**Incorporating Endogenous Attitudinal Factors in Discrete Choice Experiments: An Integrated Choice and Latent Variable Model Approach**

**Abstract**

The importance of psychological factors such as consumer attitudes and perceptions in driving preference heterogeneity has been increasingly acknowledged in recent choice experimental research. In this article, we extend the integrated choice and latent variable (ICLV) framework and explicitly consider the endogeneity of individual attitudes under information treatment by jointly modeling consumers’ attitudes and their influences on consumers’ labeling preferences.

We identify a significantly positive impact of information on shaping individuals’ attitudes toward pollinator health. Additional information on neonicotinoids increases individual environmental concerns and their willingness-to-pay (WTP) for labels disclosing the absence of insecticides. Further, individual plant choices are compared to a counterfactual situation where pollinator conservation practices are mandatory. We find significant improvements in the probability of choosing insecticide-free plants across all demographic segments of informed consumers.

*Keywords:* Counterfactual analysis; Information treatment; endogenous attitudes; integrated choice and latent variable model; neonicotinoid labeling; ornamental plants

*JEL Classification*: C35, C90, D12, Q18, Q50

**Incorporating Endogenous Attitudinal Factors in Discrete Choice Experiments: An Integrated Choice and Latent Variable Model Approach**

Traditional discrete choice models in consumer studies have focused on observable variables such as product attributes, socio-demographic characteristics, market information, and past experiences (Vij and Walker 2015). In response to increased criticism that individual tastes and preferences may vary with unobservable variables resulting in inconsistent parameter estimates (Chamberlain 1980), mixed logit models were developed as the most promising tool in discrete choice models to accommodate random taste variation, unrestricted substitution patterns, and correlation in unobserved factors (Train 2009). However, it has been increasingly realized that the mixed logit models are not without limitations. For example, mixed logit requires prior assumptions about the distribution of random parameters (Walker and Ben-Akiva 2002).

Meanwhile, studies have consistently shown the important role of psychological factors such as consumer attitudes and perceptions in driving preference heterogeneity (Abou-Zied et al. 2010; Bechtold and Abdulai 2014; Ben‐Akiva et al. 2002 a, b; Hess 2012; Paulssen et al. 2014; Sok et al. 2018) and the need for the explicit treatment of psychological factors in discrete choice models (e.g., Bamberg and Schmidt 2001; Ben-Akiva et al. 1994; Morikawa et al. 2002; Gärling et al. 2003). Ben-Akiva et al. (2002 a, b) present a methodological framework to explicitly model psychological factors as latent variables that have been ignored or treated as exogenous variables in most discrete choice modeling studies. The integrated choice and latent variable (ICLV) model overcomes the unobserved confounding problem in the choice decision by modeling unobservable factors such as individual psychological preferences.

In this study, the authors extended the ICLV framework to elicit consumer preferences for ornamental plants grown with or without controversial neonicotinoids with additional pollinator-related information provided. The endogeneity of individual attitudes is explicitly considered, and their influences on plant choices are jointly modeled under information treatment. Our study first fills the gap between the DCE literature (investigating information effects on choice decisions) and the social psychology studies (investigating information-attitudes-behavior relationship), thus linking these two fields together for a more in-depth understanding of determinants behind decision making. By demonstrating that additional information on neonicotinoids improves individual environmental concerns and further increases consumer preferences for labels disclosing the absence of neonicotinoids, we establish a complete causal mapping from information to attitudes and behavior.

We also contribute to nascent literature recognizing the importance of psychological factors in choice modeling and aiming to integrate endogenous psychological factors into consumer choices for new products (e.g., food labeling). When exploring the relationship between consumers’ attitudes toward pollinator health and preferences for neonicotinoid disclosure labels, we explicitly address the endogeneity issue of attitudes in the mixed logit model by linking attitudes to the latent variable of unobserved individual environmental concerns. Modeling the endogeneity of individual attitudes and perceptions is important

in applied econometrics and choice analysis as it corrects the bias caused by the unobserved effects influencing respondents’ choices and responses to attitudinal questions. However, few existing ICLV studies (primarily in transportation and logistics fields) except Daly et al. (2012) have established this clear representation of the ICLV model in addressing endogenous psychological factors in choice decisions.

Additionally, we contribute to the line of discrete choice analysis by modeling the impact of information treatment on the latent variable, affecting consumers’ choices. To the best of the authors’ knowledge, this is the first study directly estimating the information treatment effects within a latent variable mixed logit model framework. We found a strong information impact on consumer preferences for labels disclosing the absence of neonicotinoids, providing additional empirical evidence on increased WTP for perceived public benefits due to information treatment. By incorporating information treatment into the ICLV model, we further demonstrate the practical value of the ICLV model in discrete choice modeling as the endogeneity bias is likely exacerbated when there is an information treatment. If used appropriately, the ICLV model can be a powerful tool in estimating treatment effects in discrete choice experiments addressing the relationship between information, attitudes, and choice behaviors.

Further, we expand the application of the ICLV model to accommodate a more complicated DCE design involving multiple products such that not all products are shown in one choice set and products in each (non-opt-out) choice options are randomized. This kind of DCE design is more common in consumer preference studies such as food choices. For example, consumers make dichotomous decisions by choosing one drink from juice, soda, diet soda and water options with various sugar contents (e.g., Neuhofer et al., 2020). In contrast, choice options in transportation literature (e.g., Abou-Zeid et al., 2010; Daly et al., 2012, Johansson, Heldt, and Johansson, 2006; Kim, Rasouli, and Timmermans, 2014; Paulssen et al., 2014; Yañez, Raveau, and de Ortúzar 2010) do not involve this complexity. Attributes levels varying systematically across fixed order-of-choice options make the travel mode decision data easily adapted to the ICLV model structure. Like many DCE designs in food labeling studies, our experiment choice options contain three different products (i.e., impatiens, marigold, and pentas plants), and only two products are shown in each choice set (see Figure A1 for an example). In addition, the order of plants in repeated choice tasks is randomized in our experiment. By pairing plant type with other important attribute levels, we reduce the complexity of choice options in the ICLV model structure and demonstrate a successful application of the ICLV model to a more sophisticated DCE design. Considering existing applications of the ICLV model, this is a novel approach and can be generalized to multi-product food-related choice modeling, where the endogeneity issue of individual attitudes and perceptions is a potential concern.

Finally, we build a policy counterfactual analysis considering the implementation of a government policy protecting pollinators from exposure to potentially harmful pesticides. We show that the individual environmental concerns (latent) variable in the counterfactual case is largely improved due to conservation policy implementation. Compared to observed plant choices, the probability of choosing insecticide-free plants under the counterfactual scenario increased across all plant types and consumer demographic segments. Meanwhile, the probability of choosing plants grown with neonicotinoids and opt-out decreased. These counterfactual results provide additional insights into the impact of additional pollinator-related information on choice decisions.

# **Background on Neonicotinoid Insecticides Use and Policy Controversies**

The ICLV framework is applied to an online discrete choice experiment (DCE) data to elicit consumer preferences for neonicotinoid labeling due to the potential health risks to pollinator insects. Even though neonicotinoids are predominantly used for crop production, the turf and ornamental industry is the second-largest category for using neonicotinoids (Douglas and Tooker 2015). Ornamental plant producers are under constant pressure to control unwanted pests, an important consideration given consumers’ heightened desire for aesthetic perfection (Bethke and Cloyd 2009). Neonicotinoids represent the most effective means for controlling harmful insect pests such as aphids and whiteflies in ornamental production (Jeschke and Nauen 2008; Jeschke et al. 2011).

While the national strategy and action plan of protecting pollinators from exposure to pesticides released by the Obama Administration in 2016 was disrupted, large retail stores in the United States have imposed more restrictive retail policies such as disclosing the use of neonicotinoids on plant labels. Meanwhile, in 2018 the European Union (EU) regulators extended the ban on the use of three major neonicotinoids on outdoor pollinator-attractive crops to all field crops. Most recent studies have revealed that EU’s ban on neonicotinoids has caused yield decrease (Dewar 2016; Noleppa 2017), increased other insecticides use (Kathage et al., 2018), and increased production costs (Kathage et al 2018; Noleppa 2017). Banning neonicotinoids has forced farmers to use alternative means of pest control that may have unintended consequences such as pest resistance due to more frequent application of other insecticides that are less effective (Bass and Field 2018). Jactel et al. (2019) showed that the most common alternative to neonicotinoid insecticides is the use of another chemical insecticide (89% of cases), which is not necessarily safer for the environment. In contrast, transparent labeling practices have the potential to shift the demand curve by encouraging consumers to make informed shopping decisions on more environmentally friendly products and to shift the supply curve by decreasing friction within the ornamental plant supply chain. Ornamental producers may consider switching to alternative pest management practices in response to consumers’ preference for plants free of pesticides, including neonicotinoids.

# **Literature Review on the Information-Attitude-Behavior Relationship**

Information nudges are private or public initiatives that steer people in particular directions, but unlike mandatory mechanisms, allow them to go their own way (Thaler and Sunstein 2008; Thaler 2015). Building upon this concept that the inclusion of information treatment may increase the importance of relevant attributes, recent work in experimental economics has begun to utilize information treatments as a tool to investigate the information-behavior relationship. In other words, information treatments help researchers gain a deeper understanding of how consumers may modify their purchasing decisions when facing additional product information. For example, Aoki et al. (2014) and Aoki et al. (2019) found receiving cultivation method information increased consumers’ WTP for IBIS rice. Further, Aoki (2014) found that individuals with high environmental awareness have greater WTP for IBIS rice after receiving information about its cultivation method, which protects the crested ibis population. Su et al. (2017) showed that providing information on the insect control methods during rice storage increased WTP in their DCE. All these studies discussed individual attitudes/perceptions (environmental concerns in Aoki et al. (2014, 2019) and health concerns in Su et al. 2017) to some extent but ignored the information impacts on these variables.

As a parallel, there is a rich and varied history of examining the relationship between information and attitudes, and the relationship between attitude and behavior in psychology and other social sciences fields. While Schultz (2002) argued that information can make a difference in some circumstances but is not sufficient enough to elicit desired behaviors, Bidwell (2016) and Sturgis and Allum (2004) emphasized the important role of information on in shaping attitudes. The guiding philosophy is that providing information to a person can change the quality of their attitudes. While greater knowledge about a given issue might not lead to desired behavioral outcomes, it does change how people think about it and associated issues (Bauer, Allum, and Miller, 2007; Evans and Durant, 1995). Specifically, providing information may in some circumstances influence attitudes on issues like energy and the environment but may have little or no impact on behaviors (McKenzie-Mohr 2000; Owens and Driffill 2008). Because of this controversy, exploring the relationship between consumers’ attitudes and behavioral outcomes has been a key question for a long time in pro-environmental behavior (PEB) literature (Carrico, Fraser, and Bazuin 2012; Farrow, Grolleau, and Ibanez 2017; Staats, Jansen, and Thøgersen 2011; Thøgersen and Ölander 2003; Davies, Foxall, and Pallister 2002; Newholm and Shaw 2007; Ha and Janda 2012; Whitmarsh 2009; and Jakovcevic and Steg 2013; Lind et al. 2015). Most of the literature studying consumers’ environmental awareness and attitudes on consumption choices has highlighted their impact on improved choice behavior benefiting environment (e.g., Dean, Raats, and Shepherd 2012; McFadden and Lusk 2017; Liaukonyte et al. 2013; Paul and Rana 2012).

Due to increased recognition of the importance of psychological factors in improving explanations of consumer choices, the ICLV model has gradually gained popularity and become an important extension to discrete choice models recently in food choice and valuation literature (e.g., Alemu and Olsen 2019; O’Neill et al. 2014; Yangui, Costa‐Font, and Gil 2016; Yeh and Hartmann 2019). Nonetheless, applications of ICLV approach remain primitive due to the complexity of DCE design in food choice experiments.

# **Materials and Methods**

## *Overview of Study Design*

This study incorporated information treatment into an online DCE. Using a between-subject design, the primary objective of this study was to elicit participant’s preferences toward labels disclosing the presence of neonicotinoid insecticides by taking into consideration the endogenous attitudes under information treatment. Due to the nature of internet-based survey, the DCE was not incentivized (i.e., hypothetical). An incentivized DCE would be ideal to reduce potential hypothetical bias. However, using real DCE would limit the sample to local population only as real choice experiment requires participants’ physical presence to facilitate the economic transactions (e.g., payment to subjects). In addition, sample size for non-hypothetical choice experiment tends to be small because of budget constraints and time and space requirements for hosting experiments.

At the beginning of the internet survey, participants answered questions related to their ex-ante knowledge about pollinator insects, pollinator attractive plants, and neonicotinoid insecticides. Participants were then randomly directed to either the control or the information treatment. Participants in the control group received no additional information and completed the choice experiment based on their existing knowledge and attitudes about pollinators and neonicotinoids. Participants in the information treatment group were exposed to a 3-minute informational video. In the video, neonicotinoid insecticides applied to crops and landscapes were described as one of the leading causes for bee population declines and had the “negative and deterministic impact” on pollinator health. Webpage viewing time restrictions were set up to ensure that survey participants watched the entire video. After viewing the 3-minute informational video, participants in the treatment group made their choices in eight subsequent plant choice scenarios.

After the DCE, participants’ attitudes toward neonicotinoid insecticides and pollinator health were assessed using six statements (Table 1). For each statement, participants indicated their agreement or disagreement on a 1-7 rating scale where response options were *strongly disagree*=1, *disagree*=2, *slightly disagree*=3, neither agree nor disagree=4, *lightly agree*=5, *agree*=6, and *strongly agree*=7. The online survey concluded with questions regarding respondents’ shopping behaviors and demographic characteristics.

## *DCE Design*

As shown in Table 2, four attributes were used in the DCE. With the focus of this study on eliciting preferences for labels disclosing the absence or presence of neonicotinoids, two distinct label categories were employed. “Neonicotinoid Free (text)” and “Bee Better Certified (logo)” were used to communicate the absence of neonics. In contrast, the phrases *Treated with Neonicotinoids* and *Protected from Problematic Pests by Neonicotinoids* were used to communicate the presence of neonics. As another indicator of clean label and sustainable production practice, biodegradable containers were used to differentiate from traditional conventional plastic containers. Four price levels ($1.15, $1.65, $2.49, and $3.99) were considered in the DCE, selected based on local big box garden stores’ and independent garden centers’ prices.

To reduce the cognitive burden of survey respondents, a fractional factorial design was used to effectively decrease the number of choice scenarios.[[1]](#footnote-1) Sixteen choice scenarios divided into two blocks of eight were constructed with a D-efficiency of 95.04%. The 16 choice scenarios were constructed to maximize the variations across choices with a balanced occurrence of plants and other attributes. In each choice set, participants selected between two plants or an *I would not buy any of these plants at this time* option (see Figure A1 for a choice set example). Each respondent was randomly assigned to view one block with eight choice scenarios. This panel data structure of repeated choice tasks was accounted for in our ICLV model.

## *Participants Demographics, Ex-Ante Knowledge and Post-Attitudes*

Eight hundred forty participants drawn from a nationwide panel were evenly distributed among the control and information treatment groups (n=420 per group). Participants were prescreened to make sure they had previous experience of purchasing ornamental plants. The overall sociodemographic characteristics were homogenous in the control and information treatment groups (Appendix Table A1). The average age of participants was about 50 years, with participants in the control group being slightly older. Male participants accounted for more than 40% of the sample in both groups. The distribution across different household income categories, education levels, and ethnic groups was consistent among the control and treatment groups. The average household size was about three people. Twenty-two percent of the survey respondents in the control group indicated they had children under 18 in their households, slightly fewer than those in the treatment groups (about 30%). Approximately 30% of the sample lived in rural areas.

We used both subjective (self-reported) and objective (quiz questions) measures to assess participants’ existing knowledge about neonicotinoids and pollinator plants. Considering that the public exposure to neonics-related information is limited (Rihn and Khachatryan, 2016; Wollaeger et al., 2015; Wei et al., 2020), we asked participants to report their knowledge about neonics based on 1-7 rating scale (1 indicating *not at all knowledgeable,* 4 *neither knowledgeable nor not knowledgeable,* and 7 *extremely knowledgeable*). Participants in the control group self-reported less knowledgeable about neonicotinoids (M=2.21, SD=1.74) in comparison to those of the treatment group (M=2.59, SD=2.59). As gardening is one of the popular leisure activities for many American households, we then asked participants to answer four quiz questions to measure their real knowledge about pollinator attractive plants. According to National Garden Association (2008) and Kiesling and Manning (2010), 90 million U.S. households (78% of all U.S. households) have yards, landscapes, or gardens and 84% of US households are engaged in gardening activities. In each quiz question, participants were provided with two plant names supplemented with images of the plants and were asked to indicate the one that was pollinator attractive. We counted the number of answers out of four questions a participant could correctly answer. With mean equals 1.67 for the control and 1.69 for the treatment, the tested objective knowledge about pollinator attractive plants was similar between two groups (*p*-value=0.76). Particularly, one hundred seventy respondents (40.5%) in the control group and 156 respondents (37%) in the treatment group correctly answered two quiz questions. Sixty-seven respondents (16%) in both control and treatment groups correctly answered three quiz questions. Only 13 respondents (3.1%) in the control group and 17 (4.1%) in the treatment group answered all four questions correctly.

While some studies (e.g., Lewis et al., 2018) suggested that information treatments may decrease the selection of the neither option, we did not find this influence in our study. The selection of the *neither* option (i.e., *I would not buy any of these plants at this time*) in the control and the information treatment groups was 6.0% and 6.6% respectively.

After the eight choice tasks were completed, participants in both groups were asked to respond to six statements regarding their attitudes toward neonicotinoids (I1) and pollinators (I2, I3. I4, I5, and I6) using 7-point scale from *strongly disagree* to *strongly agree* (see a full list in Table 2). With additional information, participants in the treatment groups were more likely to agree that they were concerned about pollinators, and were less likely to agree that neonicotinoids were effective to protect plants from insect pests. Mann-Whitney tests were statistically significant for five statements (out of six) indicating a significant impact of information treatment on individual attitudes. To determine the internal consistency of the six statements, we first computed the corrected item-total correlations for each statement (Column 5, Table 2). Indicators I2, I4 and I5 have reasonably strong correlations with other items, ranging from 0.42 to 0.57. Combining with principal factor analysis results, four attitude indicators (, , , and ) were chosen to measure the latent variables in the ICLV model.

## *ICLV Model Framework*

For purposes of this study, we needed a modeling framework that allows controlling for the potential endogeneity of individual attitudes and perceptions toward pollinator conservation caused by unobserved individual characteristics such as concerns about the potential environmental impact of neonics on pollinators. We use the ICLV model to estimate the information treatment effects and determine whether introducing additional neonicotinoid-related information influences consumer plant purchasing decisions. The proposed ICLV model framework is illustrated in Figure 1. The ICLV model proposed in this investigation extends the model proposed by Ben-Akiva et al. (2002) by incorporating the information treatment effects. The ICLV model consists of two components: a discrete choice model and a latent variable model, which are described in detail in the next section.

*The latent variable model*

Socio-demographic characteristics (such as age, gender, household income, education and plant purchasing behaviors) may influence individuals’ interests or concerns toward environmental issues such as pollinator conservation, or more specifically, the use of neonicotinoids. Accordingly, the structural latent variable model can be specified below:

and (1)

where is the latent variable representing unobserved individual environmental concerns. is a vector of individual characteristics that influence the latent variable. is the information treatment indicator, which equals 1 if individual is in the information treatment group and zero if in the control group. The random error term is assumed to follow a normal distribution with mean zero and diagonal variance matrix . The latent variable is then linked to the selected attitudinal indicators using the following measurement equations[[2]](#footnote-2)

, (2)

The attitudinal indicator denotes individual ’s responses to a 7-point Likert-scale survey question regarding the levels of agreement with statement pertaining to pollinators. Specifically, denotes 2, 4, 5, 6, indicating the four indicators (, , , and ) regarding individuals’ perceptions and attitudes towards pollinators (See Section 3.3 *Participants demographics, ex-ante knowledge and post-attitudes* for more details about individual attitudes and selection of attitudinal indicators).

*The discrete choice model*

The random utility model assumes that individual derives utility from choosing alternative in choice scenario that is utility maximizing. Following Train (2004), the utility can be decomposed into a systematic component, , and a random component such that

, (3),

where, is a function of observed plant attributes () and unobserved consumer preferences () affecting the decision maker’s utility and often is assumed to be linear in . is a random error term and is assumed to have an Type I extreme distribution.

Employing a compact vector form, the structural choice model can be written as

.(4),

where, vectorcontains homogenous plant attributes such as plant types, prices whose impacts on utility are not individual specific. includes plant attributes that are influenced by unobserved individual environmental concerns. These variables represent neonic-free and biodegradable container indicators. Following Atasoy, Glerum, and Bierlaire (2011, 2013), is defined as an exponential function of as follows

, (5),

where, and are two parameters to be estimated.

*The likelihood functions*

For each single choice, the probability that person chooses alternative in choice scenario conditional on and is standard logit:

(6)

For repeated choices, denote the alternative that person chooses in scenario. Denote individual ’s sequential choice vector as (i.e., ). The probability of person ’s observed sequence of choices is the product of standard logit in Equation (6):

. (7)

Now we add the latent variables to the choice model. Assume , are independent and has a conditional distribution density . The likelihood function in Eq. (7) is then the integral of the choice model over the distribution of the latent variable:

. (8)

Since all information about the latent variable is contained in the observed indicators , we can now introduce to improve the accuracy of theestimates. Assuming the error components , , are independent, the probability of the observed choices and attitude indicators is given by

. (9)

The ICLV model was estimated using full-information maximum likelihood with Python Biogeme (Bierlaire 2003, 2018).

# **Results and Discussion**

## *ICLV Model Estimation Results*

Table 3 summarizes the estimated ICLV model results using full information maximum likelihood estimation. Two-stage sequential approach with attitudinal indicators integrated was also estimated for robustness check (Appendix Table A2). In the structural latent variable model, we identified a strong information effect on the latent variable. The estimated coefficient of information treatment is 0.337 (. This result confirmed the important role of information in shaping individual environmental attitudes and perceptions proposed by information-attitude relationship literature. In addition, most demographic characteristics (e.g., age, gender, number of children, and education level) have significant influence on individual environmental concerns formation. The estimated coefficients for the four refined attitudinal indicators are all positive and statistically significant (indicating these indicators are good measures of the latent variable with strong predictive power.

In the choice model, participants clearly obtain different utility levels from different plants. Among the three annual bedding plants, impatiens--being the most popular plant--provides highest utility level to consumers.[[3]](#footnote-3) Biodegradable container matters more to participants when it is paired with marigold or pentas plant. As defined in Eq. (5), the combination of estimated coefficients and determines the utility level participants received from labels disclosing the absence of neonicotinoids. As with the biodegradable container, utility levels from neonic-free labels also vary across plants. Given estimated and are all positive and statistically significant (except Neonic Free\_Pentas\_), participants in our sample in general exhibit higher utility levels for neonic-free labels regardless of plant type. Recall the functional form of and in Eq. (5). As includes plant attributes that are influenced by the latent variable, the combination of and captures the information treatment effect on individual’s utility by choosing neonic-free plant products. More details on this are provided in the following section where we discuss WTP estimates. The negative and significant coefficients of the three price variables (Price\_Impatiens, Price\_Marigold, and Price\_Pentas) indicated that participants were less likely to buy a plant with a higher price, as suggested by demand theory.

## *WTP Estimates*

Following Bierlaire’s (2018) procedure, we calculated marginal WTP for important plant attributes (i.e., neonic-free label and biodegradable container) that are of our interests. Marginal WTP and confidence intervals reported in Table 4 are the realizations of 100-time random draw of parameters. As expected, participants in the treatment group have a higher WTP for all three plants produced without neonicotinoids, indicating a significant positive effect of information treatment. WTP for labels disclosing the absence of neonicotinoids varies across plants. Marigold plants with neonic free labels have the highest WTP of $10.5, followed by pentas ($8.16) and impatiens ($5.65). Knowing the negative impact of neonicotinoids on pollinator health (after receiving additional information), participants in the treatment group are willing to pay $10 more for a marigold plant produced without neonicotinoids compared to a plant using neonicotinoids during the production process. For the control group, the marginal WTP are $8.48 for marigold plant with neonic free label, $6.17 for pentas with neonic free label, and $5.05 for impatiens with neonic free label.

The estimated marginal WTP for the three annual bedding plants in biodegradable containers remains the same in the control and treatment groups. They are $0.12 for impatiens, $1.87 for marigold, and $2.65 for pentas. This is due to the underlying assumption that information treatment affects only elements directly related to neonicotinoids and pollinators. Information is supposed to change participants’ preference for plant choices through its influence on attitudes. In this study, our information treatment particularly concerns the negative and deterministic impact of neonicotinoids on pollinator health. In addition, the four attitudinal indicators were refined to measure precisely individual concerns about the potential impacts of neonicotinoids on pollinator health (as opposed to general environmental concerns). By doing so, we stress the focal point of estimating the information treatment effect on consumer preference for neonic-free labels.

## *Policy Counterfactual Analysis*

To fully understand the effects of information on choices of plants free of neonicotinoids, the authors of this study further use a framework of counterfactual analysis considering a government policy change regarding pollinator conservation. Given the ongoing efforts made by the current government relating to combatting climate change and protecting the environment, we consider a governmental policy scenario that promotes pollinator conservation programs, to be supervised by the Department of Agriculture and the Environmental Protection Agency, similar to the policy once established under the Obama Administration.

Table 5 presents the observed and predicted consumer choices of plants with labels disclosing the presence or absence of neonicotinoid pesticides under actual and counterfactual conditions. Compared to the observed probability distribution, the counterfactual scenario predicts the probability of choosing plants that have been grown free of neonics will increase by 0.054, while simultaneously reducing the probability of choosing plants with neonicotinoids (-0.021) and opting out (-0.033). We further investigated the changes in purchasing probability by looking into different consumer demographic segments. Improvements occur across all consumer demographic segments and do not vary much across segments. Generation X consumers (ages ranging between 37 to 52) revealed the lowest tendency of purchasing neonic-free plants in our experiment. This group will remain least likely to purchase neonic-free plants even with a policy implementation. Similarly, consumers with high income and education levels have the lowest observed probabilities of purchasing neonic-free plants and remain the lowest in the counterfactual case. On the other hand, consumers who self-reported having heard of neonicotinoids have a slight improvement in probability of purchasing plants grown without neonicotinoids (+0.055) compared to their counterparts (+0. 053).

We also compute the observed and predicted probabilities for each specific plant with labels disclosing the absence of neonicotinoids. Results were summarized in Table A3 (Appendix). Our expectation is that pollinator conservation policy implementation will universally increase the probabilities of purchasing all plants free of neonicotinoid pesticides. The improvement in purchasing probability for neonic-free marigold and pentas plants are slightly larger than that of the neonic-free impatiens. These results imply that a policy implementation significantly increases the probability of choosing plants with labels disclosing the absence of neonicotinoids for all plants and across all consumer demographic segments. Even though the consumer segments with lower probably of purchasing neonic-free plants remain lower, the improvement is significant and non-negligible.

# **Discussion and Conclusions**

In this study, we apply the ICLV framework to jointly model consumers’ environmental attitudes and their influences on plant purchasing choices. We illustrate the application of ICLV model in analyzing the attitude-behavior pattern in the U.S. horticulture industry, a scenario that has not yet been addressed. Overall, we find participants exhibit higher WTP for labels disclosing the absence of neonicotinoids regardless of information treatment. A little caution is needed for interpreting the WTP estimates. These numbers could be higher than consumers’ true WTP due to the hypothetical nature of the DCE. Nonetheless, recognizing the potential upward hypothetical bias does not eliminate the information treatment effect.

We then generalize the ICLV framework by incorporating an information treatment. The significant impact of information on improving participants’ attitudes toward pollinator health is confirmed by both principal factor analysis and ICLV model regression results, validating the important role of information in shaping individual environmental attitudes described in information-attitudes literature. We further conduct a counterfactual analysis to verify the information treatment effects by exploring the differences between observed and counterfactual purchasing probabilities. We confirm a positive and significant increase of probabilities in purchasing all plants with labels disclosing the absence of neonicotinoids across all consumer segments.

The finding of a positive and significant effect of information and counterfactual analysis highlight several implications for horticulture industry stakeholders and policy makers. The availability of information on the impact of pesticide use on pollinators may raise consumers’ awareness of the threats posed by the declining pollinator population. This result is particularly important because it shows that public policy can play an important role in improving consumer individual attitudes toward pollinator health and shifting demand toward more environmentally friendly products, especially pollinator friendly alternatives. From a public policy perspective, the objective is to make socially optimal policies related to the use of neonicotinoid insecticides including labeling policies. Policy interventions causing less potential friction within the ornamental plant supply chain are desirable. Given the strong preference for neonic-free product, implementing a government policy protecting pollinators from exposure to pesticides is more favorable to a neonicotinoid ban. Meanwhile, major ornamental horticulture industry stakeholders may be self-motivated to use voluntary labeling strategies disclosing the absence of neonicotinoids to capture the positive consumer surplus.

Methodologically, we demonstrate the practical value of the ICLV model in estimating information treatment effects in DCEs with some degree of complexity. Under the ICLV framework, we directly estimate the information treatment effect ( on individual WTP and conduct statistical testing for comparison of WTP differences between the control and treatment groups. This cannot be achieved in traditional information treatment analysis, which typically run discrete choice models separately by treatments. WTP estimates can be computed for each group, but statistical testing is not possible as two different samples are used. Facing tradeoffs between model richness and computational traceability, we group four different types of neonicotinoid labels into two broad categories (absence vs. presence) in the ICLV model analysis. Further studies should go beyond labeling category and extend this analysis to account for different framing and pesticide use information disclosure format. The significant and positive impact of information treatment is further enriched with a policy counterfactual analysis, under which we explore the improvements in choice probabilities of neonic-free plants across different consumer demographic segments.

While we deliberately restrain our experiments and analysis to identify the impact of pollinator-related information on neonic-free products, an interesting extension for future research would be relaxing the restrictive information message to a general message of environmental benefits and using a complete set of environmental knowledge scale to construct attitudinal indicators. In addition, future research may also consider exploring the impact of information with incentivized DCE to minimize potential hypothetical commitment bias. Findings of the significantly positive increases in WTP for and purchasing probability of neonic-free plants due to information could be inflated in the hypothetical DCE setting. Nonetheless, the hypothetical nature of our results should not overshadow the fact that there is room for improvement in consumer attitudes and preferences with the implementation of conservation policies.

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# Table 1. Summary of attitudinal indicators

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Attitude indicators ()a | Mean rating | | Mann-Whitney test statistic | b | Factor 1 loadingc | Factor 2 loadingc |
| Control | Treatment  (post-treatment) |
| I1. Neonicotinoid pesticides are effective tools to protect plants from major and unwanted pests. | **4.18** | **3.70** | **3.56**  (-value=0.00) | 0.20 | --- | 0.65 |
| I2.I am concerned about the effect of neonicotinoid pesticides on pollinators. | **5.48** | **6.06** | **-6.60**  (-value=0.00) | 0.57 | 0. 82 | --- |
| I3. Use of neonicotinoid pesticides might be a cause of Colony Collapse Disorder (CCD) but I am not worried much about the extinction of bees and other pollinators. | 3.11 | 3.03 | 0.98  (-value=0.33) | 0.18 | --- | 0.80 |
| I4. We may face a pollination crisis in which crop yields begin to fall because of fewer pollinator insects. | **5.73** | **6.16** | **-4.90**  (-value=0.00) | 0.51 | 0.80 | --- |
| I5. Pollination is vitally important to terrestrial ecosystems and to crop production. | **6.29** | **6.43** | **-2.87**  (-value=0.00) | 0.42 | 0.66 | --- |
| I6. I would be willing to accept an increase in my annual taxes of $100 next year to promote pesticides-free practices. | **3.98** | **4.58** | **-4.23**  (-value=0.00) | 0.26 | 0.60 | --- |

Notes: a Participants were asked to rate on a 7-point Likert scale regarding statements about neonicotinoid insecticides and pollinators with 1 indicating *strongly disagree* and 7 indicating *strongly agree*. b : corrected item-total correlations for attitude scale. c Factor loading <0.5 is suppressed from the table.

# Table 2. Attributes and attribute levels used in DCE

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Attribute | Level 1 | Level 2 | Level 3 | Level 4 |
| Plant Type | Impatiens | Marigold | Pentas | --- |
| Neonicotinoid Label | Neonicotinoid Free (text) | Bee Better Certified (logo) | Treated with Neonicotinoids | Protected from Problematic Pests by Neonicotinoids |
| Container Type | Conventional Plastic | Bio-degradable | --- | --- |
| Pricea  (4-inch pot) | $1.15 | $1.65 | $2.49 | $3.99 |

Note: a Price was determined based on local retail outlets (e.g., big box garden stores and independent garden centers). Price was not an attribute in the experimental auction. Participants bid the price they were willing to pay for each item in the auction experiment.

# Table 3. Estimation results from latent variable structural model: full-information maximum likelihood

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Latent Variable Model** | | | | | | | |
| ***Structural Model (1 Equation)*** |  | |  | |  |  | |
| Variables | Coefficient | | Std. Err. | | -stat | -value | |
| Information treatment (τ) | 0.337 | | 0.021 | | 16.300 | 0.000 | |
| Age | 0.004 | | 0.001 | | 6.170 | 0.000 | |
| Male | -0.171 | | 0.020 | | -8.460 | 0.000 | |
| No. of children | 0.058 | | 0.023 | | 2.470 | 0.013 | |
| High education (binary) | -0.078 | | 0.026 | | -2.990 | 0.003 | |
| Income level |  | |  | |  |  | |
| Less than $20,000 | 0.180 | | 0.074 | | 2.420 | 0.015 | |
| $20,000-$39,999 | -0.080 | | 0.036 | | -2.250 | 0.024 | |
| $40,000-$59,999 | 0.030 | | 0.029 | | 1.040 | 0.299 | |
| $60,000-$79,000 | 0.039 | | 0.029 | | 1.360 | 0.174 | |
| $80,000-$99,000 | -0.033 | | 0.035 | | -0.949 | 0.343 | |
| $100,000-119,000 | -0.050 | | 0.042 | | -1.200 | 0.230 | |
| $120,000 and above | -0.074 | | 0.045 | | -1.620 | 0.105 | |
| Rural (binary) | -0.026 | | 0.021 | | -1.270 | 0.206 | |
| Heard of neonicotinoids (binary) | 0.143 | | 0.023 | | 6.350 | 0.000 | |
| Constant | 3.140 | | 0.074 | | 42.200 | 0.000 | |
| ***Measurement Model (4 Equations)*** | | | | | | | |
| Indicator Variables |  | |  | |  |  | |
| I2 | 1.590 | | 0.068 | | 23.500 | 0.000 | |
| I4 | 1.370 | | 0.040 | | 34.400 | 0.000 | |
| I5 | 0.913 | | 0.035 | | 25.800 | 0.000 | |
| I6 | 1.160 | | 0.067 | | 17.200 | 0.000 | |
| **Choice Model** | | | | | | | |
| Impatiens | 1.843 | 0.151 | | 5.590 | | | 0.000 |
| Marigold | 0.771 | 0.140 | | -1.640 | | | 0.102 |
| Pentas | 1.127 | 0.152 | | 0.835 | | | 0.404 |
| Biodegradable\_Impatiens | 0.048 | 0.102 | | 0.469 | | | 0.639 |
| Biodegradable\_Marigold | 0.418 | 0.094 | | 4.430 | | | 0.000 |
| Biodegradable\_Pentas | 0.581 | 0.087 | | 6.680 | | | 0.000 |
| Neonic Free\_Impatiens\_ | 0.332 | 0.056 | | 5.910 | | | 0.000 |
| Neonic Free\_Impatiens\_ | 0.646 | 0.141 | | 4.590 | | | 0.000 |
| Neonic Free\_Marigold\_ | 0.632 | 0.078 | | 8.070 | | | 0.000 |
| Neonic Free\_Marigold\_ | 0.213 | 0.054 | | 3.940 | | | 0.000 |
| Neonic Free\_Pentas\_ | 0.825 | 0.190 | | 4.350 | | | 0.000 |
| Neonic Free\_Pentas\_ | 0.078 | 0.055 | | 1.410 | | | 0.159 |
| Price\_Impatiens | -0.404 | 0.043 | | -9.350 | | | 0.000 |
| Price\_Marigold | -0.223 | 0.040 | | -5.520 | | | 0.000 |
| Price\_Pentas | -0.219 | 0.042 | | -5.220 | | | 0.000 |
| Sigma\_s | 0.658 | 0.245 | | 2.69 | | | 0.007 |
| **Summary statistics** | | | | | | | |
| Number of estimated parameters | 42 | | | | | | |
| Sample size | 6720 | | | | | | |
| Initial log likelihood | -163041.7 | | | | | | |
| Final log likelihood | -50286.82 | | | | | | |
| Likelihood ratio test | 225509.8 | | | | | | |
| Rho-square-bar | 0.691 | | | | | | |
| AIC | 100657.6 | | | | | | |
| BIC | 100943.8 | | | | | | |
| Number of iterations | 1000 | | | | | | |

Notes: The model was estimated using Python BIOGEME software (Bierlaire 2003, Bierlaire 2018).

# Table 4. Marginal WTP estimates

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Plant Attributes | Control Group | | Treatment Group | |
| Mean WTP | 95% CI | Mean WTP | 95% CI |
| Biodegradable\_Impatiens | $0.12\*\*\* | [-0.292, 0.67] | $0.12\*\*\* | [-0.292, 0.67] |
| Biodegradable\_Marigold | $1.87\*\*\* | [1.06, 3.13] | $1.87\*\*\* | [1.06, 3.13] |
| Biodegradable\_Pentas | $2.65\*\*\* | [1.62, 4.35] | $2.65\*\*\* | [1.62, 4.35] |
| Neonic Free\_Impatiens | $5.05\*\*\* | [3.95, 6.46] | $5.65\*\*\* | [4.53, 7.2] |
| Neonic Free\_Marigold | $8.48\*\*\* | [4.18, 13.00] | $10.5\*\*\* | [5.5, 16.2] |
| Neonic Free\_Pentas | $6.17\*\*\* | [-17.2, 8.48] | $8.16\*\*\* | [-25.8, 11] |

Notes: a WTP and confidence intervals were estimated using 100-time random draw of parameters following Bierlaire (2018) procedure. b \*\*\* indicates significance level at 1%.

# Table 5. Observed and counterfactual choice probability for the control group sample

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Demographic segments** | **Absence of Neonicotinoids** **Label** | | | **Presence of Neonicotinoids**  **Label** | | | **Opt-Out Option** | | |
| Observed | Counterfactual |  | Observed | Counterfactual |  | Observed | Counterfactual |  |
| (-value) | (-value) | (-value) |
| Control group sample total | 0.638 | 0.692 | -100.00 | 0.172 | 0.151 | 70.523 | 0.190 | 0.157 | 105.208 |
| (0.260) | (0.273) | (0.000) | (0.182) | (0.184) | (0.000) | (0.096) | (0.101) | (0.000) |
| **Age** |  |  |  |  |  |  |  |  |  |
| Boomers | 0.642 | 0.696 | -66.560 | 0.171 | 0.150 | 45.090 | 0.187 | 0.154 | 67.035 |
|  | (0.261) | (0.275) | (0.000) | (0.182) | (0.185) | (0.000) | (0.096) | (0.102) | (0.000) |
| Gen-X | 0.635 | 0.689 | -67.059 | 0.174 | 0.153 | 45.637 | 0.191 | 0.158 | 67.503 |
|  | (0.263) | (0.277) | (0.000) | (0.184) | (0.187) | (0.000) | (0.097) | (0.102) | (0.000) |
| Millennials | 0.637 | 0.691 | -44.628 | 0.170 | 0.149 | 29.251 | 0.193 | 0.160 | 45.067 |
|  | (0.249) | (0.262) | (0.000) | (0.176) | (0.176) | (0.000) | (0.093) | (0.097) | (0.000) |
| **Income** |  |  |  |  |  |  |  |  |  |
| Low | 0.638 | 0.692 | -58.553 | 0.172 | 0.152 | 39.690 | 0.189 | 0.157 | 58.978 |
|  | (0.262) | (0.276) | (0.000) | (0.183) | (0.186) | (0.000) | (0.096) | (0.102) | (0.000) |
| Middle | 0.643 | 0.697 | -74.821 | 0.170 | 0.149 | 50.538 | 0.187 | 0.154 | 75.372 |
|  | (0.259) | (0.273) | (0.000) | (0.181) | (0.183) | (0.000) | (0.095) | (0.101) | (0.000) |
| High | 0.624 | 0.677 | -43.356 | 0.178 | 0.157 | 29.019 | 0.198 | 0.166 | 43.674 |
|  | (0.258) | (0.271) | (0.000) | (0.182) | (0.184) | (0.000) | (0.095) | (0.100) | (0.000) |
| **Education** |  |  |  |  |  |  |  |  |  |
| Lower than college | 0.645 | 0.700 | -81.535 | 0.169 | 0.147 | 54.845 | 0.186 | 0.153 | 82.186 |
| (0.258) | (0.271) | (0.000) | (0.180) | (0.182) | (0.000) | (0.095) | (0.100) | (0.000) |
| College degree or above | 0.627 | 0.681 | -65.279 | 0.177 | 0.157 | 44.328 | 0.195 | 0.162 | 65.694 |
| (0.263) | (0.277) | (0.000) | (0.184) | (0.187) | (0.000) | (0.096) | (0.102) | (0.000) |
| **Awareness of Neonicotinoids** |  |  |  |  |  |  |  |  |  |
| No | 0.633 | 0.686 | -92.050 | 0.175 | 0.154 | 62.257 | 0.193 | 0.160 | 92.694 |
|  | (0.275) | (0.275) | (0.000) | (0.183) | (0.185) | (0.000) | (0.096) | (0.101) | (0.000) |
| Yes | 0.659 | 0.714 | -49.360 | 0.162 | 0.141 | 33.126 | 0.179 | 0.146 | 49.781 |
|  | (0.255) | (0.268) | (0.000) | (0.177) | (0.180) | (0.000) | (0.094) | (0.100) | (0.000) |

Notes: a). Boomers were born between 1946-1964. Generation X were born between 1965-1980 and Millennials were born between 1981-1996.

# Figure 1. ICLV analysis framework



# Appendix

# Table A1. Participants demographics and ex-ante knowledge about neonics and pollinators

|  |  |  |  |
| --- | --- | --- | --- |
|  | Control | Treatment | test-statistica  (-value) |
| No. of respondents | 420 | 420 | --- |
| Age (mean) | 54.19 | 51.77 | 2.27(0.02) |
| Household size (mean) | 2.90 | 2.66 | 1.01(0.31) |
| Male (%) | 41.19% | 45.00% | -1.11(0.27) |
| Children under 18 in the household (%) | 22.38% | 30.71% | -2.74(0.01) |
| Household income (%) |  |  |  |
| Less than $19,999 | 10.95% | 11.19% | 0.44(0.66) |
| $20,000 – $39,999 | 20.95% | 22.62% |
| $40,000 – $59,999 | 23.10% | 20.71% |
| $60,000 – $79,999 | 14.52% | 18.33% |
| $80,000 – $99,999 | 13.57% | 10.00% |
| $100,000 – $119,999 | 6.90% | 7.86% |
| More than $120,000 | 10.00% | 9.29% |
| Education level (%) |  |  |  |
| Some high school | 1.90% | 1.67% | 0.49(0.62) |
| High school diploma / GED | 19.76% | 15.95% |
| Some college | 25.00% | 22.14% |
| 2 year or Associate’s degree | 13.33% | 15.95% |
| 4 year Bachelor’s degree | 23.10% | 28.33% |
| Some graduate school | 2.86% | 4.52% |
| A graduate or professional’s degree | 14.05% | 11.43% |
| Ethnicity (%) |  |  |  |
| White | 86.90% | 86.67% |  |
| African American | 6.43% | 4.76% | -1.06(0.29) |
| Hispanic | 2.38% | 2.38% |  |
| Asian | 2.38% | 3.33% |  |
| Native American | 0.48% | 0.95% |  |
| Pacific Islander | 0.00% | 0.24% |  |
| Other | 1.43% | 1.67% |  |
| Rural (%) | 31.9% | 33.1% | -0.37(0.71) |
| Subjective knowledge about neonics (mean) | 2.21 | 2.59 | -2.93(0.00) |
| Objective knowledge about pollinator attractive plants (mean) | 1.67 | 1.69 | -0.31(0.76) |

Note: a For continuous demographic characteristics (e.g. age, household size) pairwise t-test was used, while the Mann-Whitney test was used for the categorial variables (e.g., gender, income, education, ethnic groups, etc.) to test the difference between the control and treatment groups.

# Table A2. Sequential estimation results: Latent model followed by choice model

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Latent Variable Model** | | | | | | | |
| Structural Model (1 Equation) |  | |  | |  | |  |
| Variables | Coefficient | | Std. Err. | | -stat | | -value |
| Information treatment (τ) | 0.622 | | 0.051 | | 12.20 | | 0.000 |
| Age | 0.006 | | 0.002 | | 2.85 | | 0.004 |
| Male | -0.291 | | 0.050 | | -5.79 | | 0.000 |
| No. of children | 0.112 | | 0.044 | | 2.53 | | 0.012 |
| High education (binary) | -0.119 | | 0.053 | | -2.24 | | 0.025 |
| Income level |  | |  | |  | |  |
| Less than $20,000 | -0.142 | | 0.066 | | -2.15 | | 0.032 |
| $20,000-$39,999 | 0.053 | | 0.054 | | 0.99 | | 0.322 |
| $40,000-$59,999 | 0.122 | | 0.056 | | 2.18 | | 0.029 |
| $60,000-$79,000 | -0.082 | | 0.067 | | -1.22 | | 0.223 |
| $80,000-$99,000 | -0.100 | | 0.082 | | -1.22 | | 0.222 |
| $100,000-119,000 | -0.094 | | 0.093 | | -1.02 | | 0.310 |
| $120,000 and above | -0.077 | | 0.039 | | -1.98 | | 0.047 |
| Rural | 0.328 | | 0.042 | | 7.84 | | 0.000 |
| Heard of neonicotinoids | 2.940 | | 0.117 | | 25.10 | | 0.000 |
| Constant | 0.622 | | 0.051 | | 12.20 | | 0.000 |
| Measurement Model (4 Equations) | | | | | | | |
| Indicator Variables |  | |  | |  | |  |
| I2 | 0.909 | | 0.042 | | 21.600 | | 0.000 |
| I4 | 0.643 | | 0.034 | | 18.700 | | 0.000 |
| I5 | 0.343 | | 0.044 | | 7.760 | | 0.000 |
| I6 | 0.868 | | 0.163 | | 5.330 | | 0.000 |
| Number of estimated parameters | 26 | | | | | | |
| Sample size | 6720 | | | | | | |
| Initial log likelihood | -483117.1 | | | | | | |
| Final log likelihood | -47387.1 | | | | | | |
| Likelihood ratio test | 871459.9 | | | | | | |
| Rho-square-bar | 0.902 | | | | | | |
| AIC | 94826.2 | | | | | | |
| BIC | 95003.33 | | | | | | |
| Number of iterations | 112 | | | | | | |
| **Choice Model** | | | | | | | |
| Impatiens | 0.880 | 0.166 | | 5.300 | | 0.000 | |
| Marigold | -0.137 | 0.161 | | -0.851 | | 0.395 | |
| Pentas | 0.551 | 0.174 | | 3.160 | | 0.002 | |
| Biodegradable\_Impatiens | 0.098 | 0.112 | | 0.877 | | 0.381 | |
| Biodegradable\_Marigold | 0.259 | 0.109 | | 2.370 | | 0.018 | |
| Biodegradable\_Pentas | 1.000 | 0.137 | | 7.360 | | 0.000 | |
| Neonic Free\_Impatiens\_ | 0.316 | 0.095 | | 3.340 | | 0.001 | |
| Neonic Free\_Impatiens\_ | 0.330 | 0.196 | | 1.680 | | 0.093 | |
| Neonic Free\_Marigold\_ | 0.956 | 0.121 | | 7.870 | | 0.000 | |
| Neonic Free\_Marigold\_ | 0.006 | 0.005 | | 1.310 | | 0.189 | |
| Neonic Free\_Pentas\_ | 1.040 | 0.125 | | 8.320 | | 0.000 | |
| Neonic Free\_Pentas\_ | 0.003 | 0.002 | | 1.280 | | 0.202 | |
| Price\_Impatiens | -0.442 | 0.048 | | -9.180 | | 0.000 | |
| Price\_Marigold | -0.231 | 0.048 | | -4.790 | | 0.000 | |
| Price\_Pentas | -0.635 | 0.119 | | -5.340 | | 0.000 | |
| Sigma\_s | 1.270 | 0.136 | | 9.370 | | 0.000 | |
| Number of estimated parameters | 16 | | | | | | |
| Sample size | 6720 | | | | | | |
| Initial log likelihood | -7382.68 | | | | | | |
| Final log likelihood | -5212.87 | | | | | | |
| Likelihood ratio test | 4339.61 | | | | | | |
| Rho-square-bar | 0.292 | | | | | | |
| AIC | 10457.74 | | | | | | |
| BIC | 10566.74 | | | | | | |
| Number of iterations | 68 | | | | | | |

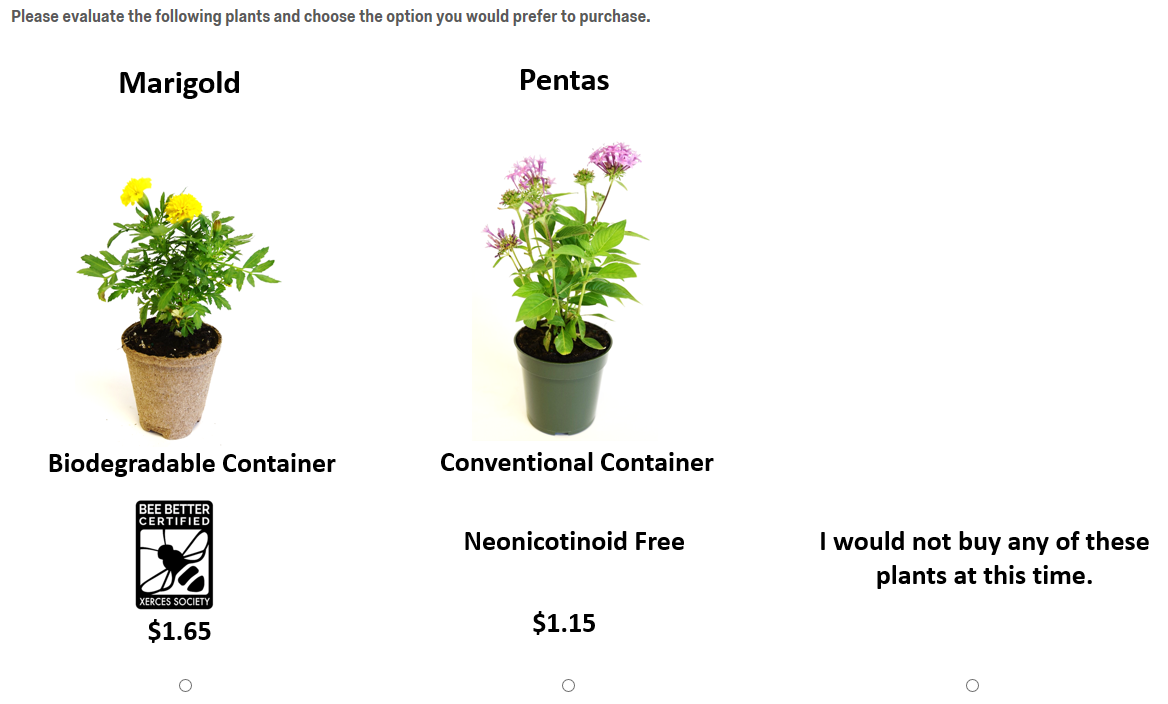
Notes: The model was estimated using Python BIOGEME software (Bierlaire 2003, Bierlaire 2018).

# Table A3. Observed and counterfactual probability of choosing individual plants with neonic-free labels

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Demographic segments** | **Neonic Free\_Impatiens** | | | **Neonic Free\_Marigold** | | | **Neonic Free\_Pentas** | | |
| Observed(S.D.) | Counterfactual (S.D.) | -test | Observed(S.D.) | Counterfactual(S.D.) | -test | Observed(S.D.) | Counterfactual(S.D.) | -test |
| (-value) | (-value) | (-value) |
| **Control group sample total** | 0.239 | 0.242 | -6.712 | 0.284 | 0.301 | -23.814 | 0.286 | 0.300 | -18.290 |
| (0.300) | (0.314) | (0.000) | (0.266) | (0.302) | (0.000) | (0.268) | (0.303) | (0.000) |
| **Age** |  |  |  |  |  |  |  |  |  |
| Boomers | 0.239 | 0.242 | -4.142 | 0.286 | 0.303 | -15.138 | 0.288 | 0.301 | -11.828 |
|  | (0.301) | (0.315) | (0.000) | (0.269) | (0.305) | (0.000) | (0.270) | (0.305) | (0.000) |
| Gen-X | 0.244 | 0.247 | -4.120 | 0.283 | 0.300 | -15.593 | 0.282 | 0.295 | -11.865 |
|  | (0.301) | (0.315) | (0.000) | (0.266) | (0.302) | (0.000) | (0.268) | (0.302) | (0.000) |
| Millennials | 0.225 | 0.229 | -3.410 | 0.284 | 0.301 | -9.722 | 0.297 | 0.310 | -7.325 |
|  | (0.296) | (0.309) | (0.001) | (0.260) | (0.296) | (0.000) | (0.262) | (0.297) | (0.000) |
| **Income** |  |  |  |  |  |  |  |  |  |
| Low | 0.241 | 0.244 | -3.572 | 0.284 | 0.301 | -13.473 | 0.285 | 0.298 | -10.364 |
|  | (0.301) | (0.315) | (0.000) | (0.267) | (0.303) | (0.000) | (0.269) | (0.303) | (0.000) |
| Middle | 0.237 | 0.240 | -4.756 | 0.286 | 0.303 | -16.902 | 0.290 | 0.303 | -13.234 |
|  | (0.301) | (0.315) | (0.000) | (0.268) | (0.304) | (0.000) | (0.270) | (0.305) | (0.000) |
| High | 0.240 | 0.243 | -3.146 | 0.280 | 0.297 | -9.989 | 0.294 | 0.294 | -7.198 |
|  | (0.297) | (0.311) | (0.002) | (0.258) | (0.293) | (0.000) | (0.260) | (0.294) | (0.000) |
| **Education** |  |  |  |  |  |  |  |  |  |
| Lower than college | 0.234 | 0.237 | -5.191 | 0.287 | 0.304 | -18.252 | 0.292 | 0.306 | -14.388 |
| (0.301) | (0.314) | (0.000) | (0.269) | (0.305) | (0.000) | (0.270) | (0.306) | (0.000) |
| College degree or above | 0.246 | 0.249 | -4.255 | 0.281 | 0.298 | -15.298 | 0.279 | 0.291 | -11.289 |
| (0.300) | (0.314) | (0.000) | (0.262) | (0.298) | (0.000) | (0.264) | (0.298) | (0.000) |
| **Awareness of Neonicotinoids** |  |  |  |  |  |  |  |  |  |
| No | 0.242 | 0.245 | -6.001 | 0.282 | 0.300 | -21.268 | 0.283 | 0.296 | -15.966 |
|  | (0.300) | (0.314) | (0.000) | (0.264) | (0.299) | (0.000) | (0.266) | (0.300) | (0.000) |
| Yes | 0.228 | 0.231 | -3.001 | 0.292 | 0.308 | -10.723 | 0.301 | 0.315 | -8.921 |
|  | (0.302) | (0.315) | (0.003) | (0.275) | (0.311) | (0.000) | (0.094) | (0.312) | (0.000) |

Notes: Boomers were those born between 1946-1964. Generation X were born between 1965-1980 and Millennials were born between 1981-1996.

# Figure A1: Sample choice set from the online survey



1. Given the fact that we had three annual bedding plants, four neonicotinoid labels, two container types, four price levels and participants were only shown two different plants in one choice scenario to choose from, a full factorial design would produce a total of 3072 =choice scenarios. [↑](#footnote-ref-1)
2. There were six statements regarding participants’ attitudes toward neonicotinoids and pollinators. Based on the corrected item-total correlations and principal factor analysis, Indicators , , , and were selected for the model. [↑](#footnote-ref-2)
3. The sales ranking for impatiens, marigold and pentas are the 5th, 7th and 25th respectively according to sales values reported in the 2014 USDA NASS Survey results. [↑](#footnote-ref-3)