a range of hypotheses in the current literature as to why consumers purchase foods with sustainability and carbon labels. The majority of current research emphasizes environmental concern as a key motivator, yet other factors are found to be important, such as shopping habits and health concerns (Grunert et al., 2014; Menozzi et al., 2015; Mohd Suki, 2016; Ricci et al., 2018). An important factor that may affect consumer willingness to pay more for products with environmentally, climate, or ethically friendly credence attributes is risk discounting. Environmental issues such as climate change are often viewed as having uncertain consequences, a delayed onset, and are perceived to be less probable in an individual's locale (Gattig and Hendrickx, 2007). This discounting can present a psychological barrier to environmentally sustainable behavior, as greater discounting of environmental risk could lead to less environmentally sustainable viewpoints and behaviors (Gifford, 2011). It is thus important to understand how people evaluate their own environmental risk, especially climate change risk. Consumers' purchasing behavior could stem from their assessment of the reality of their personal or the global climate change threat, and therefore understanding such behavior could prove insightful on how to encourage more environmentally sustainable purchases among consumers. This may be especially true for food and beverage purchases since agricultural production both contributes to and is harmed by a changing climate.

Consequently, the objective of the present study is to ascertain consumer interest and motivations for purchasing products that have a lower carbon footprint. The study focuses specifically on examining how consumer characteristics, climate change knowledge and risk perception influence interest in products that are more climate friendly.

METHODS

Green tea as a case study product

Chinese green tea was used as the case study product in this study for several reasons. First, this study was part of a larger multi-year research project funded by [institution redacted for review] to understand the impacts of climate change on consumer demand for tea and tea farmer livelihoods. Thus, the results of this study will be incorporated into findings from supply-facing components of the larger project. In addition, tea offered unique characteristics for better understanding consumer interests and motivations for purchasing low carbon foods and beverages. This is because tea is grown in only small amounts in the U.S. and does not provide substantial calories. These facts allowed participants in the study to ignore local food security or local and national economic concerns for the agricultural sector and focus only on the global impact of climate change. Second, tea products available for purchase in the U.S. are marketed with a variety of credence attributes, including organic certification, fair trade certification, and some health claims. Consequently, consumer interest and motivation in reduced GHGs in tea production, a hypothetical attribute, can be compared directly to consumer interest in credence attributes already available for purchase on teas sold in the U.S.

Study sites and participant recruitment

Participants were recruited into the study at three sites in the Boston metropolitan area in Massachusetts between April and August 2015 and at one site in Bozeman, Montana in September 2015. These sites include: (1) a small natural foods and supplement retailer in the Boston area, (2) a cooperative grocery store with two locations in the Boston area (3) a weekly farmers' market in Medford, MA, and (4) a tea house in Bozeman, MT. Sites sold a variety of tea products, including boxed and bulk green tea and other teas, tea kettles, and other tea accessories at varying price and quality levels.

The study was advertised in electronic newsletters sent out by each site in advance of data collection, as well as advertised to shoppers at each site during on-site data collection. Individuals could sign-up to participate in advance for pre-set time slots through an online form or by phone. Pre-set time slots were arranged at various times of day and days of the week (including weekends) to ensure data was collected from a diverse sample of consumers. Advertisements described the length of the study (15 to 20 minutes) and the compensation for participating (gift cards to the store where the participant completed the choice experiment). Participants completed the choice experiment and survey on tablet computers. The choice experiment and survey questions were programmed using Qualtrics survey software and an open source tool to implement choice experiments in Qualtrics available through Harvard University

(Strezhnev et al., 2014).

Choice experiment design

A discrete choice experiment was used to elicit consumer preference and willingness to pay (WTP) for brewed green tea attributes. A choice experiment is a stated preference method to assess consumer valuation of a product's attributes (Hensher et al., 2005). In a choice experiment participants choose between two or more products that have differing combinations of attributes and attribute-levels. The attributes and levels presented in a choice experiment are often available on consumer products in real markets, including the price of the product. Alternatively, choice experiments can be used to elicit WTP for attributes and levels that are hypothetical and not found on products for purchase in markets. Estimating WTP for non-market product attributes can be used to determine if there is substantial demand for a new attribute in the market. Each participant chooses an alternative in several choice sets, and data generated from their choices made in each choice set are used to estimate marginal WTP for product attribute levels.

In this study's choice experiment, brewed green tea attributes and levels were determined using two methods. First, qualitative in-person focus groups (six groups, 40 participants total) composed of costumers shopping at study sites were conducted to determine the population's interest in green tea product attributes. The research team also conducted a survey of green tea attributes commonly for sale at study sites by visiting study sites and noting common attributes and their levels. The attributes commonly found on brewed green tea at the study sites included the USDA Organic label, various fair-trade certification labels, nutrition facts panels and ingredient information, and price. Attributes that focus group participants expressed interest in included the nutritional quality of the tea (as measured by the antioxidant level in the tea), the scale of tea production (e.g. small or large farm grown tea), and the season of harvest. Focus group participants were asked if the amount of greenhouse gases that were produced in tea production or other food products mattered to them, and if they would be interested in a labelling scheme denoting a food producer's efforts to mitigate greenhouse gas emissions. Focus group participants generally expressed interest in such an attribute and noted general concern about climate change and the food systems contribution to climate change.

Store data on product attributes and levels, as well as focus group interest in attributes, was combined to determine which attributes and levels to include in the study choice experiment. Table 1 provides the actual attributes and levels presented to participants in the choice experiment. Figure 1 provides an illustration of a choice set participants completed in the study. Each participant completed 8 choice sets and the presentation of attributes and levels were fully randomized across participants. The choice set design employed a full-factorial design using the Conjoint Survey Design Tool (Strezhnev et al., 2014).

Instructions on how to complete a choice experiment were provided to participants in the study. Participants were instructed to envision a real world setting where they would be buying a box of tea containing 18 sachets (a common way tea is purchased in the retail stores at the study sites and in the U.S.) and to choose the product they preferred most in this real world setting, or they could chose the "I prefer neither option". These instructions, or "cheap talk", are used to reduce hypothetical bias in responses to choice experiment questions (Carlsson et al., 2005).

Assessment of Climate Change Knowledge and Risk Perception

After participants completed the choice experiment they answered questions about their knowledge of climate change and the risks that climate change pose to society and the environment. A climate change knowledge test developed by O'Connor et al (1999) was used to assess participant climate change knowledge and risk perception level. Participants were asked to decide which phenomenon was a major cause, minor cause, or not a cause of climate change. The phenomena included: "pollution/emissions from business/industry"; "people driving cars"; "use of coal/oil by utilities/electric companies"; "use of aerosol spray cans"; "chemicals that destroy the ozone layer"; "nuclear power generation; people heating/cooling their homes"; "destruction of forests". Up to two points were awarded per question if the participant answered correctly. Participants could obtain a score of zero if they got none of the answers correct, or up to 18 if they answered all questions correctly.

To assess risk perception participants were asked the following question: "Suppose the average global temperature does increase by 3-4 degrees Fahrenheit over the next 50 years as a result of climate change, how likely do you think the following events will be?". The six events included: many people's quality of living will decrease; my quality of living will decrease; starvation will occur in much of the world; starvation will occur where I live; rates of serious disease will increase; my chance of suffering from a serious disease will increase. A 7-point Likert scale was used to assess their perception of the risk that climate change poses for the listed events, where 1=Very Unlikely and 7=Very Likely. Higher scores chosen on the Likert scale indicated that a participant was more concerned about the risk of climate change than if they chose a lower score on the Likert scale. From these questions one continuous measure of risk perception was generated using principal component analysis (PCA). PCA is used to convert multiple Likert scale responses to one variable that measures different key components of individual attitudes and beliefs (Jiang et al., 2005).

Participants also responded to questions to assess their socioeconomic status and demographics, which included: annual income, gender, race and ethnicity, age, educational attainment and location where the survey was completed (either Boston, MA metropolitan area or Bozeman, MT). Annual income was used to classify participants as high or low income, using the U.S. Bureau of Labor Statistics average income values for the Boston metropolitan area or the Midwest U.S. Households above the average income values for their respective location were classified as high income.

Data Analysis Strategy

Estimating Consumer Marginal Willingness to Pay for Greenhouse Gas Mitigation in Tea Production

Discrete choice experiments rely on the assumptions of Lancastrian consumer theory and Random Utility Theory (RUT) (Lancaster, 1966; McFadden, 1973). These theories assume that consumers seek a product yielding the highest utility, and the utility they derive from choosing the product with the highest utility can be decomposed as a linear combination of a product's attribute-levels and a random error component. Consequently, the probability of selecting a particular product in a choice set can be modeled as a linear function of the attributes and levels presented to the participant in a choice experiment, where:

$$U_{ij} = \widehat{U}_{ij} + \varepsilon_{ij} \tag{1}$$

$\widehat{U}_{ij}$ is the utility derived from participant *i*'s product selection in a choice set *j* and ε_{ij} is the random error component. $\widehat{U}_{ij}$ is a linear function of the attributes for each product in the choice set,

$$\widehat{U}_{ij} = \mathbf{X}_{\mathrm{ij}}\boldsymbol{\beta} \tag{2}$$

where $\boldsymbol{\beta}$ represents a vector of parameters to be estimated and $\mathbf{X}$ represents a vector of variables representing the characteristics of each product in choice set *j*.

Theoretically, the probability of a product being chosen from choice set *j* is equal to the probability that the utility of that product is greater than all other products in the choice set. This can be described more precisely as:

$$P_{ij} = Prob\big(U_{ij} \geq U_{ik}\big), for\ all\ k \in C_i\ with\ k \neq j) \tag{3}$$

where U_{ij} is the utility derived from the product chosen in choice set *j.*

Using RUT as the analytical foundation, a multinomial logistic regression model was used to estimate the probability of consumer *i* choosing alternative j in choice set *k*. The probability of selection can be formally expressed as:

$$Prob_i\ \{y_i = j\} = \frac{e^{x_i \beta}}{\sum_{k=1}^{j} e^{x_i \beta}}\ with\ k \in C_i \tag{4}$$

This function is then estimated with maximum likelihood simulation, where:

$$\begin{aligned} U_{ij} = \ & \beta_0 + \beta_1 Price_{ij} + \beta_2 Footprint_{ij} + \beta_3 Antioxidants_{ij} \\ & + \beta_4 Scale_{ij} + \beta_5 Season_{ij} + \beta_6 Fair\ trade_{ij} + \beta_7 Organic_{ij} \\ & + \beta_8 Footprint_{ij} * knowledge_i + \beta_9 Footprint_{ij} * risk_i + \beta_{10} Neither \\ & + \beta_{11} Neither_{ij} * knowledge_i + \beta_{12} Neither_{ij} * risk_i \\ & + \boldsymbol{\beta_s} \sum sociodemographics_i + * Neither_{ij} + \varepsilon_{ij} \end{aligned} \tag{5}$$

Where *Price, Footprint, Antioxidants, Scale, Season Fair Trade, Organic, Footprint, and Neither* are attributes described in Table 1. $knowledge_i$ is the variable measuring participant climate change knowledge and $risk_i$ is the variable measuring participant risk perception of climate change computed using PCA. $\boldsymbol{\beta_s}$ represents a vector of coefficients for each consumer characteristic interacted with the neither attribute. This equation is also re-estimated and sociodemographic characteristics are interacted with *Footprint* to determine if WTP varies by observable consumer characteristics. Willingness to pay for each attribute-level combination can be calculated as the ratio of each attribute's coefficient from the multinomial logistic (MNL) regression model estimated using equation (5) divided by the price attribute coefficient in equation (5).

Identifying preference and WTP heterogeneity across observable and unobservable participant characteristics

Two types of RPL models are employed in this study to assess preference heterogeneity – Mixed Logit and Latent Class Logit Models. In both types of models, MNL model coefficients are permitted to vary randomly over consumers, instead of being fixed. Consequently, a distribution of logit coefficients for the sample of participants are estimated for each attribute. In the Mixed Logit model, the distribution of coefficients can be assumed to be continuous and follow a normal distribution (McFadden and Train, 2000) and (2) is modified to be:

$$\widehat{U}_{ij} = \mathbf{X}_{\mathrm{ij}}\boldsymbol{\beta}_{\boldsymbol{n}} \tag{6}$$

Where $\boldsymbol{\beta}_{\boldsymbol{n}}$ is allowed to be random and the probability that participant *i* chooses alternative *j* is the standard logit formula in (4). But, because $\boldsymbol{\beta}_{\boldsymbol{n}}$ is random, the unconditional probability that participant *i* chooses alternative *j* is:

$$P_{ni} = \int L_{ni}(\beta) f(\beta|\theta) d\beta \tag{7}$$

Where L_{ni} θ are the mean and variance of the distribution of $\boldsymbol{\beta}_{\boldsymbol{n}}$ over the population, and $f(\beta|\theta)$ has a normal distribution.

By contrast, latent class analysis identifies unobservable – or latent – subgroups with a population based on observable characteristics and choice experiment responses (Collins and Lanza, 2013; McCutcheon, 1987). In latent class analysis participants are sorted into *s* classes and participants are assumed to have homogenous preferences within classes but heterogeneous preferences across classes (Boxall and Adamowicz, 2002). To determine latent class membership the probability that participant *i* chooses alternative *j* is estimated as in equation (4), but modified to account for latent class-specific utility parameters:

$$P\left(x_{ijk}|s\right) = \frac{e^{x_i\beta}}{\sum_{k=1}^{j} e^{x_i\beta}} \tag{8}$$

Then, for a given class assignment *s*, the probability of participant *i* making a series of choices would have the joint probability as:

$$P_i(s) = \prod_{j=1}^{J}\prod_{k=1}^{K}\left(\frac{e^{x_i\beta}}{\sum_{k=1}^{j} e^{x_i\beta}}\right)^{y_{ijk}} \tag{9}$$

Where y_{ijk} is equal to 1 if participant *i* chooses alternative *j* in choice set *k*, and 0 otherwise.

A fractional multinomial logit model is estimated to determine the probability that participant *i* falls into class *s*, using the following equation:

$$\lambda_{is}(\theta) = \frac{e^{\theta_s z_i}}{1 + \sum_{k=1}^{S-1} e^{\theta_s z_i}} \tag{10}$$

Where *z* are observed choices made by participant *i* and θ is the vector of class membership parameters (Collins and Lanza, 2013).

Then, the probability that participant *i* belongs to class *s* is estimated:

$$ln(S) = \sum_{i=1}^{I} ln \sum_{s=1}^{S} \lambda_{is}(\theta)\, P_i(s) \tag{11}$$

The log likelihood function is then estimated for participants in the sample by summing their log likelihoods:

$$M = \sum_{i=1}^{I} ln \sum_{s=1}^{S} \lambda_{is}(\theta)\, P_i(s) \tag{12}$$

Finally, posterior estimates of the probability that participant *i* belongs to class *s* evaluated at the s^{th} iteration is calculated using Bayes theorem (Greene and Hensher, 2003).

$$T_{is}(\theta^s) = \frac{P_i(s)\lambda_{is}(\theta^s)}{\sum_{s=1}^{S} P_i(s)\lambda_{is}(\theta^s)} \tag{13}$$

As is standard in the literature Aikaike Information Criteria (AIC), Consistent Aikaike Information Criterion (CAIC), and Bayesian Information Criterion (BIC) were used to determine the optimal number of classes to model choices among the participants in the study (Collins and Lanza, 2013).

Comparison WTP for greenhouse gas mitigation by consumer characteristics, climate change knowledge, risk perception, and latent class membership

Multivariate linear regression is used to determine how probability of latent class membership and heterogeneous preference for the attribute representing greenhouse gas mitigation in tea production is associated with climate change knowledge and risk perception, adjusted for participant observable characteristics:

$$\begin{aligned} P(membership)_{is} \\ &= \beta_0 + \beta_1 Knowledge_i + \beta_2 Male_i \\ &+ \beta_3 Age_i + \beta_5 Race_i + \beta_6 Ethnicity_i + \beta_7 Education_i + \beta_8 High\ Income_i \\ &+ + \beta_9 Location_i\ \varepsilon_i \end{aligned} \tag{11}$$

where the dependent variable $P(membership)$ is the posterior probability that participant *i* is a member of latent class *s (s=1, 2….S)*. The variable $knoweldge_i$ is the knowledge score for participant i in latent class *s*. The model also contains sociodemographic characteristics including: gender, race, ethnicity, participant highest level of educational attainment, high income status, and location where the survey was completed. Similarly, to show the relationship between participant risk perception of climate change and latent class membership in tea production, equation (6) was modeled by substituting the variable $risk\ perception$ with participant the risk perception score calculated using principal components analysis.

Data analysis was completed in Stata 15.1/SE.

RESULTS

A total of 380 participants were included in the final analysis sample. Table 2 presents demographic characteristics for these participants. The sample was predominately female (74.2%), Caucasian/Whites (81.8%), and people aged 34 years or younger (75.3%). 68.0% of the sample had earned a college or degree or higher. 24.0% of the sample was classified as high income. Figure 2 shows the variation in knowledge and risk perception scores across the sample. The mean knowledge score was 11.6 (Standard error (SE) 0.022) and the mean score on risk perception measures was 4.5 (SE 0.011).

Results from the MNL model are listed in Table 3. Column 1 reports MNL results unadjusted for participant sociodemographic characteristics and Column 2 reports results adjusting for sociodemographic characteristics. All the coefficients in the MNL model in Column 1 are significant at the 1% level, including the coefficient for the "I prefer neither" tea option. The sign of this coefficient was negative, indicating that on average participants in the sample had a preference for the tea options available in the choice sets presented compared to alternatives not presented. The coefficient for price is negative, indicating that an increase in the price decreases a participants utility and their probability of selecting a tea option. The coefficient for reduced GHGs in tea production is positive suggesting that participants on average preferred teas with reduced GHGs in tea production compared to no GHG mitigation. The magnitude of the coefficient for reduced GHG in tea production is larger than coefficients for all other attributes presented in the choice experiment. This indicates that the Reduced GHG in tea production attribute had the greatest impact on participant tea selections.

Given that the reduced GHG in tea production attribute is hypothetical (i.e. not available currently in U.S. markets where participants shop), it is important to note that the magnitude of the coefficient relative to the attributes presented in the choice experiment that were available for purchase in U.S. markets. For example, the estimated coefficient for reduced GHGs in tea production was significantly larger than the estimated coefficient for fair trade or organic certified tea. This suggests that reduced GHGs in tea production more strongly influenced participant tea selection compared to whether or not the tea was organic or fair trade certified.

Estimated coefficients in the adjusted and unadjusted models did not differ in any significant way. However, the probability of selecting a tea alternative presented in the choice experiment varied significantly by participant age, ethnicity, race, income status, and by the location where they completed the survey, suggesting heterogeneity in participant interest in the attributes presented in the choice experiment.

Table 4 reports results from the MNL models where participant sociodemographic characteristics and knowledge and risk perception scores are interacted with the reduced GHG in tea production attribute. Column 1 shows that high income participants have less interest in reduced GHG in tea production compare to all other participants in the sample, since the sign on the interaction term High Income * Reduced GHG in tea production is negative and statistically significant ($\beta = -0.36, p = 0.05$). Participants in Bozeman, Montana had more interest in reduced GHG in tea production compared to participants completing the survey in the Boston area ($\beta = -0.289, p = 0.006$). Colum 2 shows that on average the probability of selecting a tea alternative is significantly associated with a participant's climate change knowledge and risk perception score. However, the coefficients for reduced GHGs in tea production interacted with the knowledge and risk perception scores are not statistically different from zero, indicating that climate change knowledge and risk perception scores were not associated with participant interest in reduced GHGs in tea production and probability of tea selection.

Average WTP and 95% confidence intervals for each attribute included in the base MNL model are summarized in Table 5. Reduced GHGs in tea production has the highest average WTP compared to all other attributes presented in the choice experiment. Additionally, average WTP for reduced GHGs in tea production is not statistically different than average WTP for fair trade and certified organic tea, and spring tea. Average WTP for reduced GHGs in tea production is statistically higher than WTP for tea with high antioxidant levels and small-scale tea production.

Results from the mixed logit (RPL) model are reported in Table 6. The log likelihood value for the RPL model was significant lower than the MNL models in Table 3, suggesting increased explanatory power in the RPL model compared the MNL models. Means and standard deviations for all coefficients in the RPL model are significant at the 1% level, with the exception of the antioxidant level attribute. The coefficient for antioxidant level does not vary significantly across participants in the sample given that its standard deviation is not statistically different from zero. There is, however, significant preference heterogeneity for reduced GHGs in tea production, given that the mean and standard deviation of the coefficient are statistically different from zero.

Tables 7-9 show results from the latent class analysis. The information criteria presented in Table 7 show that a 6 class model is optimal. Consequently Table 8 show estimated coefficients for each of the classes in the 6 class model. There is significant variation in the coefficient values for all of the attributes presented in the choice experiment. In particular, the coefficients for reduced GHG in tea production vary significantly across the latent classes. The coefficient for reduced GHG in tea production is largest for class 5, followed by class 1, and class 4.

Table 9 shows the association between participant characteristics and the probability of latent class membership to each class of the six classes. Participant age, gender, and geographic location significantly predicted the probability of membership to multiple latent classes. Race and ethnicity were predicators of probability of membership to class 5, but no other classes. Table 10 shows the association between participant knowledge score and the probability of latent class membership to each class of the six classes. Participant knowledge score and risk perception were negatively associated with probability of membership to class 2, but at the 10% level.

DISCUSSION

This is the first study in the U.S. to comprehensively examine consumer willingness to pay for reduced GHG in agricultural production. One of the key strengths of this study is that it directly compared conference preference for hypothetical credence attributes (i.e. reduced GHG in tea production) to preferences for credence attributes available in the U.S. tea market currently. Even though green tea was the product of focus in the study, the methodological approach developed here can be used to study other types of food and beverages products. In particular, the study can motivate future research in the U.S. to investigate how consumer knowledge and concerns about climate change influence purchase preferences for foods, beverages and other products and services.

Results indicate significant willingness to pay for reduced GHGs in tea production among the U.S. subpopulation sampled. This is an important finding given that very little prior research quantified WTP for reduced GHGs in agricultural production among the U.S. population. The result is also important for tea producers in the developing world and other actors across the tea supply chain. Tea producers and other actors in the tea supply chain could develop marketing schemes or labels to donate any efforts to reduced GHGs in tea production. The development of these marketing schemes and labels could have two important impacts: increased revenue or profits for tea producers and reduced GHGs for the tea production sector.

The findings of this study also indicate variation in willingness to pay for reduced GHG in tea production based on gender, income, and geographic location, but not other characteristics such as ethnicity, race, or age. Climate change knowledge and risk perception were not associated with increased willingness to pay for reduced GHG in tea production. Results from the mixed logit and latent class model also indicate significant variability in willingness to pay for reduced GHG in tea production across the consumer sample studied. This variation in willingness to pay for reduced GHG in tea production could be exploited for marketing purposes or to target educational efforts to consumers most likely to purchase more climate friendly products. However, no strong association between climate change knowledge, risk perception and WTP for reduced GHGs in tea production was found. This result is concerning because it means that knowledge or concern about climate change may not result in consumer interest or motivation to purchase more climate friendly products.

This study has limitations which warrant discussion. First, the consumer sample was not constructed to represent the U.S. population or the U.S. population that consumes tea. Future research could utilize the methods used in this study to examine willingness to pay for other food or beverage products and among a broader or more representative population of U.S. tea consumers. Second, stated preference valuation methods such as choice experiments suffer from hypothetical bias (de-Magistris et al., 2013). Thus, willingness to pay estimates generated in this study should be considered upper bounds. Valuation methods that mitigate hypothetical bias could be employed to more accurately or precisely estimate willingness to pay for reduced GHG in tea or agricultural production. Third, the measures used to assess consumer climate change knowledge and risk perception were not validated and may need refinement. Future work could develop a validated and more robust measure of climate change knowledge and risk perceptions.

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Table 1. Choice experiment product attributes and levels

Attribute	Levels
Carbon footprint mitigation	1. Farmer lowers carbon footprint of tea production by reducing use of nitrogen fertilizers that cause greenhouse gases. 2. Farmers make no attempt to lower carbon footprint.
Scale of tea production	1. Small scale production 2. Large scale production
Nutritional quality	1. Low antioxidant content 2. High antioxidant content
Price (18 tea sachet box)	Ranging from $1.99 - $12.99, in $1 increments
Fair trade certification	1. Not fair trade certified 2. Fair trade certified
Organic certification	1. Not certified organic 2. Certified organic
Season harvested	1. Pre-monsoon season 2. Monsoon season

Figure 1. Illustration of the choice sets faced by consumers in the study

Based on this information and what is provided below, which of these choices would you prefer to buy if given the choice?

	Tea 1	Tea 2
Nutritional quality	High antioxidant content	High antioxidant content
Organic certified	Certified organic	Not certified organic
Carbon footprint	Farmer lowers carbon footprint of tea production by reducing use of nitrogen fertilizers that cause greenhouse gases.	Farmer lowers carbon footprint of tea production by reducing use of nitrogen fertilizers that cause greenhouse gases.
Price (for box of 18 bags)	$3.99	$10.99
Fair trade certification	Not fair trade certified	Fair trade certified
Season harvested	Pre-monsoon season	Monsoon season
Scale of production	Small scale	Large scale

Tea 1	Tea 2	I prefer neither option
○	○	○

Table 2. Demographic summary statistics (n=380)

	% of total
Gender	
Female	74.2
Male	25.8
Age Group	
18-24	31.3
25-34	44.0
35-44	11.6
45-54	8.0
55-64	3.7
>65 years	1.6
Education Level	
No college	32.1
Some college	54.0
College graduate or higher	14.0
% High Income	24.5
Race/ethnicity	
White	81.8
Asian	4.2
Black or African American	8.2
Other race/multiple race	5.8
Hispanic or Latino	97.4
Location of survey participant	
Boston, MA	79.0
Bozeman, MT	21.0

Figure 2. Distribution of knowledge and risk perception scores (n=380)

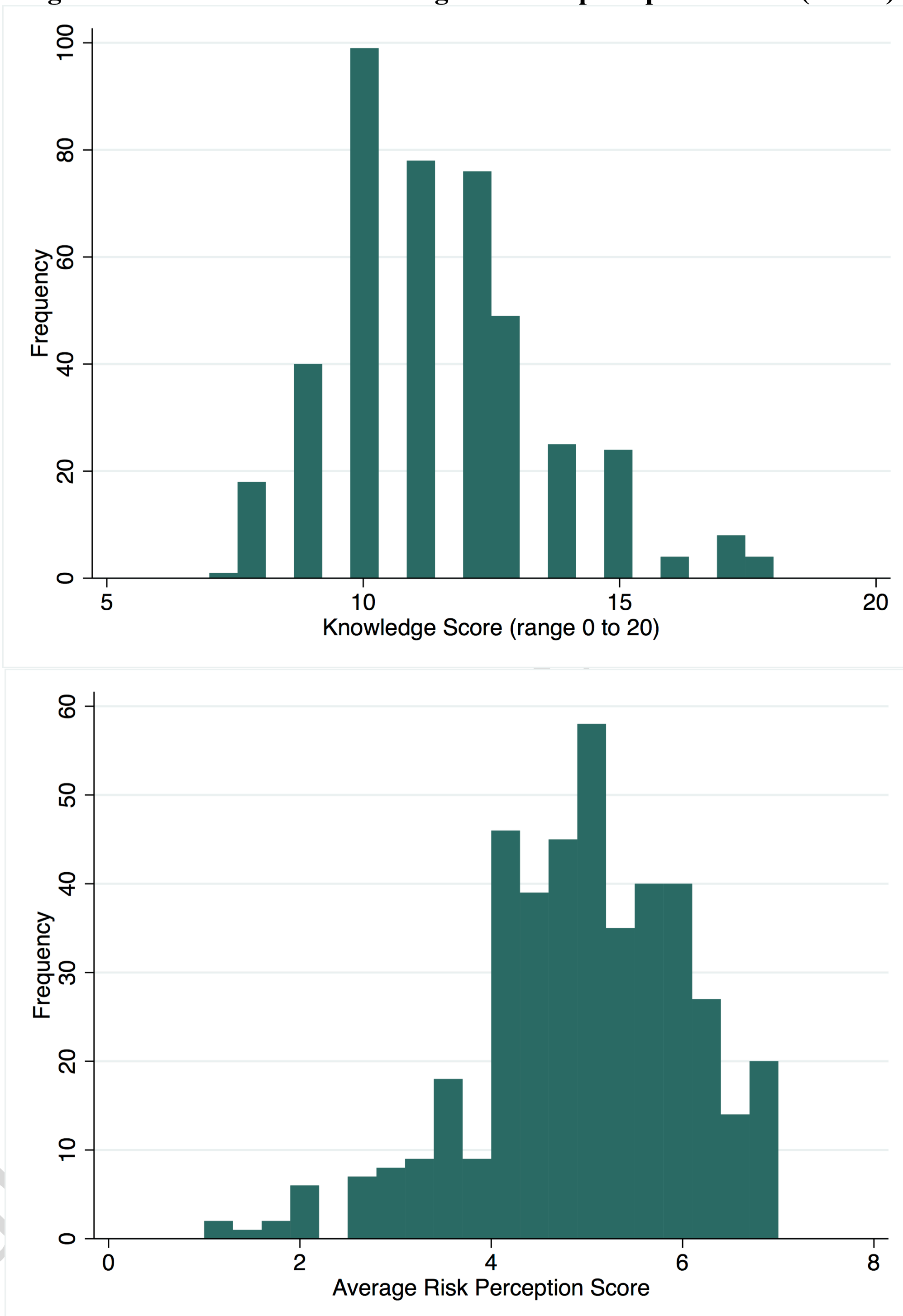

Table 3. Conditional Logit Model results showing association between attributes and probability of selecting a tea alternative, unadjusted and adjusted for participant sociodemographics (Columns 1 and 2), and sociodemographic interactions with Reduced GHG in tea production attribute.

Attributes	Base model		Base model + sociodemographics		Base model + sociodemographic interactions with Reduced GHG in tea production attribute	
Neither tea	-0.605**	(0.0996)	-0.204	(0.390)	-0.198	(0.390)
Spring tea	0.574**	(0.0562)	0.575**	(0.0562)	0.574**	(0.0565)
Large scale production	-0.229**	(0.0560)	-0.232**	(0.0560)	-0.235**	(0.0563)
Reduced GHGs in tea production	0.645**	(0.0563)	0.646**	(0.0563)	0.955*	(0.379)
High antioxidants	0.363**	(0.0561)	0.363**	(0.0561)	0.359**	(0.0564)
Fair trade certified	0.474**	(0.0561)	0.472**	(0.0562)	0.473**	(0.0564)
Organic certified	0.490**	(0.0561)	0.490**	(0.0561)	0.493**	(0.0564)
Price	-0.106**	(0.00780)	-0.106**	(0.00781)	-0.108**	(0.00786)
Neither tea * Male			-0.347**	(0.105)	-0.352**	(0.105)
Neither tea * Age 25-34			-1.026**	(0.318)	-1.003**	(0.318)
Neither tea * Age 35-44			-1.065**	(0.314)	-1.047**	(0.314)
Neither tea * Age 45-54			-0.179	(0.322)	-0.182	(0.322)
Neither tea * Age 55-64			-0.320	(0.336)	-0.337	(0.336)
Neither tea * Age >64			-0.393	(0.364)	-0.383	(0.364)
Neither tea * Black			-0.433*	(0.169)	-0.434*	(0.169)
Neither tea * Asian			-0.799**	(0.270)	-0.789**	(0.270)
Neither tea * Other race			-0.563*	(0.222)	-0.575**	(0.222)
Neither tea * High Income			-0.133*	(0.0552)	-0.0080	(0.0697)
Neither tea * Boston, MA			0.971**	(0.132)	0.935**	(0.133)
Neither tea * Some college			0.0938	(0.140)	0.0814	(0.140)
Neither tea * College degree or higher			0.176	(0.134)	0.175	(0.134)
Neither tea * Hispanic/Latino			0.0758	(0.272)	0.0872	(0.273)
Reduced GHGs in tea production * Male					0.202*	(0.0901)
Reduced GHGs in tea production * Age 25-34					0.0544	(0.321)
Reduced GHGs in tea production * Age 34-44					-0.0351	(0.317)
Reduced GHGs in tea production * Age 45-54					-0.429	(0.329)
Reduced GHGs in tea production * Age 55-64					-0.129	(0.343)
Reduced GHGs in tea production * Age >64					-0.512	(0.371)
Reduced GHGs in tea production * Black					0.0490	(0.179)
Reduced GHGs in tea production * Asian					0.263	(0.264)
Reduced GHGs in tea production * Other race					0.177	(0.222)
Reduced GHGs in tea production * High income					-0.236*	(0.120)
Reduced GHGs in tea production * Boston, MA					-0.289**	(0.105)
Reduced GHGs in tea production * Some college					0.0173	(0.129)
Reduced GHGs in tea production * College degree or higher					-0.135	(0.119)
Reduced GHGs in tea production * Hispanic/Latino					0.102	(0.241)
Observations	9,120		9,120		9,120	
χ^2	722.6		890.7		934.8	
$P(\chi^{2})$	<0.0001		<0.0001		<0.0001	
Log-likelihood	-5414		-5330		-5308	

Notes: Standard errors in parentheses, coefficient values statistically significant from zero denoted by: ** p<0.01, * p<0.05.

Table 4. Conditional Logit Model results showing association between attributes and probability of selecting a tea alternative, including interaction term for knowledge and risk perception of climate change, unadjusted and adjusted for participant sociodemographic characteristics.

Attributes	**Base model + Knowledge and Risk Perception Scores**		**Base model + Knowledge and Risk Perception Scores + sociodemographics**	
Neither tea	-0.0240	(0.238)	-0.0714	(0.439)
Spring tea	0.558***	(0.0530)	0.575***	(0.0562)
Large scale production	-0.206***	(0.0528)	-0.232***	(0.0560)
Reduced GHGs in tea production	0.430**	(0.210)	0.704***	(0.226)
Neither tea * Knowledge score	-0.0455**	(0.0192)	-0.00708	(0.0225)
Neither tea * Risk perception score	-0.0370*	(0.0205)	-0.0569**	(0.0236)
Reduced GHGs in tea production * Knowledge score	0.0152	(0.0177)	-0.00499	(0.0188)
Reduced GHGs in tea production * Risk perception score	0.0263	(0.0193)	0.0147	(0.0204)
High antioxidants	0.334***	(0.0529)	0.363***	(0.0561)
Fair trade certified	0.438***	(0.0530)	0.472***	(0.0562)
Organic certified	0.482***	(0.0529)	0.489***	(0.0561)
Price	-0.102***	(0.00733)	-0.106***	(0.00781)
Neither tea * Male			-0.377***	(0.107)
Neither tea * Age 25-34			-1.095***	(0.326)
Neither tea * Age 35-44			-1.133***	(0.322)
Neither tea * Age 45-54			-0.246	(0.327)
Neither tea * Age 55-64			-0.415	(0.342)
Neither tea * Age >64			-0.468	(0.371)
Neither tea * Black			-0.424**	(0.170)
Neither tea * Asian			-0.856***	(0.274)
Neither tea * Other race			-0.557**	(0.223)
Neither tea * High Income			-0.136**	(0.0553)
Neither tea * Boston, MA			1.018***	(0.135)
Neither tea * Some college			0.0804	(0.140)
Neither tea * College degree or higher			0.142	(0.134)
Neither tea * Hispanic/Latino			0.0762	(0.273)
Observations	9,120		9,120	
χ^2	736.3		897.3	
P($\chi^{2)}$	<0.0001		<0.0001	
Log-likelihood	-6110		-5327	

Notes: Standard errors in parentheses, coefficient values statistically significant from zero denoted by: *** p<0.01, ** p<0.05, * p<0.01.

Table 5. Mean marginal willingness to pay for greenhouse gas mitigation in tea production and other attributes presented in the choice experiment (n=9,120)

	Mean WTP (95% Confidence Intervals in parentheses)
Spring tea	5.43 (4.16, 6.70)
Large scale production	-2.16 (-3.25, -1.08)
Reduced GHGs in tea production	6.09 (4.76, 7.43)
High antioxidants	3.43 (2.29, 4.56)
Fair trade certified	4.47 (3.27, 5.69)
Organic certified	4.63 (3.41, 5.85)

Table 6. Mixed logit model results

	Mean (M)	Standard error	Standard deviation (SD)	Standard error
Attributes				
Neither	-1.407***	(0.180)	2.304***	(0.162)
Spring tea	0.907***	(0.114)	1.681***	(0.129)
Large scale production	-0.371***	(0.0799)	0.395**	(0.154)
Reduced GHGs in production	1.056***	(0.0865)	0.568***	(0.141)
High Antioxidant content	0.505***	(0.0804)	0.448***	(0.159)
Fair trade certified	0.715***	(0.0831)	0.521***	(0.142)
Organic certified	0.779***	(0.0816)	0.362*	(0.203)
Price	-0.170***	(0.0120)	0.0770***	(0.0175)
Observations			9,120	
χ^2			877.5	
$P(\chi^{2)}$			<0.0001	
Log likelihood			-2,537	

Notes: Standard errors in parentheses, coefficient values statistically significant from zero denoted by: *** p<0.01, ** p<0.05, * p<0.01.

Table 7. AIC, CAIC, and BIC information criteria values for latent class models with 2-6 classes.

Classes	Log likelihood	AIC	CAIC	BIC	Number of parameters
2	-3022.26	6078.51	6164.68	6147.68	17
3	-2954.11	5960.22	6092.00	6066.00	26
4	-2909.87	5889.75	6067.14	6032.14	35
5	-2886.75	5861.49	6084.50	6040.50	44
6	-2850.64	5807.29	6075.92	6022.92	53

Table 8. Association between attributes and levels presented in the choice experiment and probability of selecting a tea alternative by latent class and estimated percent of participants per class.

Attribute	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6
Prefer neither tea	-1.069***	1.739	1.792**	0.620***	-13.29	-3.845***
	(0.389)	(1.561)	(0.875)	(0.235)	(12.15)	(0.858)
Spring tea	0.591***	1.069	-3.132***	1.252***	17.36	0.278
	(0.176)	(0.898)	(0.890)	(0.160)	(12.24)	(0.212)
Large scale production	-0.117	1.900	-1.011**	-0.413***	1.227*	-0.354*
	(0.188)	(1.898)	(0.411)	(0.128)	(0.723)	(0.200)
Reduced GHGs in tea production	1.528***	-1.284	-0.0398	0.775***	2.180***	0.641***
	(0.266)	(1.076)	(0.376)	(0.132)	(0.756)	(0.193)
High antioxidants	0.570***	-6.115	0.731*	0.595***	2.157**	0.353
	(0.166)	(8.128)	(0.438)	(0.130)	(0.906)	(0.239)
Fair trade certification	0.769***	-0.197	0.637*	0.784***	-1.911*	0.410**
	(0.209)	(0.928)	(0.358)	(0.133)	(1.061)	(0.209)
Organic certification	0.763***	-0.351	2.016***	0.668***	2.309***	0.538***
	(0.167)	(0.910)	(0.472)	(0.137)	(0.772)	(0.208)
Price	-0.0449	-0.350*	-0.134***	-0.126***	-0.387***	-0.287***
	(0.0330)	(0.203)	(0.0476)	(0.0178)	(0.141)	(0.0583)
Class share	28.4%	6.8%	6.1%	29.5%	5.1%	24.1%
Observations				380		

Notes: Standard errors of estimated coefficients reported in parentheses. Coefficients statistically significant from zero denoted with: *** p<0.01, ** p<0.05, * p<0.10.

Table 9. Association between probability of membership to each latent class and sociodemographic characteristics

Participant characteristics	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6
Age (<25 years is reference group)						
25-34 years	-0.0132	-0.0249	0.0241	0.0455	-0.0349	0.00351
	(0.0413)	(0.0224)	(0.0271)	(0.0484)	(0.0256)	(0.0400)
35-44 years	-0.146***	0.102*	-0.0227	0.136*	-0.00888	-0.0598
	(0.0484)	(0.0582)	(0.0236)	(0.0749)	(0.0399)	(0.0606)
45-54 years	-0.00739	0.0936	0.0187	0.0285	-0.0742***	-0.0592
	(0.0777)	(0.0635)	(0.0469)	(0.0875)	(0.0231)	(0.0648)
55-64 years	0.0359	0.0123	0.0341	0.136	-0.0153	-0.203***
	(0.122)	(0.0689)	(0.0669)	(0.142)	(0.0690)	(0.0419)
>65 years	0.0229	0.122	-0.0545**	0.120	-0.0748**	-0.135
	(0.171)	(0.139)	(0.0275)	(0.209)	(0.0302)	(0.109)
Male (female is reference group)	0.0566	-0.0150	-0.0363*	-0.104**	0.0351	0.0634
	(0.0418)	(0.0240)	(0.0218)	(0.0465)	(0.0301)	(0.0409)
High Income (low income is reference group)	-0.0389	0.0558*	-0.0193	0.0177	0.0208	-0.0360
	(0.0426)	(0.0334)	(0.0231)	(0.0556)	(0.0256)	(0.0405)
Educational attainment (No college is reference group)						
Some college	-0.0359	0.00735	-0.00253	0.0597	0.000775	-0.0294
	(0.0402)	(0.0302)	(0.0236)	(0.0487)	(0.0236)	(0.0383)
College graduate or higher	-0.00776	0.0184	0.00775	0.0309	-0.0292	-0.0200
	(0.0599)	(0.0393)	(0.0317)	(0.0685)	(0.0291)	(0.0552)
Race (White is reference group)						
Black	0.0561	-0.0229	0.0304	-0.128	-0.0113	0.0762
	(0.0989)	(0.0488)	(0.0400)	(0.111)	(0.0705)	(0.0906)
Asian	0.0542	0.00961	0.0432	-0.0510	-0.0570***	0.00106
	(0.0705)	(0.0414)	(0.0495)	(0.0781)	(0.0160)	(0.0609)
Other/multiple race	-0.00618	0.0163	-0.000898	0.0856	-0.00696	-0.0879
	(0.0754)	(0.0489)	(0.0483)	(0.0995)	(0.0387)	(0.0588)
Hispanic or Latino	-0.0643	-0.0280	-0.0179	0.136	-0.0597**	0.0342
	(0.0885)	(0.0187)	(0.0418)	(0.133)	(0.0250)	(0.104)
Boston, MA site	-0.123***	0.0225	-0.0812**	0.200***	0.0300	-0.0486
	(0.0474)	(0.0268)	(0.0355)	(0.0486)	(0.0249)	(0.0453)
Observations			380			

Notes: Statistical significance denoted by *P<0.10 **P<0.05, ***P<0.01

Table 10. Association between probability of membership to each latent class and sociodemographic characteristics

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6
Knowledge score	0.00272	-0.0107*	-0.00116	-0.000545	0.00168	0.00804
	(0.00852)	(0.00592)	(0.00410)	(0.00937)	(0.00589)	(0.00747)
Risk perception score	0.000195	-0.0122*	0.00103	0.00909	-0.00239	0.00431
	(0.00919)	(0.00742)	(0.00427)	(0.0104)	(0.00528)	(0.00890)
Observations			380			

Notes: Statistical significance denoted by *P<0.10 **P<0.05, ***P<0.01