Willingness to Pay or Not to Pay: Valuing Foods Some Respondents Find Distasteful

Jiahui Ying  
Department of Agricultural and Applied Economics  
University of Georgia: JiahuiYing@uga.edu

Vanessa P. Shonkwiler  
Center for Agribusiness & Economic Development  
University of Georgia: v.shonkwiler@uga.edu

Benjamin Campbell  
Department of Agricultural and Applied Economics  
University of Georgia: bencamp@uga.edu

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Abstract

Understanding consumers’ preference and the segment of markets is crucial for agricultural marketing strategies, especially for specialty or exotic food markets like the pepper market. By adopting a random effect indicator for respondents who have never purchased hot peppers before in the mixed logit model, this paper was able to distinguish the potential distaste of these “non-consumers” instead of just assuming them with a neutrality attitude. With an online discrete choice survey of 181 effective respondents in Connecticut, the empirical analysis shows non-consumers’ utility is decreased significantly with hot pepper consumptions, implying their distaste on hot peppers. The result also reveals respondents’ strong preference for the Locally produced peppers and their dislike of genetically modified organisms (GMO) peppers. Also, consumers’ strong belief in Local food is likely to lower their satisfaction toward Organic food, especially when information on the genetically modified material is also provided.

Key words: Non-consumers, Willingness to Pay, Mixed Logit Models, Hot Peppers, Local Food, Genetically Modified Organisms (GMO), Organic
Introduction

While considerable research has been devoted to eliciting willingness to pay (WTP) for a wide range of attributes of a variety of foods, little research has been devoted to placing a value on foods with which consumers are unfamiliar or foods which some consumers may actually dislike.

Today, differentiation is one of the most successful marketing strategies for agribusinesses navigating in a very competitive landscape. The food marketing sector is responding to an increased level of consumer interest in products with an increasingly wide array of attributes. However, one size does not fit all consumers when it comes to food attributes.

Recent papers have examined consumer preferences and willingness to pay for specialty or exotic foods with the objective of measuring consumer preferences for certain characteristics of the foods and the products themselves. Developing value-added products or growing specialty crops not only offers a way to develop a niche market and may also generates premiums for growers. The choice in terms of specialty product, labeling, certification and type of outlet, just to mention a few marketing elements, is wide.

Targeting the “right” consumers is a core part of marketing. What is to be done when the respondents in a choice experiment may have little to no intention of buying exotic or ethno-cultural food being considered? How does one characterize the market potential and separate the indecisive respondents from the definite non-buyers?

This study aims to identify consumer attitudes toward the consumption of fresh peppers—namely Bell, Jalapeno, Chili, and Habanero peppers (the latter three are termed herein as hot peppers). It is unique in the sense that both certain characteristics of the peppers and the peppers themselves are valued. This study has two objectives: 1. To determine attributes for which respondents have
a higher willingness to pay; and 2. To determine whether there is a segment of respondents who are either unfamiliar and neutral with the products or, on the contrary, who are definite non-buyers due to actual or perceived dislike for the products.

Background and hypotheses

The U.S. production and trade statistics aggregate hot peppers in a broad category called “chile peppers”. Since 2000, U.S. production of hot peppers decreased from 653.9 Mlbs to 403.4 Mlbs in 2015, continuing a downward trend that dates back to the early nineties. Comparatively, the country has been producing over 1,515.5 Mlbs of bell peppers (2015). Most of the country’s production of chile peppers originates from California and New Mexico, 63% and 31% respectively. The largest U.S. import supplier of chile peppers (fresh-market) is Mexico (804.7 Mlbs in 2013).

With the rapid increase of the Hispanic population in North America and the increase in the popularity of Mexican and Southwest-style cooking, consumption of hot peppers has been growing in the U.S. market (US Aid- Acceso, 2014). For the American population in general, the habanero's heat, its flavor, and its floral aroma have made it a popular ingredient in hot sauces and spicy foods. According to the USDA, approximately 41% of US hot pepper production goes to the fresh market while the remainder is used for processed products such as salsa, frozen entrees, and appetizers. Varieties such as jalapeno and chili peppers are ubiquitous at most large supermarkets. However, habaneros are often considered specialty peppers and they are more difficult to find. Importantly, for many North American consumers, fresh hot peppers are too pungent and thus, remain an unexplored domain. Therefore, market trends for particular types of hot peppers such as the habanero are difficult to pinpoint.
Consumers’ perceptions, preferences and WTP are influenced by the product’s intrinsic attributes as well as by extrinsic indicators and cues provided by the seller of the product (Caswell et al., 2002). Foods can be classified as search, experience and credence goods according to the level of quality that can be discovered by the consumer at different stages (Nelson, 1970; Darby and Karni, 1973; followed by Sloof, Tijskens, and Wilkinson (1996)). Unlike search attributes (e.g. price, size, colour) and experience attributes (e.g. taste, firmness, durability) which can be observed during purchase or determined after consumption, respectively, credence attributes (e.g. healthiness, mode of production, origin) are less apparent and involve a high level of uncertainty from the consumers' perspective (Botelho et al., 2017). As pointed out by Napolitano et al. (2010), credence attributes are extrinsic and must be communicated to be perceived by consumers as they cannot be confirmed either before or after purchase. The provision of information may therefore increase consumers' awareness and expectations, and probably impact their willingness to pay (WTP) for products with specific intangible attributes.

Results from recent economic research on these different attributes have suggested that consumers are willing to pay price premiums for produce with specific production practices, such as organic produce (Goldman and Clancy, 1991; Yiridoe, Bonti-Ankomah and Martin, 2005; Batte et al., 2007; Haghiri et al., 2009), for a “locally-grown” crop (Patterson et al., 1999; Jekanowski, Williams and Schiek, 2000; Brown, 2003; Giraud et al., 2005; Darby et al., 2008; Carpio et al., 2009; Onken and Bernard 2010), or for a label indicating the absence of genetically engineered material (McFadden and Lusk, 2017). Most of the studies would actually compare these attributes to one another (Loureiro and Hine, 2002; Thilmany et al., 2008; Adams and Salois, 2010; James et al., 2009; Yue and Tong, 2009; Bernard and Bernard, 2010; Onozaka et McFadden, 2011; Onken et al., 2011; Campbell et al., 2014; Chen, Gao and House, 2015, McFadden and Huffman, 2017).
These studies convey one general idea on consumer behavior when purchasing produce; consumers tend to be guided by the combination of “locally grown” and organic as opposed to an unknown origin and conventional production practice. Results even show that the attribute “local” is increasing in relevance when compared to organic, certification, and origin (Moser et al., 2011). It also appears that younger, wealthier and well educated individuals are more likely to be willing to pay a premium for these labels.

Beyond these attributes, recent literature has been focusing on niche products for which their market has been growing substantially. Two recent papers have examined consumer preferences for these exotic foods: Grebitus, Peschel, and Hughner (2016) for Medjool dates and Kapllani, House, and Guan (2016) for pomegranates. Both studies had the objective of measuring consumer preferences for certain characteristics of the produce but also the preferences for the produce itself. Overall, results on pomegranates show that consumers respond to region of origin and production method labelling such as “organic”. Surprisingly enough, results on dates show that consumers from Arizona State are not willing to pay a larger premium for dates grown in Arizona but rather they would give their preference to a State with a “reputation” in growing produce like California.

These credence attributes are proven more difficult to evaluate precisely as it opens the doors to consumers’ misperceptions (Lee and Yun, 2015). Several studies underline a somewhat contradictory response of consumers in terms of judging the importance of attributes (Moser and al., 2011). For example, US consumers perceive pesticide free and organic differently, and second, organic claims are only somewhat important. McFadden and Lusk (2017) recently pointed out that in presence of a non-GM material label, organic is not necessarily valued i.e., consumers are not willing to pay more for both labels as their perception is that organic does not include GM material.
Although, in most studies on agricultural products and/or specialty crops, only actual buyers’ behavior was studied. No information was provided about the characterization of a potential attractiveness and willingness to pay from non-buyers for the specialty product itself. In their study, Dost et al. (2014) offered a novel targeting approach which recommended prioritizing indecisive buyers and they validated their claim with a large-scale experiment conducted in the context of a consumer engagement campaign that includes observed purchase behavior (i.e., choice of the advertised item).

Data

An online survey was administered in Fall 2015 whereby 760 consumers from Connecticut completed a survey on their purchasing habits of ethno-cultural vegetables, including different varieties of peppers. A total of 200 consumers were randomly selected to complete the pepper portion of the survey, and 181 respondents fully finished the survey. The survey was focused on Connecticut residents for several reasons, notably due to the funding agency’s interest in the Connecticut market. Furthermore, unlike many other states, Connecticut has a stricter definition (i.e., produced within the state or 10 miles from point of purchase) around the use of the term local.

Summary statistics on demographic characteristics of the 181 respondents is provided in Table 1 with a comparison to the Connecticut state data from the 2010 census. The survey sample was representative of the Connecticut population with respect to age, race, family size in general. While still some differences are observed especially the higher percentage of female in our sample, which may potentially due to women’s higher enthusiasm in the daily purchase and thus results in a higher response rate in consumption surveys. To this extent, our sample is more representative for
Caucasians, higher educated and relatively elder respondents who would be more likely to participate in household purchasing decisions.

Table 1. Demographic Characteristics of the Sample and Connecticut

<table>
<thead>
<tr>
<th></th>
<th>Connecticut</th>
<th>Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>49%</td>
<td>33%</td>
</tr>
<tr>
<td>Female</td>
<td>51%</td>
<td>67%</td>
</tr>
<tr>
<td>Age</td>
<td></td>
<td></td>
</tr>
<tr>
<td>19-34</td>
<td>24%</td>
<td>22%</td>
</tr>
<tr>
<td>35-64</td>
<td>57%</td>
<td>50%</td>
</tr>
<tr>
<td>65+</td>
<td>19%</td>
<td>28%</td>
</tr>
<tr>
<td>Race</td>
<td></td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>78%</td>
<td>88%</td>
</tr>
<tr>
<td>African American</td>
<td>10%</td>
<td>4%</td>
</tr>
<tr>
<td>Asian</td>
<td>4%</td>
<td>4%</td>
</tr>
<tr>
<td>Other</td>
<td>8%</td>
<td>3%</td>
</tr>
<tr>
<td>Education</td>
<td></td>
<td></td>
</tr>
<tr>
<td>High school graduate or higher</td>
<td>90%</td>
<td>99%</td>
</tr>
<tr>
<td>Bachelor's degree or higher</td>
<td>38%</td>
<td>44%</td>
</tr>
<tr>
<td>Average Household Size</td>
<td>2.56</td>
<td>2.75</td>
</tr>
</tbody>
</table>

Choice Experiment

A Choice Experiment (CE) was designed to reveal consumers’ attitude towards specific attributes and the type of peppers in their consumption. CE is an efficient method to investigate trade-offs between several competing product attributes and to determine the relative importance of various attributes in consumers’ choice process (Hanemann and Kanninen, 2001).

In our design, each participant was given ten questions via the Qualtrics software platform. For each type of pepper (bell, chili, habanero and jalapeno), attributes were varied and included: organic, genetically modified organisms (GMO), locally (Connecticut) produced, and imported. Prices of the peppers varied from $1.99 per pound to $5.99 per pound. A summary of the attributes and levels adopted in our survey is listed in Table 2.
Table 2. Attributes (Levels) and Types of Pepper in Choice Experiment

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product Method</td>
<td>Organic</td>
</tr>
<tr>
<td></td>
<td>No Information (base)</td>
</tr>
<tr>
<td>Genetically modified</td>
<td>GMO</td>
</tr>
<tr>
<td>organisms</td>
<td>Non-GMO / No Information (base)</td>
</tr>
<tr>
<td>Product Origin</td>
<td>Connecticut</td>
</tr>
<tr>
<td></td>
<td>Imported (South Asia, Mexico, or Central/South America)</td>
</tr>
<tr>
<td></td>
<td>United States (base)</td>
</tr>
<tr>
<td>Price Per lb</td>
<td>$1.99; $2.99; $3.99; $4.99; $5.99</td>
</tr>
<tr>
<td>Type</td>
<td>Bell Pepper</td>
</tr>
<tr>
<td></td>
<td>Chili Pepper</td>
</tr>
<tr>
<td></td>
<td>Habanero Pepper</td>
</tr>
<tr>
<td></td>
<td>Jalapeno Pepper</td>
</tr>
</tbody>
</table>

SAS software was used to create the experiment design. For every question, four alternatives with different combinations of attribute levels and pepper types were provided. At the same time, the respondent was provided with a fifth category of “None of the above”; in other words, a non-purchase option. A sample question is provided in Figure 1.

Figure 1. Sample Choice Set in the Choice Experiment

Additionally, respondents were asked if they had ever consumed habanero or chili peppers in their daily life. Of the 181 respondents completing the survey, only 29 percent and 44 percent, respectively, claimed to have (See Figure 2). In contrast, for the most common bell pepper, 80 percent respondents claimed to have consumed it before. Clearly this raises the question as to whether the non-consumers are unfamiliar (neutral) with the products or have a distaste for them.
To some extent, this is answered by the result that fully 36 participants (20 percent) chose the “None of the above” option—as opposed to one of the four types of peppers—for every one of the ten valuation questions. Thus, our analysis must address the fact that there are respondents who did not choose any pepper under any scenario offered in the choice experiment.

**Methodology**

We specify a mixed (random parameter) logit model to account for the dataset’s feature that majority consumers have no purchase experience with hot peppers in which we are interested in. Following the approach of Walker, Ben-Akiva, and Bolduc (2007), an error component is assigned to the “None of the above” alternative. In a normal error component logit mixture, a randomly distributed normal variable is associated with the alternative as opposed to modifying the parameter on an explanatory variable. This treatment of the “None of the above” alternative essentially accounts for variability occasioned by a large number of choices (48 percent) of this alternative by all respondents.

Because we consider the type of pepper is an attribute as much as the attributes associated with type of production and origin, we can infer a WTP for each type of pepper by dividing its attribute
coefficient by the price coefficient. We assume that those respondents identifying themselves as non-consumers are qualitatively different from pepper consumers and therefore introduce a random dummy variable for non-consumers for each type of hot pepper (habanero, chili, and jalapeno).

Additionally, respondents were not queried regarding their consumption of jalapeno peppers, so we will use the chili pepper response as a proxy of their consumption of jalapenos. We discuss a consequence of this approach in the result section. By specifying these three dummy variables as random we are implicitly trying to capture the variability that would occur if some non-consumers are unfamiliar with hot peppers (and perhaps curious) or if the non-consumer has a distaste for hot peppers (and will never purchase any). Thus, we hypothesize that these dummy variables will not be statistically significantly different than zero if the non-consumer is unfamiliar and neutral towards hot peppers, and will be significantly less than zero if the non-consumer harbors a dislike for hot peppers.

More specifically, the three non-consumer dummy variables, together with the variable “None of the above” alternative (the fifth alternative) in each question, construct a multivariate normal distribution such as:

\[
\begin{pmatrix}
I_{\text{none of the above}} \\
I_{\text{Habanro-NC}} \\
I_{\text{Chili-NC}} \\
I_{\text{Jalpno-NC}}
\end{pmatrix} \sim N_4 \left( \begin{pmatrix} 0 \\ \beta_{\text{Habanro-NC}} \\ \beta_{\text{Chili-NC}} \\ \beta_{\text{Jalpno-NC}} \end{pmatrix}, \begin{bmatrix} \sigma_0^2 & \sigma_1^2 & 0 \\ \sigma_1^2 & \sigma_2^2 & \sigma_0^2 \\ 0 & \sigma_2^2 & \sigma_3^2 \end{bmatrix} \right)
\]

Here \( I() \) denotes an indicator variable and \( N/C \) denotes a non-consumer.

Then the utility individual \( i \) would obtain from choosing alternative \( t \) in question \( j \) could be expressed as
\[ U_{ijt} = \beta_{price} Price_{ijt} + \beta_{GMO} GMO_{ijt} + \beta_{Organic} Organic_{ijt} + \beta_{CT} CT_{ijt} + \beta_{Imported} Imported_{ijt} \]
\[ \quad + \beta_{Habnro} Habnro_{ijt} + (\beta_{Habnro-N/C} I_{Habnro-N/C})_{ijt} + \sigma_1 \epsilon_1 \]
\[ \quad + \beta_{Chilli} Chilli_{ijt} + (\beta_{Chilli-N/C} I_{Chilli-N/C})_{ijt} + \sigma_2 \epsilon_2 \]
\[ \quad + \beta_{jalpno} Jalpno_{ijt} + (\beta_{jalpno-N/C} I_{jalpno-N/C})_{ijt} + \sigma_3 \epsilon_3 \]
\[ \quad + \epsilon_{ijt} \]

Where \( i \in [1, \ldots, 181] \), \( j \in [1, \ldots, 10] \), \( t \in [1, \ldots, 5] \).

The random part of non-consumers’ coefficients is defined to follow a standard normal distribution \( \epsilon_k \sim N(0, 1) \), \( k=1,2,3 \). And the error terms of the utility function are independently and identically distributed as standard (Gumbel) extreme value \( \epsilon_{ijt} \sim EV(0,1) \).

Under this form, the probability that consumer \( i \) chooses alternative \( t \) in question \( j \) is:

\[
P_{ijt} = \int_{\mu} \frac{\exp(U_{ijt})}{\sum_{i=1}^{5} \exp(U_{ijt})} \frac{\exp(-\frac{1}{2}E \Sigma^{-1} E')}{(2\pi)^{4/2}|\Sigma|^{1/2}} \, d\epsilon_1 \ldots d\epsilon_3
\]

Where \( E=[\epsilon_1 \ldots \epsilon_3] \) and \( \Sigma \) is the variance-covariance matrix of \( E \).

Usually, mixed logit models are estimated through maximum simulated likelihood (MSL), although it should be noted that MSL estimators incur simulation errors including both simulation bias and simulation noise (Train, K. E., Chapter 10, 2009). Previous research also showed that increase in the number of draws does not guarantee the resulting estimator is closer to the true model in an empirical setting (Czajkowski and Budzinski, 2017). This is because random draws in MSL are generated without any specific order, direction, or range.
As an alternative to MSL, we employ the Gauss-Hermite (G-H) quadrature approach in the estimation of the mixed logit model with repeated choices and with uncorrelated random parameters. In a recent paper, Shonkwiler and Ying (2018) extend the Gauss-Hermite integration method that was first introduced by Breffle et al. (2005) in the estimation of a Probit choice model. We briefly outline this approach in Appendix 1.

Results

*Estimation of Utility Function through Mixed Logit Model*

The exact maximum likelihood estimation result of the utility function with the Gauss-Hermite Integration is presented in Table 3. Our results largely confirms our expectations. First, estimated coefficients for all attributes are highly significant (p<0.01) except for Organic, indicating the important effect of these attributes in deciding consumer’s utility from pepper consumption. Second, the coefficient of Price is significantly negative, the same with coefficients of GMO and Imported, reflecting the decreasing effect of the three attributes towards consumers’ utility. In contrast, Connecticut obtains a significant positive coefficient, showing its important role in enhancing consumers’ utility from peppers consumptions. Regarding the type of peppers, consumers who once purchased those peppers before have significantly positive coefficients for all the four types of peppers, showing the positive utility they would gain from pepper consumption. However, non-consumers’ coefficients towards the three hot peppers are all significantly negative, meaning their utility would be decreased if they purchase hot peppers.
Table 3. Mixed Logit Model Estimators of the Utility Function with G-H Integration  
(Evaluation Points = 21312, LLF=-1587.1)

<table>
<thead>
<tr>
<th></th>
<th>Estimate</th>
<th>Std.Err.</th>
<th>z-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>-0.5847</td>
<td>0.0346</td>
<td>-16.922***</td>
</tr>
<tr>
<td>GMO</td>
<td>-0.7254</td>
<td>0.1441</td>
<td>-5.034***</td>
</tr>
<tr>
<td>Organic</td>
<td>-0.0029</td>
<td>0.102</td>
<td>-0.028</td>
</tr>
<tr>
<td>Connecticut Grown</td>
<td>0.5287</td>
<td>0.1162</td>
<td>4.549***</td>
</tr>
<tr>
<td>Imported</td>
<td>-1.344</td>
<td>0.114</td>
<td>-11.793***</td>
</tr>
<tr>
<td>Habanero</td>
<td>1.7794</td>
<td>0.3565</td>
<td>4.991***</td>
</tr>
<tr>
<td>Chili</td>
<td>2.077</td>
<td>0.3508</td>
<td>5.921***</td>
</tr>
<tr>
<td>Bell</td>
<td>2.4626</td>
<td>0.3386</td>
<td>7.274***</td>
</tr>
<tr>
<td>Jalapeno</td>
<td>2.421</td>
<td>0.3475</td>
<td>6.967***</td>
</tr>
<tr>
<td>Habanero N/C</td>
<td>-2.0408</td>
<td>0.3588</td>
<td>-5.687***</td>
</tr>
<tr>
<td>Chili N/C</td>
<td>-1.9733</td>
<td>0.3502</td>
<td>-5.635***</td>
</tr>
<tr>
<td>Jalapeno N/C</td>
<td>-2.9642</td>
<td>0.5078</td>
<td>-5.837***</td>
</tr>
<tr>
<td>Sigma “None of the above”</td>
<td>3.0829</td>
<td>0.2980</td>
<td>10.346***</td>
</tr>
<tr>
<td>Sigma Habanero N/C</td>
<td>1.7365</td>
<td>0.3153</td>
<td>5.5080***</td>
</tr>
<tr>
<td>Sigma Chili N/C</td>
<td>1.2796</td>
<td>0.3178</td>
<td>4.0260***</td>
</tr>
<tr>
<td>Sigma Jalapeno N/C</td>
<td>2.0718</td>
<td>0.4451</td>
<td>4.6550***</td>
</tr>
</tbody>
</table>

Note: 1) N/C means non-consumers  
2) * means significant at 10% level, ** means significant at 5% level, *** means significant at 1% level.

Further, standard deviations of the random components in non-consumers’ dummy variables are all significantly greater than zero (p<0.01), as is also the standard deviation of the error component associated with the “None of the above” alternative. Note that the estimated standard error for Jalapeno non-consumers (Sigma Jalapeno N/C) is larger than that for non-consumers of the other hot peppers. This likely reflects the fact that we do not actually observe consumption of jalapenos since we used the non-consumption of chili peppers as a proxy for jalapenos.

**Willingness to Pay for Attributes and Type of Hot Peppers**

To further investigate consumers’ evaluation for each attribute, we calculate their willingness to pay (WTP) to capture the highest monetary value consumers would like to pay for a certain
attribute or a certain type of pepper. Usually, the (negative of the) price coefficient is interpreted as the marginal utility of income, so the WTP for a certain attribute can be obtained by dividing the coefficient of this attribute over the (negative of the) coefficient of price. At the same time, the variance of WTP can be calculated through the Delta method to show the variation in consumer’s WTP. Specific calculation formulas are provided in Appendix 2.

With these algorithms, consumer’s willingness to pay for each attribute and corresponding standard error are shown in Table 4.

<table>
<thead>
<tr>
<th>Attributes</th>
<th>WTP ($)</th>
<th>95% CI of WTP ($)</th>
<th>Std.Err. of Mean WTP</th>
<th>z-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>GMO</td>
<td>-1.2406</td>
<td>[-1.7490, -0.7322]</td>
<td>0.2594</td>
<td>-4.7827***</td>
</tr>
<tr>
<td>Organic</td>
<td>-0.0050</td>
<td>[-0.3468, 0.3368]</td>
<td>0.1744</td>
<td>-0.0284</td>
</tr>
<tr>
<td>Connecticut Grown</td>
<td>0.9042</td>
<td>[0.5171, 1.2913]</td>
<td>0.1975</td>
<td>4.5784***</td>
</tr>
<tr>
<td>Imported</td>
<td>-2.2986</td>
<td>[-2.7363, -1.8609]</td>
<td>0.2233</td>
<td>-10.2938***</td>
</tr>
<tr>
<td>Habanero</td>
<td>3.0433</td>
<td>[1.9018, 4.1848]</td>
<td>0.5824</td>
<td>5.2254***</td>
</tr>
<tr>
<td>Chili</td>
<td>3.5522</td>
<td>[2.4662, 4.6382]</td>
<td>0.5541</td>
<td>6.4108***</td>
</tr>
<tr>
<td>Bell</td>
<td>4.2117</td>
<td>[3.1758, 5.2476]</td>
<td>0.5285</td>
<td>7.9692***</td>
</tr>
<tr>
<td>Jalapeno</td>
<td>4.1406</td>
<td>[3.0659, 5.2153]</td>
<td>0.5483</td>
<td>7.5517***</td>
</tr>
<tr>
<td>Habanero N/C</td>
<td>-0.4471</td>
<td>[-1.9416, 1.0474]</td>
<td>0.7625</td>
<td>-0.58632</td>
</tr>
<tr>
<td>Chili N/C</td>
<td>0.1774</td>
<td>[-1.2518, 1.6066]</td>
<td>0.7292</td>
<td>0.24322</td>
</tr>
<tr>
<td>Jalapeno N/C</td>
<td>-0.9290</td>
<td>[-2.6203, 0.7623]</td>
<td>0.8629</td>
<td>-1.07663</td>
</tr>
</tbody>
</table>

Note: 1) N/C means non-consumers
2) * means significant at 10% level, ** means significant at 5% level, *** means significant at 1% level.

Discussion

Surprisingly, the attribute Organic is insignificant in consumers’ utility with a WTP close to zero ($-0.005). One may assume consumers’ utility on pepper consumption to be enhanced with Organic certifications since Organic food is generally believed to have a higher nutritional content (Lea and Worsley, 2005) and is supposed to be more environmentally friendly (Goldman and Clancy, 1991) in terms of production practice. However, deeper investigation in literature shows
such a “contradictory” result is not uncommon, especially when attributes *Local* and *GMO* are also available in the choice set. For example, James *et al.*, (2009) show that consumers were willing to pay *more for locally* grown applesauce compared to applesauce that was labeled USDA organic, low fat, or no sugar added. Costanigro *et al.*, (2011) find that for fresh apples the value of the “*Local*” label *trumps* that of “*Organic*” regardless of model specification and experiment design. Such conclusion is also consistent with previous research involving other produces (Loureiro and Hine, 2002; Onozaka *et al.*, 2010). Similarly, Wirth *et al.*, (2011) found the production method—organic *versus* conventional—had no significant impact on consumers’ preference of apple consumption, while *Local* (Pennsylvania-grown) was statistically significant in consumers’ apple preference. Also, Moser *et al.*, (2011) compare 40 publications and show that the attribute *Local* is increasing in relevance when compared to organic, certification and origin in the U.S. In terms of the *GMO* attribute, McFadden and Lusk (2017) find that participants perceive the *Non-GMO* Project verified and *Organic* label as *substitutes*, since the Willingness to Pay (WTP) premiums for a product with both *Non-GMO* Project verified and *Organic* labels is about the same as the WTP premium when either label is present in isolation. Our study verified the finding that consumers’ sensitivity towards *Organic* would be largely reduced if either *GMO* or *Local* label is also provided. We suppose it illustrates well the substitution effect between *Organic*, *Local*, and *GMO* label (i.e. consumers may assume overlaps between Organic and other labels, and thus don’t want to pay for both labels with similar effect) and somewhat, the consumers’ misperception on *Organic* (i.e., lack of precise knowledge on Organic).

In contrast, the attribute *Connecticut-Grown* is highly significant and positive in the utility function, corresponding to a WTP premium of $0.90 that is significantly higher than zero. This value is on a similar scale with other studies’ estimation (i.e., Darby *et al.*, (2008) find WTP
premium for strawberry by direct market shoppers is $0.92). The popularity of Local attributes has been verified in a lot of studies, suggesting local products are believed to be fresher and better tasting, safer and easier to trace back, healthier, more environmental friendly, and they may enhance the trust of consumers who personally know the producers of their fruit and vegetables (Midmore et al., 2005; Rodriguez-Ibeas, 2007; Thilmany et al., 2008; Moser et al., 2011, Feldmann and Hamm, 2015). The State of Connecticut has a strict definition of the term Local, i.e. “Only farm products grown and eggs produced in Connecticut shall be advertised or sold in Connecticut as “Connecticut-Grown”. Farm products grown and eggs produced within a ten-mile radius of the point of sale for such farm products or eggs may be advertised or sold in Connecticut as ‘Native’, ‘Native-Grown’, ‘Local’, or ‘Locally-Grown’” (Connecticut Department of Agriculture, 2016). Such a stricter\(^1\) regulation would further enhance consumers trust on the Local attribute. At the same time, local food was not perceived as being more expensive per se (Brown, 2003; Conner et al., 2010; Sirieix, et al., 2011; Weatherell et al., 2003), which may lead to more favourable attitudes compared to organically produced food.

Correspondingly, Imported is observed to have a significant negative WTP premium of $-2.30. Such a loss of utility with imported food may be due to consumers perception that domestic products are either associated with higher quality (Loureiro and Umberger, 2003; Chambers et al., 2007) or would support protectionism, or because of consumers’ ethnocentrism (Lusk and Anderson, 2004). In general, our WTP for Imported is much higher in absolute value than that in other literature concerning “common” produce such as apples or tomatoes (e.g. Onozaka and Mcfadden, 2011). We think the respondents’ higher unfamiliarity towards the three hot peppers

\(^1\)Usually the definition of local food refers to distances ranges from 10 to 30 miles up to 100 miles (Adams and Adams, 2011; Chambers et al., 2007; Hu et al., 2010; Khan & Prior, 2010; Wageli and Hamm, 2013)
may further enhance their concern on food quality and induce a higher WTP premium loss for Imported factor.

GMO also has a significant negative impact on respondents’ utility function and the WTP premium is significantly less than zero ($-1.24). Such a high sensitivity towards GM product has also been found in previous studies. For example, Huffman et al., (2003) conclude participants in the experiment discounted GM-labeled food by approximately 14% in their WTP relative to their standard-label counterparts. Bernard and Gifford (2006) verify that both Non-GM and Organic labeling strategies have significant positive WTP premiums among respondents. Additionnally, our results show a differentiated sensitivity of respondents to GMO relative to Organic depending on their consumption, which has scarcely been emphasized in previous studies (such as Bernard and Gifford, 2006; McFadden and Lusk, 2017). We think the simultaneous appearance of the three attributes (GMO, Organic and Local) all together, and the fact that our survey provided both GMO and the baseline of “Non-GMO/no label”, may incur respondent’s higher sensitivity to GMO as a clearer description of GMO content is provided, and the relative importance of GMO may be further enhanced under a comparison with Organic. Again, another possible reason is consumer’s unfamiliarity with hot peppers so that they may be more cautious on credence factors like GMO.

In our effort to evaluate consumers’ preferences toward different type of peppers, a separation of consumers from non-consumers is necessary. For consumers who have ever purchased a particular kind of peppers before, their utility would be significantly increased by consuming that type of pepper. The values consumers placed on the four types of peppers are all significantly positive and varies from $3.04 per pound to $4.21 per pound. Bell peppers are the most highly valued ($4.21), followed by the three hot peppers Jalapeno ($4.14), Chili ($3.55) and Habanero ($3.04). Such an order corresponds to our expectation that Bell peppers are the most common pepper for consumers
and thus would have the highest demand and valuation. *Habanero*, on the opposite, would be the least popular for most consumers as a raw vegetable. Note also that the difference between WTP of *Bell* pepper and *Jalapeno* pepper is not that large and not statistically significant, indicating Jalapeno peppers may also be quite popular.

In contrast, the utility of respondents who have never purchased hot peppers would be decreased significantly from consumption of hot peppers, justified by their “neutrality” or their general *distaste* for hot peppers. This distinction is crucial. More specifically, non-consumers’ mean WTP towards *Jalapeno* and *Habanero* peppers are both negative ($-0.93$ and $-0.45$, respectively). At the same time, we note that standard errors of non-consumers’ mean WTPs are all very large and lead to wide 95% confidence intervals. Such a high standard error compared to the mean WTP could be seen as an indicator of the considerable variation of non-consumers’ preference toward hot peppers. We would argue that such a big variation reflects their lack of information towards hot peppers: some of them may just choose the alternative “None of the Above” as a risk-averse strategy and present a general distaste for hot peppers. This is further verified by the fact that, Among the 36 respondents who chose “None of the Above” for all the ten questions, 81% are non-consumers for both Habanero and Chili peppers, another 14% are non-consumers for Habanero peppers but once consumed Chili peppers (see Figure 3). A Non-parametric test (Sign test) further shows the probability such a “reluctant” respondent (who choose “None of the Above” for all the 10 questions) to be a Habanero non-consumer is over 75%, and the probability is over 60% for Chili non-consumers ($p<0.001$).
To this extent, our results show that an opt-out alternative should be included if it is suspected the respondent has little value for the good or even an aversion to it. As well known in the stated literature, it is important to account for respondents’ familiarity with the good being valued. Non-consumers who would very likely dislike hot peppers and consequently wouldn’t represent a potential market for these produce, shouldn’t be evaluated. Additionally, potential consumers should be discriminated in the survey from actual consumers. The results would be more relevant for stakeholders in terms of the importance of each attribute and the WTP for it, knowing that they could differentiate actual consumers’ answers from the ones potentially interested in.

**Conclusion**

Understanding consumers’ valuation towards specific attributes and food types is quite crucial for companies in their seeking of effective marketing strategies, especially when it comes to exotic food. This paper explored consumers preference for peppers consumption through a mixed logit model with the Choice Experiment data from Connecticut that including 181 effective respondents. By adopting a random effect indicator for respondents that never purchased hot peppers before,
our model was able to distinguish the potential distaste of these “non-consumers” instead of just assuming them with a neutrality attitude.

The empirical analysis first shows consumers in Connecticut have a strong preference for Locally produced peppers with a significantly positive willingness to pay (WTP) premium. In contrast, consumers’ WTP premium for GMO and Imported are both significantly less than zero. It is also worth noticing that the WTP premium for Organic is insignificant when such attribute is presented together with Local and GMO information. Consumers’ strong belief in Local food (e.g. higher quality, safer, and healthier) likely lower their satisfaction toward Organic, especially when information on GM material is also provided.

For consumers who have some purchase experience on certain peppers, their WTPs are significantly positive for that type of peppers, and this is true for all four types of peppers in our survey; Bell peppers being the most highly valued. On the contrary, respondents who have never purchased hot peppers before show a significant decreased utility for hot pepper consumptions, showing their distaste on hot peppers. Those non-consumers have negative mean WTPs for hot peppers in general, while the standard errors for the mean WTPs are quite large and indicating considerable variations in their preference.

While it is important to study attributes/labeling strategy to consumer preferences and their willingness to pay for exotic food, it is equally important to understand if there is a market potential and profitability associated with a potential investment from growers. Our study shows that a product culturally too far from a consumer’s food habits and knowledge such as hot peppers might never be thought as attractive if nothing is done with consumers’ unfamiliarity of certain food. To this extent, our results show that an opt-out alternative should be included. However, indecisive buyers could be turned into actual buyers if information were provided. For example, improving
the interaction between the producer and/or the seller and the consumer, through direct marketing at farmers markets or specialty stores could be a more effective strategy (Moser et al., 2011), targeting motivated consumers for exotic/ethnic food.
References


Perceptions and Preferences toward Organic versus Conventionally Produced Foods: A Review

Appendix 1: Gauss-Hermite Integration applied in the Mixed Logit Model

With the Gauss-Hermite integration, we can approximate any integral with the form

\[ \int_{-\infty}^{+\infty} g(\varepsilon) \, d\varepsilon = \int_{-\infty}^{+\infty} e^{-\varepsilon^2} \, h(\varepsilon) \, d\varepsilon \]

as the weighted average of the evaluation point \( w_h \), that is

\[ \int_{-\infty}^{+\infty} e^{-\varepsilon^2} f(\varepsilon) \, d\varepsilon \approx \sum_{h=1}^{d} w_h \, f(\varepsilon_h). \]

Here the approximation is defined by a Hermite orthogonal polynomial of degree \( d \), \( H_d(\varepsilon) \), with associated weights \( w_h \) \((h=1, 2, \ldots, d)\). For a standard normal random variable, a change of variable results in

\[ (2\pi)^{-1/2} \int_{-\infty}^{+\infty} e^{-\varepsilon^2/2} f(\varepsilon) \, d\varepsilon \approx \sum_{h=1}^{d} w_h^* \, f(\varepsilon_h^*), \]

where \( \varepsilon_h^* = \sqrt{2} \varepsilon_h \) and \( w_h^* = w_h / \sqrt{\pi} \). Note that \( \sum w_h^* = 1 \).

For the mixed logit model we defined in the text, a 4-dimensional integration is required towards the multivariate-normal distributed dummies for non-consumers. To extend the Gauss-Hermite integration for the mixed logit model, we first define the set \( H \) as the Cartesian product

\[ H = \varepsilon_1^* \times \varepsilon_2^* \times \varepsilon_3^* \times \varepsilon_4^* \]

(H is of dimension \( d^4 \) by 4), and define the set \( W = w_1^* \times w_2^* \times w_3^* \times w_4^* \).

Also, we let \( w_4 \) be the product of the columns of \( W \) such that it is now a \( d^4 \) by 1 vector whose sum is one. Finally, we define \( E_k^* = \sigma_k^* \, H_k \) \((k = 0, 1, 2, 3)\).

Then the utility respondent \( i \) would obtain from choosing alternative \( t \) in question \( j \) could be rewrote as:

\[
V_{ijt} = \beta_{\text{price}} Price_{ijt} + \beta_{\text{GMO}} I_{\text{GMOijt}} + \beta_{\text{Organic}} I_{\text{Organicijt}} \\
+ \beta_{\text{Habnro}} I_{\text{Habnroijt}} + \left( \beta_{\text{Habnro-N/C}} I_{\text{Habnro-N/Cijt}} + E_1^* \right) I_{\text{Habnro-N/Cijt}} \\
+ \beta_{\text{Chili}} I_{\text{Chiliijt}} + \left( \beta_{\text{Chili-N/C}} I_{\text{Chili-N/Cijt}} + E_2^* \right) I_{\text{Chili-N/Cijt}} \\
+ \beta_{\text{Jalpno}} I_{\text{Jalpnoijt}} + \left( \beta_{\text{Jalpno-N/C}} I_{\text{Jalpno-N/Cijt}} + E_3^* \right) I_{\text{Jalpno-N/Cijt}} \\
+ \beta_{\text{CT}} I_{\text{CTijt}} + \beta_{\text{Imported}} I_{\text{Importedijt}} + \varepsilon_{ijt}
\]

The probability for respondent \( i \) to choose alternative \( t \) in question \( j \) is

\[ P_{ij(T)} \approx w_i' \frac{\exp(V_{ij(T)})}{\sum_{t=1}^{5} \exp(V_{ijt})} \]
Where $T$ indicates the chosen alternative for question $j$, and $V_{ij(T)}$ is the correspondingly utility respondent $i$ would obtain from his/her choice in question $j$.

By assuming the ten questions answered by the same respondent are independent from each other, the joint probability of respondent $i$’s choices for the ten questions is the product of the probability for each question’s chosen alternative.

$$P_{ij(T)} \approx w_m' \left[ \prod_{j=1}^{10} \frac{\exp(V_{ij(T)})}{\sum_{t=1}^{5} \exp(V_{ijt})} \right]$$

Under the assumption that each respondent’s choices are independent of each other, the joint probability of all respondents’ choice sets is the product of all the 181 respondents’ probability on the ten questions, and thus the maximum likelihood estimation could be applied.

For integrations in the empirical analysis, we choose Hermite orthogonal polynomial of degree 32, and the corresponding abscissas and weights are listed in Table 1 of the appendix. The largest weight ($w_i^*$) for abscissas is 0.0198, while the smallest weight is only 2.86E-89 (<0.0000001) and quite close to 0. Note that the weight $w_i^*$ decreases rapidly as the absolute value of abscissas increasing. Considering the probability in mixed logit model would always be less than 1 for any given abscissas, we trimmed those abscissas whose weight is less than one-tenth of the mean weight of all evaluation points. That is, abscissas with weight is less than 9.5367e-08 are dropped. In this way, we greatly reduce the estimation point from 1048576 to 21312, and only paying a very small cost in losing a total weight of 0.00040038, which is a negligible proportion compared to the sum of all weight as 1. At the same time, we rescale the weights for remaining abscissas to assure they sum to one. Such an approach contributes significantly to reduce evaluation points and to increase the estimation efficiency. At the same time, we are able to ensure the 21312 evaluation points is a good representative of the shape of the multivariate normal distribution.
Table 1. 32\textsuperscript{th} Degree Abscissas and Weights

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Appendix 2: Calculation Formula for the Variance of WTP

(1) For WTPs derived from non-random coefficients, such as the WTP for GMO, 

\[ WTP_{GMO} = - \frac{\beta_{GMO}}{\beta_{Price}} \]

the first partial derivatives of \( WTP_{GMO} \) towards each of the parameters are:

\[ \frac{\partial WTP_{GMO}}{\partial \beta_{Price}} = \frac{\beta_{GMO}}{\beta_{Price}^2}, \quad \text{and} \quad \frac{\partial WTP_{GMO}}{\partial \beta_{GMO}} = - \frac{1}{\beta_{Price}} \]

Thus,

\[ \text{var}(WTP_{GMO}) = \text{var}\left(- \frac{\beta_{GMO}}{\beta_{Price}}\right) \]

\[ = \left[ \nabla \left(- \frac{\beta_{GMO}}{\beta_{Price}}\right) \right]^T \text{cov}(\beta_{Price}, \beta_{GMO}) \nabla \left(- \frac{\beta_{GMO}}{\beta_{Price}}\right) \]

\[ = \left( \frac{\beta_{GMO}}{\beta_{Price}^2} - \frac{1}{\beta_{Price}} \right) \begin{pmatrix} \sigma_{Price}^2 & \sigma_{Price,GMO} \\ \sigma_{Price,GMO} & \sigma_{GMO}^2 \end{pmatrix} \begin{pmatrix} \beta_{GMO} \\ -1 \end{pmatrix} \]

(2) For WTPs derived from random coefficients, such as the WTP of non-consumers toward Habanero, 

\[ WTP_{Habnro-N/C} = - \frac{\beta_{Habnro} + \beta_{Habnro-N/C} + \sigma_{Habnro-N/C} \cdot \varepsilon}{\beta_{Price}} \]

Since \( \varepsilon \sim N(0,1) \), \( E(\varepsilon) = 0 \)

\[ E\left(WTP_{Habnro-N/C}\right) = E\left(- \frac{\beta_{Habnro} + \beta_{Habnro-N/C}}{\beta_{Price}}\right) \]

Correspondingly, the first partial derivatives of \( WTP_{Habnro-N/C} \) to each of the parameters are:

\[ \frac{\partial WTP_{Habnro-N/C}}{\partial \beta_{Price}} = \frac{\beta_{Habnro} + \beta_{Habnro-N/C}}{\beta_{Price}^2} \]

\[ \frac{\partial WTP_{Habnro-N/C}}{\partial \beta_{Habnro}} = - \frac{1}{\beta_{Price}} \]
\[
\frac{\partial WTP_{Habnro-N/C}}{\partial \beta_{Habnro-N/C}} = -\frac{1}{\beta_{Price}}
\]

For \(\sigma_{Habnro-N/C}\).

\[
\frac{\partial WTP_{Habnro-N/C}}{\partial \sigma_{Habnro-N/C}} = -\frac{\varepsilon}{\beta_{Price}}
\]

\[
E \left( \left( \frac{\partial WTP_{Habnro-N/C}}{\partial \sigma_{Habnro-N/C}} \right)^2 \right) = E \left( \frac{\varepsilon^2}{\beta_{Price}^2} \right) = \frac{1}{\beta_{Price}^2}
\]

In order to account for the sampling variation in \(\partial \sigma_{Habnro-N/C}\), define

\[
\frac{\partial WTP_{Habnro-N/C}}{\partial \sigma_{Habnro-N/C}} = \text{sign} \left( \frac{\partial WTP_{Habnro-N/C}}{\partial \sigma_{Habnro-N/C}} \right) \sqrt{E \left( \left( \frac{\partial WTP_{Habnro-N/C}}{\partial \sigma_{Habnro-N/C}} \right)^2 \right)} = -\frac{1}{\beta_{Price}}
\]

Thus,

\[
\text{var}(WTP_{Habnro-N/C}) = \text{var} \left( \frac{-\beta_{Habnro} + \beta_{Habnro-N/C} + \sigma_{Habnro-N/C} \cdot \varepsilon}{\beta_{Price}} \right) =
\]

\[
\begin{pmatrix}
\sqrt{\text{cov}(\beta_{Price}, \beta_{Habnro})}, \sqrt{\text{cov}(\beta_{Price}, \beta_{Habnro-N/C})}, \sqrt{\text{cov}(\beta_{Price}, \sigma_{Habnro-N/C})}, \sqrt{\text{cov}(\beta_{Price}, \sigma_{Habnro-N/C})}
\end{pmatrix}^T
\]

\[
\begin{pmatrix}
\text{cov}(\beta_{Price}, \beta_{Habnro}), \text{cov}(\beta_{Price}, \beta_{Habnro-N/C}), \text{cov}(\beta_{Price}, \beta_{Habnro-N/C}), \text{cov}(\beta_{Price}, \sigma_{Habnro-N/C})
\end{pmatrix}
\]

\[
\begin{pmatrix}
\sqrt{\text{var}(\beta_{Habnro-N/C})}, \sqrt{\text{var}(\beta_{Habnro-N/C})}, \sqrt{\text{var}(\beta_{Habnro-N/C})}, \sqrt{\text{var}(\beta_{Habnro-N/C})}
\end{pmatrix}
\]

The variance-covariance matrix of the parameters has the familiar form, except for the third row and column

\[
\text{var}(\beta_{Habnro-N/C}) = \text{var}(\beta_{Habnro-N/C}) + \text{Var}(\sigma_{Habnro-N/C})
\]

Thus, the variance of WTP for habanero non-consumers is

\[
\text{var}(WTP_{Habnro-N/C}) =
\]

\[
\begin{pmatrix}
\beta_{Hab} + \beta_{Hab-N/C} \\
\beta_{Price} \\
\beta_{Price} \\
1
\end{pmatrix}^T
\begin{pmatrix}
\text{cov}(\beta_{Price}, \beta_{Hab}) & \text{cov}(\beta_{Price}, \beta_{Hab-N/C}) & \text{cov}(\beta_{Price}, \beta_{Hab-N/C}) & \text{cov}(\beta_{Price}, \sigma_{Hab-N/C}) \\
\text{cov}(\beta_{Hab}, \beta_{Hab}) & \text{cov}(\beta_{Hab}, \beta_{Hab-N/C}) & \text{cov}(\beta_{Hab}, \beta_{Hab-N/C}) & \text{cov}(\beta_{Hab}, \sigma_{Hab-N/C}) \\
\text{cov}(\beta_{Hab-N/C}, \beta_{Hab}) & \text{cov}(\beta_{Hab-N/C}, \beta_{Hab-N/C}) & \text{cov}(\beta_{Hab-N/C}, \beta_{Hab-N/C}) & \text{cov}(\beta_{Hab-N/C}, \sigma_{Hab-N/C}) \\
\text{cov}(\sigma_{Hab-N/C}, \beta_{Hab}) & \text{cov}(\sigma_{Hab-N/C}, \beta_{Hab-N/C}) & \text{cov}(\sigma_{Hab-N/C}, \beta_{Hab-N/C}) & \text{cov}(\sigma_{Hab-N/C}, \sigma_{Hab-N/C})
\end{pmatrix}
\begin{pmatrix}
\beta_{Hab} + \beta_{Hab-N/C} \\
\beta_{Price} \\
\beta_{Price} \\
1
\end{pmatrix}
\]

\[
= \begin{pmatrix}
\text{var}(WTP_{Habnro-N/C}) \\
\text{cov}(\beta_{Price}, \beta_{Hab-N/C}) \\
\text{cov}(\beta_{Price}, \beta_{Hab-N/C}) \\
\text{cov}(\beta_{Price}, \beta_{Hab-N/C})
\end{pmatrix}
\]