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Can We Reduce Attribute Non-Attendance, Satisficing Behavior, and WTP Bias in Online Samples? Evidence from a US Blueberry Experiment

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Introduction and Motivations

Online surveying through web panels, probability based or otherwise is a hugely popular platform for WTP research in agricultural marketing and policy. However, compensated online research through web-panels has many potential drawbacks that must be considered to ensure the validity of data and resulting estimates[1]. Incentive offers for participation may induce individuals to attempt to falsely "qualify" in the survey screening period and/or exert little or no effort within the survey – estimated at 8-25% of the sample respondents[2] – with many respondents simply desiring to finish and collect payment. These poor respondents are often referred to in literature as "satisficers".

Sobering questions that researchers must ask themselves are as follows:

(1) Are all of the panel respondents in my survey exerting sufficient and genuine effort in their answers? and,
(2) If not, what potentially negative effects are these poorly behaving respondents introducing into the resulting dataset?

Survey Design

In fall 2013, four survey versions were randomly assigned to 1,880 respondents recruited through a major US web panel firm who indicated they are over 18, the primary household grocery shopper, and have purchased fresh blueberries in the last year. Versions all contained metrics to quarantine satisficing respondents (below) along with behavioral and attitudinal questions and a CE eliciting preferences for fresh blueberries[3]. The only variation between survey versions was the placement and frequency of trap questions, with versions pooled to achieve adequate sample size for analysis.

Table 1: Quarantining Metric Elaborations

Common Quarantining Metric	Description
Low-Probability (LP) Screening Questions	Fraudulence metric; Inclusion of improbable or nearly impossible use/purchase history options in initial screening section (≥2 of 3 options - fresh goji berries, fresh red currants, and fresh muscadine grapes in survey)
Trap Questions (TQs) (aka "Red Herring" or "Validation" Questions)	Inattention metric; Simple embedded directive, (*"Please select 'disagree' for this line. Thank you for reading carefully."* in survey)
"Speeding"	Inattention metric; Unrealistically fast completion of key survey segments (avg. ≤4 sec. per CE choice in survey)
Demographics Consistency	Inattention metric; Inconsistency in reporting. (≥2 yr. disparity in reported age vs. birth year)

Fresh blueberry attributes include price, organic vs. conventional production, and local vs. non-state US production location.

Table 2: Choice Experiment Attributes

CE Attributes	
Attributes	**Levels**
Production Method	Organic, Conventional
Production Location	"Local" (within state of residence), "U.S." (outside state of residence)
Price (USD/pint)	$1.49, $2.49, $3.49, $4.49

Econometric Approach

The Equality Constrained Latent Class (ECLC) method identifies *inferred* attribute non-attendance (ANA) in preference space by probabilistically sorting respondents into fixed utility functions from individual CE preference data (table 3). ANA is identified through insignificant individual $\hat{\beta}$ attribute estimates. Potentially quarantined *satisficing* respondents are hypothesized to attend less attributes. Increased price ANA, violating core economic theory, is further hypothesized to lead to inflated WTP estimates.

Table 3: ECLC Fixed Latent Class Utility Functions

Latent Class	Linear Utility Functions
1. Full Attendance	$U(Blueberries) = \beta_1 price + \beta_2 organic + \beta_3 local + \varepsilon$
2. Full Non-Attendance	$U(Blueberries) = \varepsilon$
3. Attend Local Only	$U(Blueberries) = \beta_3 local + \varepsilon$
4. Attend Org. Only	$U(Blueberries) = \beta_2 organic + \varepsilon$
5. Attend Price Only	$U(Blueberries) = \beta_1 price + \varepsilon$
6. Ignore Local Only	$U(Blueberries) = \beta_1 price + \beta_2 organic + \varepsilon$
7. Ignore Org. Only	$U(Blueberries) = \beta_1 price + \beta_3 local + \varepsilon$
8. Ignore Price Only	$U(Blueberries) = \beta_2 organic + \beta_3 local + \varepsilon$

The Scaled Mixed Logit Model (SMXLM) is a random parameter estimation method in WTP space accounting for both scale and preference heterogeneity. Offending *satisficers* are hypothesized to both increase unobserved scale heterogeneity in the model (τ coefficient in below derivation) and inflate similarly WTP estimates.

$$Prob(choice_{it} = j | x_{it}, z_i, v_i) = \frac{\exp(V_{it,j})}{\sum_{j=1}^{J_{it}} \exp(V_{it,j})}$$

where $V_{it} = \beta_i' \mathbf{x}_{it,j}$ and

$$\beta_i = \sigma_i[\beta + \Delta \mathbf{z}_i] + [\gamma + \sigma_i(1-\gamma)]\Gamma \mathbf{v}_i$$

where $\sigma_i = \exp(\bar{\sigma} + \delta' \mathbf{h}_i + \tau w_i)$

$\mathbf{x}_{it,j}$ = the set *K* of attributes composing alternative *j* in choice *t* observed by individual *i*
$\mathbf{z}_i$ = the set of *M* characteristics of individual *i* which influence the mean of the taste parameters
$\mathbf{v}_i$ = the vector of *K* random variables with mean=0 and known variances and zero covariances
σ_i = the standard deviation of the individual-specific error term
$\mathbf{h}_i$ = the set of *L* characteristics of individual *i* which may overlap with $\mathbf{z}_i$
δ = parameters in the observed part of the heterogeneity in the scale term
w_i = unobserved heterogeneity, the distribution of which is assumed to be standard normal
γ = weighting parameter indicating the level of variance in the residual preference heterogeneity which varies with scale, estimated between 0 and 1
$\bar{\sigma}$ = mean parameter in the variance
τ = the coefficient of the unobserved scale heterogeneity

Results

Extrapolation of probabilistic fixed class assignment (table 4) demonstrates that offending *satisficers* failing quarantining metrics are five times more likely to fall into the class not attending to any of the three attributes. Removing offenders through real-time quarantining metrics would decrease this Full ANA class by 38.5 - 40.6%, reduce sum-totals of ANA for every attribute, and improve all goodness-of-fit metrics for both ECLC model runs.

Further analysis through the SMXLM (table 5) reveals a consistent decline in variance and unobserved scale heterogeneity by removing offending *satisficers*, as evidenced by sharp disparities in the tau variance parameter. Importantly, offending respondents artificially inflated WTP estimates in the full sample, linked to offenders' noted higher rates of price ANA. While removing these poor respondents does not significantly alter WTP estimates in the ECLC model, SMXLM estimates are statistically significantly reduced by 12.3% and 7.4% for organic and local attributes, respectively (figure 1).

Table 4: Probabilistic Fixed Class Assignment with ECLC Model

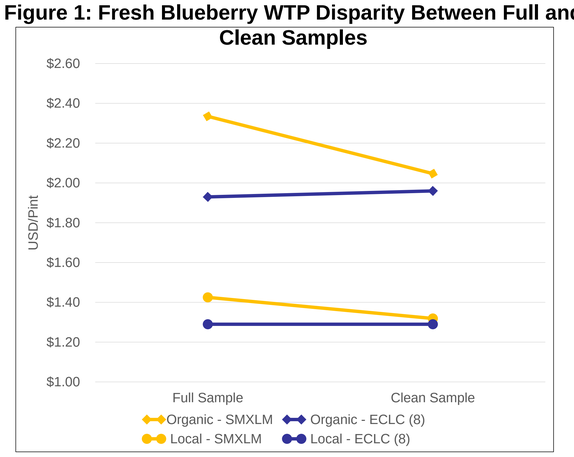
Fixed Latent Classes	8 Latent Classes: Composition % (Full Linear Utility Function Possibilities)			5 Latent Classes: Composition % (Only Unsound Classes Controlled)		
	Total Sample	Without Offenders (84%)	Offenders (16%)	Total Sample	Without Offenders (84%)	Offenders (16%)
1. Full AA	38.1%*	41.3%*	18.5%*	62.2%*	68.8%*	28.3%*
2. Full ANA	14.3%*	8.5%*	42.6%*	13.0%*	8.0%*	41.0%*
3. Attend Local Only	3.6%*	4.0%*	2.1%*	4.4%*	4.9%*	2.5%*
4. Attend Org. Only	4.2%*	2.9%*	13.0%*	5.8%*	3.5%*	15.6%*
5. Attend Price Only	6.1%*	6.2%*	5.5%*	-	-	-
6. Ignore Local Only	0.0%	0.0%	2.2%	-	-	-
7. Ignore Org. Only	22.1%*	25.5%*	10.6%*	-	-	-
8. Ignore Price Only	11.5%*	11.6%*	5.6%*	14.6%*	14.9%*	12.6%*
L-L	-8,726.7	-6,513.2	-2,079.4	-9,199.9	-6,970.0	-2,107.9
Adjusted R^2	0.4847	0.5428	0.2282	0.4568	0.5107	0.2176
AIC/N	0.715	0.635	1.075	0.753	0.679	1.088
Observations	24,440	20,553	3,887	24,440	20,553	3,887
Sum-Total ANA Rate						
Price	33.6%	27.1%	63.3%	37.8%	31.3%	71.7%
Organic	46.1%	44.2%	60.8%	17.4%	12.9%	43.5%
Local	24.6%	17.7%	63.3%	18.8%	11.5%	56.6%

Table 5:Scaled Mixed Logit Model Results

Coeff. in WTP Space, USD/pint	Total Sample	Removing Offending Respondents	"Offending" Respondents
Organic [vs. conventional]	2.335***	2.047***	3.959***
95% CI	[2.296 – 2.374]	[2.013 – 2.081]	[3.877 – 4.041]
Local [vs. non-state U.S.]	1.425***	1.319***	1.562***
95% CI	[1.418 – 1.432]	[1.313 – 1.325]	[1.558 – 1.566]
Standard Deviations			
Organic	3.080***	2.422***	2.569***
Local	0.515***	0.422***	0.126
τ-Variance Parameter	1.131***	1.102***	1.901***
$\bar{\sigma}$	0.977	0.974	0.824
L-L	-9,009.31	-6,676.48	-2,124.92
Adj. R^2	0.468	0.531	0.210
AIC/n	0.738	0.650	1.096
Observations (n)	24,440	20,553	3,887

Note: *** signifies significance at the 99% confidence level

Figure 1: Fresh Blueberry WTP Disparity Between Full and Clean Samples



Conclusions

Poorly behaving respondents fraudulently entering surveys and/or paying little to no attention to survey questions are present in web panel samples and most likely harming data quality. Use of simple, real-time quarantining filters in online surveying can prevent these respondents from skewing resulting data, proving more confidence in overall estimates.

In this study we show that failing to quarantine *satisficers* from the sample results in greater attribute non-attendance, especially those failing to attend any attributes at all, and artificially increased unobserved scale heterogeneity. While a minority of respondents in the cleaned sample still fall into fixed classes ignoring some or all attributes, the ANA rates for all attributes are consistently reduced with filtering.

The ultimate effect of inflated WTP estimates when including *satisficers* in the mixed logit model is worrying for online WTP research. By quarantining these individuals, WTP estimates are reduced by 12.3% and 7.4% for the organic and local attributes, respectively. Negligible WTP effects are seen in the ECLC model, as this model already censors all included classes other than full attendance. As *satisficers* are much less likely to sort into the full attendance class, their effect is almost automatically controlled. However, as the literature includes many more examples of advancements with mixed logit models, results from the scaled mixed logit model are particularly pertinent to most WTP researchers.

We conclude by strongly recommending the use of simple, real-time quarantining tools in online surveying. While we show these easily programmable metrics are particularly important for WTP researchers, *satisficers* may be present in any online panel sample and remain important to control to ensure reliable data and, ultimately, reliable conclusions.

References and Acknowledgements

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