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Mitigation of Hypothetical Bias in Estimating Consumers' Willingness to Pay for Best Management Practice Labels

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Abstract

While estimating the value of non-market goods/services, taking care of the hypothetical bias (HB) in the stated preference (SP) method is a significant challenge. The consequentiality of choice is an essential factor in revealing a product or its attributes' actual preference. Cheap talk is an ex-ante method widely used to control the HB. Consequentiality script is another method usually used in the valuation of public goods. This study intends to study consumer preference and willingness to pay (WTP) for the Best Management Practices (BMP) label. As the BMP label is currently unavailable in the market, consumers' choice will have consequences on the BMP certification program and the BMP certified products' price in the market. This allows us to study the effect of consequentiality script on the private good. We compare the effectiveness of cheap talk and consequentiality scripts and examine the extent of hypothetical bias reduction using a choice experiment (CE). A nationwide online survey was conducted where respondents were randomly assigned to one of the two treatment groups or to a control group. The choice data of each HB mitigation treatment were analyzed using the mixed logit model (MIX) as it allowed us to consider heterogeneous preferences among consumers. Estimation shows that the consequentiality script significantly reduces the WTP for the BMP labels. However, the cheap talk treatment accounts for a higher reduction in WTP for BMP labels as well as other attributes.

Keywords: Hypothetical bias, choice experiment, willingness to pay (WTP), best management practices, eco-label, mixed logit model, preference space, WTP space

1. Introduction

Stated preference (SP) methods are widely used for eliciting preference and valuation of public and private goods. Hypothetical bias (HB) is a long-studied limitation of SP methods. Evidence suggests that the respondents overstate the willingness to pay (WTP) values significantly in hypothetical context (i.e., a survey) compared to the real-market interactions (Aadland et al. 2012). In response, several ex-ante methods such as cheap talk (Cummings, Harrison and Osborne 1995), consequentiality(Carson and Groves 2007), and honesty priming (Loomis 2013) have been used in the SP method literature to mitigate the HB. As there is no established consensus in the literature on which tool would be more efficient in mitigating the HB, it is necessary to create evidence of efficacy by comparing these ex-ante methods. In a recent study, researchers have evaluated the effectiveness of cheap talk and honesty priming to control the HB when measuring the WTP of organic food (Gschwandtner & Burton, 2020). Though Landry & List (2007) and Penn et al. (2018) compared the effectiveness of cheap talk and consequentiality treatment using the contingent valuation (CV) approach, a few studies compared these bias reduction methods in a choice experiment (CE) setting. Besides, consequentiality treatment is frequently used using public goods (Landry and List 2007). A few studies examine its efficacy in bias reduction for private goods. To fill the gap, we study the effect of cheap talk and consequentiality treatment to mitigate the HB in a CE that is designed to elicit consumers' preference for agricultural Best Management Practices (BMPs) label.

Agricultural BMPs are a keystone of state and federal agricultural water quality policies, and they include soil and water conservation practices and other management techniques and social actions that producers can use to mitigate pollution transport to surface waters (Sharpley et al. 2006). Adopting BMPs usually requires additional costs, such as equipment upgrades, additional infrastructure, paperwork, or reduction of planted/harvested acres (Shaffer and Thompson 2013). These costs can affect the profitability of small and medium-sized farms. In addition to existing government cost-share programs to induce BMP adoption, market incentives such as premiums for products produced with BMPs may increase producers' net returns and, therefore, increase BMP adoption levels, potentially improving environmental outcomes.

Given the context, we attempt to explore the marketing opportunities of BMP labels by measuring the consumers' WTP. A significant premium for market goods produced with BMPs implies a strong economic incentive for growers' to adopt BMPs. Policymakers could use such information to develop BMP labeling programs to help reduce the information asymmetry regarding BMP implementation between growers and consumers. Appropriately designed BMP labeling programs can benefit both consumers and growers by supplying the products sought by consumers and at the same time providing financial compensation to growers who adopt BMPs.

Hence, this study has two objectives: (1) to compare the efficacy of two methods – cheap talk and consequentiality scripts –to mitigate the hypothetical bias (HB) in the CE and find an optimal bias reduction technique; and (2) to elicit the preferences and WTP of consumers for BMP labels. It is worth mentioning that no existing studies have explored the marketing opportunities of BMP labels using consumer surveys.

2. Data and Choice Experiment

An online survey was conducted to collect nationally representative consumer data (May 2021) through the Qualtrics consumer panel. All the respondents are adults (18 years old or higher), US primary grocery shoppers (shop more than 50% of the time), and purchased strawberries in the last six months in grocery shopping. To eliminate the respondents with satisficing behavior, we added two trap questions in the middle of the survey (Gao, L. House and Bi 2016; Gao, L. A. House and Xie 2016) to collect quality responses.

We design a choice experiment (CE) to estimate the WTP for the BMP labels using strawberries (16 oz. clamshell pack). Strawberry is selected as the focal product in the experiment because it is the most consumed fruit among US consumers (Economic Research Service; US Department of Agriculture). The attributes of the strawberries considered in the experiment are the Best Management practices (BMP) label, USDA Organic, USDA GAP&GHP, origin, and price. **Table 1** presents all the attributes and associated levels of the strawberries defined in the experiment. Since there are no BMP labels in the market, three BMP labels were designed and tested based on existing labels such as organic, non-GMO, and other labels in the market. We also considered other attributes of the strawberries, such as USDA organic (environmental label), USDA Good Agricultural Practice and Good Handling Practices, i.e., GAP & GHP (food safety label), and origin. Based on this market price distribution of conventional and organic strawberries, we select four price levels ($1.99, $3.49, $4.99, and $6.49) in our experiment to capture the highest and lowest possible price of a 1lb clamshell strawberry pack.

Table 1: Attribute and levels of the strawberries (1lb. clamshell pack)

Attribute	Level	Description
BMP label	No label (base)	No BMP label
	BMP label 1	Only BMP label- no slogan
	BMP label 2	BMP label with slogan- "Preserving Water Quality"
	BMP label 3	BMP label with slogan- "Promoting Sustainable Water"
Organic	No label (base)	No organic label
	USDA Organic label	USDA certified organic label
GAP&GHP	No label (base)	No GAP&GHP label
	USDA GAP&GHP label	USDA certified GAP&GHP label
Origin	Product of your state (base)	Product origin is from respondent's state
	Product of USA	Product origin is from USA
Price (USD/16 oz.)	1.99, 3.49, 4.99,6.49	Price of the strawberries

Given the attributes and their levels, a full factorial design results in 128 product profiles (4^2x2^3). We use SAS %choiceff macro (Kuhfeld 2010), which optimizes the variance matrix assuming a non-linear model and reduces the number of choice sets to ten with four alternatives— three strawberry choices and a none-option. The design maintains the ability to identify all main effects and interactions between the BMPs and product origin. Initially, we collected 62 samples. Then we estimated coefficients and standard errors using those data and used them as priors to generate the final choice sets using the Bayesian efficient design (Bliemer, Rose and Hess 2008). Choice sets were presented in random order to control the learning effects.

Respondents were randomly assigned to the cheap talk, consequentiality, or control group. As the CE is hypothetical, the consumers' response will play a vital role in deriving the future policy. Therefore, we used the consequentiality script to let the respondents know that their choice could affect the producers, traders, and retailers' decisions and influence the adoption of BMPs. In consequence, their choices may affect the future product price. The cheap talk script informs the respondents that consumers' choice results in bias in hypothetical choices and reminds them to reveal truthful and realistic choices to reduce bias. See Appendix A1 and A2 for the consequentiality and cheap talk script used in the experiment.

Figure 1: Three BMP labels used in the CE

Figure 2: An example of a choice set

Table 2: Demographic characteristics of the respondents

Variables	US Census	Pooled (799)	Control (263)	Consequentiality (277)	Cheap talk (259)	Pearson Chi2 (P-value)
Demographics (%)						
Gender-Female[a]	50.8	60.83	57.41	63.18	61.78	2.02(0.363)
Age[a]						
18 to 24 years	11.9	11.26	10.65	13.72	9.27	26.69(0.479)
25 to 34 years	17.9	17.27	17.49	17.69	16.60	
35 to 44 years	16.4	20.65	21.29	20.22	20.46	
45 to 54 years	16	15.02	11.03	16.61	0.17	
55 to 64 years	16.6	18.90	19.77	17.33	19.69	
65 years or older	21.2	16.90	19.77	14.44	16.60	
Race[a]						
White alone	76.3	79.35	75.67	80.51	81.85	4.94(0.293)
Black or African American alone	13.4	11.01	13.69	9.03	10.42	
Ethnicity-Hispanic[a]	18.5	15.52	15.97	16.97	13.51	1.27(0.528)
Marital status-Married	-	50.19	49.81	50.9	49.81	0.086(0.958)
Education[b]						
Less than high school graduate	9.55	11.26	10.65	10.47	12.74	10.02(0.263)
High school graduate (include equivalency)	27.77	24.16	26.24	23.47	22.78	
Some college or associate's degree	27.04	25.91	19.77	28.16	29.73	
Bachelor's degree	22.51	23.9	27	23.83	20.85	
Graduate or professional degree	13.12	14.77	16.35	14.08	13.9	
Annual household (HH) income, before tax (2020)[a]						
Less than $15,000	9.8	9.64	9.13	10.47	9.27	16.56(0.414)
$15,000-$24,999	8.3	14.02	16.35	12.64	13.13	
$25,000-$34,999	8.4	13.77	14.07	11.91	15.44	
$35,000-$49,999	11.9	12.52	12.55	11.19	13.9	
$50,000-$74,999	17.4	18.4	14.45	20.94	19.69	

Variables	US Census	Pooled (799)	Control (263)	Consequentiality (277)	Cheap talk (259)	Pearson Chi2 (P-value)
$75,000-$99,999	12.8	8.51	10.65	7.22	7.72	
$100,000-$149,999	15.7	13.52	12.55	14.08	13.9	
$150,000-$199,999	7.2	6.51	7.98	6.5	5.02	
$200,000 or above	8.5	3.13	2.28	5.05	1.93	
Household size						
1	-	19.9	22.43	19.49	17.76	
2	-	34.54	34.22	32.13	37.45	
3	-	17.15	17.87	16.61	16.99	15.12(0.654)
4	-	17.52	16.73	19.86	15.83	
5 or more	-	10.89	8.75	11.91	11.97	
Weekly food expenditure (grocery shopping only)						
Less than $50		8.14	9.51	7.94	6.95	
$50-$99	-	20.78	22.43	18.77	21.24	
$100-$149	-	22.53	22.05	23.1	22.39	11.91(0.291)
$150-$199	-	14.27	12.17	15.16	15.44	
$200 or more	-	32.18	31.56	34.66	30.12	
Not sure	-	2.13	2.28	0.36	3.86	
Political Affiliation						
Independent	-	30.66	30.42	30.69	30.89	
Democrat	-	39.8	43.35	39.35	36.68	9.39(0.153)
Republican	-	26.53	21.67	28.52	29.34	
Other	-	3	4.56	1.44	3.09	

a: US Census Bureau, American Community Survey 2019.
b: US Census Bureau, Current Population Survey, 2020 Annual Social and Economic Supplement

3. Model Specification

Lancaster's theory states that utility depends on the quality of the product characteristics instead of the product itself. We assumed that the consumer preference follows the random utility theory framework (McFadden 1974) as stated in equation (1).

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt} \quad (1)$$

Consumer i maximizes utility by choosing alternative j from the choice set t. According to Eq. (1), utility consists of two parts, deterministic part V_{ijt} and unobservable random part ε_{ijt}. The deterministic part of the utility depends on the price and non-price attributes of the commodity. Furthermore, as we are allowing the no-purchase option in the choice to recreate the real shopping scenario, the deterministic part has an alternative specific constant (ASC). Hence, we can define the deterministic part of the utility (Van Asselt et al. 2022) as

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt} = V_{ijt} + \varepsilon_{ijt} = \alpha\, ASC_{it} + \beta_i'\, X_{ijt} \quad (2)$$

Here, α is the marginal utility coefficient from the no-purchase decision for consumer i, and β_i' is the vector of marginal utility coefficients of the price and non-price attributes for consumer i. We can estimate parameters of Eq. (2) using the conditional logit model under the assumption of homogeneous consumer preference where ε_{ijt} is assumed to be independently and identically distributed () following Gumbel distribution/ Type 1 extreme value distribution. However, the assumption of the consumer's heterogeneous preference of product attributes would be more realistic and can be modeled in the mixed logit model (Train 2009). Then we can specify $\beta_i = \bar{\beta} + L \cdot u_i$, where $\bar{\beta}$ is the mean of the attribute. L is the lower triangular matrix used to calculate the covariance of random parameters $\sum = L \cdot L'$. And ui is independently identically distributed (iid) with certain distribution. Because ui is random and unknown, under this specification, we estimate the mixed logit model by simulating the maximum likelihood function defined as follows (Train 2009)-

$$L_{it}(\beta) = \prod_{t=1}^{T} \left[\frac{e^{\alpha\, \mathrm{ASCit}\; + \beta i\prime\, \mathrm{Xijt}}}{\sum_{J=1}^{J} e^{\alpha\, \mathrm{ASCit}\; + \beta i\prime\, \mathrm{Xijt}}} \right] \quad (3)$$

where conditional choice probabilities of consumer i is defined as

$$P_{it}(Y_i|X_i, \Sigma) = \int_{-\infty}^{+\infty} L_{it}\,(\beta) f(\beta) d\beta \qquad (4)$$

After estimating the model parameters, we can calculate the WTP by taking the negative ratio of the individual parameter assumed to be normally distributed and the price parameters assumed as fixed. A fixed price distribution scales the WTP distribution, which may not be empirically demanding. On the other hand, assuming normal or log-normal assumptions can result in positive estimates of the price coefficient, or ridiculously small price coefficient makes the WTP distribution extremely large(Train 2009).

Recent findings suggest that we can reparametrize consumer preference in the WTP space and get the WTP directly (Greene and Hensher 2010; Xie et al. 2016). Hensher & Greene (2011) showed that estimating the model in WTP space is more appealing than the preference space for capturing behaviorally reasonable WTP distribution. Another intriguing advantage of this approach is that the WTP distribution is normally distributed and found to be efficient (Thiene and Scarpa 2009). This

We estimate the mixed logit model in preference and the WTP space using R. The GMNL package estimates the models by simulating a log-likelihood with 500 Halton draws (Sarrias and Daziano 2017). Models are estimated for all three hypothetical bias treatments separately. To test the difference between different hypothetical bias treatments, we estimate individual-level WTP for both models using Bayes Theorem (Sarrias and Daziano 2017; Train 2009).

Table 3: Estimates from Mixed logit and GMNL model for all the treatment groups

	Mixed Logit Model-Preference space			Generalized Mixed Logit Model-WTP space		
Attributes	Control (1)	Consequentiality (2)	Cheap talk (3)	Control (4)	Consequentiality (5)	Cheap talk (6)
Mean estimates						
Price	-0.388 ***	-0.365 ***	-0.444 ***	**1 (fixed)**	**1 (fixed)**	**1 (fixed)**
BMP label 1	0.946 ***	0.88 ***	0.922 ***	2.461 ***	2.435 ***	2.051 ***
BMP label 2	1.119 ***	0.889 ***	0.935 ***	2.925 ***	2.505 ***	1.993 ***
BMP label 3	1.016 ***	0.751 ***	0.873 ***	2.75 ***	2.175 ***	1.996 ***
GAP & GHP	0.783 ***	0.773 ***	0.7 ***	1.969 ***	2.072 ***	1.494 ***
USDA Organic	1.093 ***	1.072 ***	1 ***	2.546 ***	2.799 ***	1.945 ***
Origin (USA)	-0.249 ***	-0.247 ***	-0.252 ***	-0.667 ***	-0.712 ***	-0.499 ***
None	-2.991 ***	-3.627 ***	-3.526 ***	-3.789 ***	-7.882 ***	-8.006 ***
Std. Dev estimates						
sd.BMP label 1	0.003	0.009	0.009	0.014	0.046	0.008
sd.BMP label 2	0.033	0.004	0.044	0.051	0.009	0.107
sd.BMP label 3	0.009	0.016	0.003	0.158	0.192	0.043
sd.GAP & GHP	0.402 ***	0.433 ***	0.399 ***	1.057 ***	1.205 ***	0.876 ***
sd.USDA Organic	1.177 ***	0.838 ***	0.99 ***	2.897 ***	2.28 ***	2.074 ***
sd.Origin (USA)	0.347 ***	0.008	0.082	0.848 ***	0.063	0.194
sd.None	2.001 ***	2.288 ***	1.579 ***	9.444 ***	10.175 ***	3.997 ***
Log Likelihood	-2555.73	-2668.84	-2408.30	-2619.94	-2702.37	-2411.47
No of Observation	2630	2770	2590	2630	2770	2590
No of Respondents	263	277	259	263	277	259

Table 4: WTP estimates in preference and WTP space

Attributes	Mixed Logit Model-Preference space: Mean WTP			Generalized Mixed Logit Model-WTP space: Mean WTP		
	Control	Consequentiality	Cheap talk	Control	Consequentiality	Cheap talk
BMP label 1	2.44[2.44,2.44]	2.41[2.41,2.41]	2.08[2.08,2.08]	2.46[2.46,2.46]	2.43[2.43,2.44]	2.05[2.05,2.05]
BMP label 2	2.89[2.89,2.89]	2.44[2.44,2.44]	2.11[2.11,2.11]	2.93[2.92,2.93]	2.51[2.51,2.51]	1.99[1.99,1.99]
BMP label 3	2.62[2.62,2.62]	2.06[2.06,2.06]	1.97[1.97,1.97]	2.75[2.75,2.75]	2.17[2.17,2.18]	2[2,2]
GAP & GHP	2.01[1.95,2.07]	2.11[2.04,2.18]	1.58[1.52,1.63]	2.01[1.95,2.07]	2.12[2.05,2.19]	1.51[1.46,1.56]
USDA Organic	2.83[2.53,3.13]	2.94[2.74,3.14]	2.27[2.06,2.48]	2.84[2.55,3.13]	2.95[2.75,3.15]	2.13[1.94,2.33]
Origin (USA)	-0.64[-0.68,-0.59]	-0.68[-0.68,-0.68]	-0.57[-0.57,-0.57]	-0.65[-0.69,-0.61]	-0.71[-0.71,-0.71]	-0.5[-0.5,-0.5]

Note: WTP estimates are from individual WTP distribution, and 95% confidence intervals (CIs) are in parentheses.

Table 5: Mean differences in WTP of strawberry attributes across treatments in WTP space

Attributes	Change in mean WTP (WTP space)			Change in mean WTP in % (WTP space)		
	Consequentiality - Control	Cheap talk-Control	Cheap talk - Consequentiality	Consequentiality - Control	Cheap talk-Control	Cheap talk - Consequentiality
BMP label 1	-0.03***	-0.41***	-0.38***	-1.22%	-16.67%	-15.64%
BMP label 2	-0.42***	-0.94***	-0.52***	-14.33%	-32.08%	-20.72%
BMP label 3	-0.58***	-0.75***	-0.17***	-21.09%	-27.27%	-7.83%
GAP & GHP	0.11**	-0.50***	-0.61***	5.47%	-24.88%	-28.77%
USDA Organic	0.11	-0.71***	-0.82***	3.87%	-25.00%	-27.80%
Origin (USA)	-0.06***	0.15***	0.21***	9.23%	-23.08%	-29.58%

Note: The values are the differences between the marginal WTP estimates in values and in percent, and asterisks ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

4. Results

We have collected 799 valid responses. Respondents are randomly assigned to one of the three hypothetical bias mitigation treatment groups - 277 to consequentiality, 259 to cheap talk, and 263 to the control group. Summary statistics of each treatment group are presented in Table 2. Pearson Chi2 test shows that the demographic characteristics between the treatment groups are the same.

We specified the consumer utility function is specified as follows

$$U_{ijt} = \alpha_{none} ASC_{it} + \beta_p P_{ijt} + \beta_{bmp1} BMP1_{ijt} + \beta_{bmp2} BMP2_{ijt} + \beta_{bmp3} BMP3_{ijt} + \beta_{gap\&ghp} GAP\&GHP_{ijt} + \beta_{organic} Organic_{ijt} + \beta_{originUS} USA_{ijt} + \epsilon_{ijt} \quad (5)$$

The deterministic part of the consumer utility depends on the strawberry attributes and associated marginal utility parameter, β. All attribute levels – BMP label 1 (*BMP1*), BMP label 2 (*BMP2*), BMP label 3 (*BMP3*), USDA GAP and GHP label (*GAP&GHP*), USDA Organic label (*Organic*), Product of USA (*USA*)– are dummy coded and price (*P*) is defined as continuous. The base level of the attributes is defined in Table 1.

Table 3 presents the results of the mixed logit model specified above. The first three columns present the model estimates for three treatment groups in the preference space. Similarly, the last three columns of table 3 show the WTP space's estimation, and the estimates are the mean WTP for each attribute level. We evaluated the main effects of both models for each information treatment group. All the estimated parameters are highly significant from zero.

The negative price coefficient in the preference space confirms the law of the demand for a normal good.

Furthermore, the negative coefficient of the "no-buy" option reveals that the consumers get higher utility from the consumption of strawberries. It is essential to mention that the standard deviation (SD) estimates of all three BMP labels are insignificant for all three treatments in preference and WTP space models. It implied that the preference of the BMP labels is homogenous. This is a new label that we first introduced in this experiment. Moreover, consumers would rarely find any label in the US market that represents a similar eco service as the BMP label (water quality). Hence, it is not surprising that BMP labels have homogenous preferences, unlike USDA organic and GAP&GHP labels. Interestingly, the SD of USA-origin strawberries is significant in the control group but not in the other two treatments.

The Control group refers to those respondents who do not see any of the two scripts that intend to curb the hypothetical bias. So, we can find out the general preference pattern for strawberries from this group. We can see that the consumers have a positive preference for the BMP labels. Additionally, BMP label 2 (see figure 1) is the most preferred label, followed by labels 3 and 1. The least preference for label 1 fits our expectations as this label has no message that conveys the meaning and purpose of the BMP label. However, organic is the most preferred label among all labels considered in the study. The WTP for GAP&GHP is lower than that for the BMP, and Organic labels indicate that consumers have a higher preference for the eco or environmental labels than the food safety labels. The coefficient of the "Product of USA" reveals that consumers prefer local strawberries (originated from the consumer's state) to the product of the USA.

Alternatively, consequentiality and cheap-talk treatment groups represent those consumers who have seen the respective script before taking the choice experiment (see Appendix A1 and A2 for the consequentiality and cheap talk script). We expect that respondents assigned to one of these treatments would reveal their true preferences for the attributes and curb the bias. Another way of stating the fact is that the preference of the attributes will be statistically different across the treatment groups.

To better understand the effect of the different bias curbing scripts on preference, it is better to compare the WTP of the attributes. WTP of the strawberry attributes is presented in Table 4 from both model spaces. The mean and the 95% confidence interval (CI) are calculated from the individual coefficient for each attribute. WTP estimates from both model spaces are similar. Therefore, we refer to the WTP space model's WTP estimates in the subsequent discussion. We can see that the confidence interval of the BMP labels is small as consumers have a homogenous preference for this eco-label. Comparable results also follow for the USA origin label in the consequentiality and cheap talk treatment.

Table 5 presents the differences between the groups' WTP in absolute and percentage terms. Analysis shows that the cheap talk script reduces the HB significantly compared to the control group for all the attributes. Similarly, the consequentiality script significantly mitigates the bias for the BMP labels. Nevertheless, the magnitude of the bias reduction is lower for the consequentiality script than for the cheap talk. For instance, cheap talk accounts for a 32.08%

reduction, where consequentiality treatment mitigates only 14.33% of the HB for the most preferred BMP label. Surprisingly, WTP for the organic and GAP & GHP label increased instead of decreasing when consumers faced consequentiality treatment. However, the increase is insignificant for the former attribute but significant for the latter. Therefore, WTP for the organic label in the consequentiality treatment is the same as the control group. We also find that cheap talk significantly reduces the WTP for all the attributes of the strawberries.

Our results show that the consequentiality and cheap talk script both reduces the WTP of the BMP labels, indicating the presence of upward bias. The consequentiality script effectively reduces BMP labels' bias more than the other attributes within the treatment group. This result makes sense as consequentiality treatment stated that the consumers' decision would affect the BMPs adoption, certification, and the product's price with BMP labels. However, no consequence of choice was mentioned for the other attributes. As a result, we do not observe any treatment effect on the organic label. Unexpected though, we see significant positive effects of this treatment on the WTP of the GAP&GHP label, and the magnitude is only about 5.5%.

On the contrary, the cheap talk script informs respondents about the bias and its direction in general. The script's message is not confined to any one attribute of the product. When comparing the magnitude of the reduction in WTP, the cheap talk outperforms the consequentiality treatment, not only for BMP labels but also for other attributes. For instance, the WTP of the organic label decreased by about 25% when faced with cheap talk compared to the control group.

5. Conclusion

This study analyzed the preference for a new environmental label for the fresh produce (strawberries) grown with Best Management Practices. Results suggest promising marketing opportunities for the BMP label that could foster the adoption level and strengthen the national and state-level priorities to control and mitigate the nonpoint source (NPS) pollution from the agriculture sector. Findings suggest that the consequentiality treatment can only attenuate the bias of the intended attributes. Alternatively, cheap talk has a more significant curbing effect on all the attributes. Thus, cheap talk proved to be more effective than consequentiality in controlling the bias of the WTP estimates. However, we are uncertain whether these methods have eliminated the bias, as we have no counterfactual experiment where respondents must make an actual payment (Landry & List, 2007; Morrison & Brown, 2009).

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Appendix A1

Consequentiality script

We would like to inform you that the summary survey results will become available to producers, traders, and retailers of agricultural products as well as to the government agencies, wider general public of consumers. This means that this survey could affect the decision of producers, traders, and retailers to adopt a Best Management Practices (BMPs) certification system for strawberries as well as the average price of strawberries.

Appendix A2

Cheap talk scripts

Past research has shown that participants' choices in a hypothetical scenario, such as the following hypothetical scenarios, may be biased. Your truthful and realistic choices in the scenarios we will present will help reduce this hypothetical bias. Please make selections in this survey as you would choose in a real shopping experience. In addition, please assume that all the scenarios presented are independent of each other, so your choice in one scenario should not depend on your choice in other scenarios.

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