Eye Tracking to Model Attribute Attendance

Daniel Chavez[1], Marco Palma[2] and Alba Collart

[1]Corresponding author. Research Assistant, Department of Agricultural Economics, Texas A&M University 2124 TAMU, College Station, Texas, 77843
(979)-587-4492 danieleduardo11@tamu.edu

[2]Associate Professor and Extension Economist, Department of Agricultural Economics, Texas A&M University. 2124 TAMU, College Station, Texas, 77843
(979)-845-5284 mapalma@tamu.edu

[3]Assistant Extension Professor, Department of Agricultural Economics, Mississippi State University. P.O. Box 5187. Mississippi State, MS 39762
(662)-325-0413 collart@agecon.msstate.edu

Selected Poster prepared for presentation at the Southern Agricultural Economics Association (SAEA) Annual Meeting, San Antonio, Texas, February 6-9, 2016.

Using Eye Tracking to Model Attribute Non-Attendance in Choice Experiments

ABSTRACT

The literature on choice experiments has been dealing with ways to refine preference elicitation from subjects and predictive power of models. Technological advances such as eye tracking has improved our understanding on how much of the attributes and attribute levels presented to participants is being considered in the decision making process in these kind of experiments. This study investigates subjects' degree of attendance to attributes and how it influences their choices. The amount of time the subjects spent observing each attribute, relative to all available information on each choice set is used to estimate the attribute attendance. This indicates the *revealed attendance* to the attributes in the experiment. A simple econometric approach compares the parameter estimates from revealed attribute attendance adjusted models using data from an eye tracking device and a model endogenously inferring the probabilities of using information from each attribute in the choice. The results show that the assumption that participants use all the available information to make their decisions produces significant differences in the parameter estimates, leading to potential bias. The results also illustrate that model fit and predictive power is greatly increased by using revealed attendance levels using eye tracking measures. The most significant improvement however, is to endogenously infer attribute attendance; even more so with revealed attendance indicators.

Key words: Choice Experiments, Eye-Tracking, Attribute Attendance

JEL codes: C91, C18

INTRODUCTION

It should come as no surprise that as the necessity to inquire about consumers' decisions about goods has increased, the use of multi-attribute choice experiments (CE) has increased as well. CEs have become the weapon of choice in stated preference elicitation research (Hess, Hensher, and Daly 2012). With this growth, some of the assumptions of CE have taken more relevance (Hensher, Rose, and Greene 2005), in particular on the behavioral component of decision making, and how much are CEs capturing realistic behavior. One topic that has gained interest in the CE literature is how much attention are subjects giving to the attributes presented to them (Hensher 2006). In other words, are subjects ignoring certain attributes or attribute levels to make their selections in CE? This phenomenon has been dubbed attribute non-attendance (ANA). A distinction must be made at this point: attendance should not be confused with attention. An attribute in a choice set CE may have been paid attention to, but if the marginal impact of that attribute on the final decision is not relevant it would have not been attended to (Balcombe, Fraser, and McSorley 2015). Several approaches to ANA have been reported and their effects explored in the literature (Hensher et al. 2005, Balcombe, Burton, and Rigby 2011, Scarpa et al. 2012). One of them is stated ANA: when the subjects are asked *ex-post* if they chose to ignore any attributes or attribute levels to make their decisions. The measure of stated ANA in predictive power has been investigated by comparing it with the inferred ANA. Inferred, or endogenous, ANA is inferring by the choices whether the attributes were attended or non-attended (Hole 2011). Both measures have been found to be complementary to each other and improve the predictive power of choice models (Hole, Kolstad, and Gyrd-Hansen 2013). Another complementary measure is to directly monitor the visual process that subjects are executing to gauge attendance (and non-attendance) to the attributes in CE: visual ANA (Balcombe et al. 2015). For this measure though, the use of an eye tracking device is needed.

The advent of eye tracking technology allows for a non-invasive exploration of the behavior of decision makers. The principle behind eye tracking taps into the complexity of eye movements as participants gather information during an experiment. The fovea, the portion of the retina that is responsible for processing visual information, gets projected only about 2% of the visual field at any given moment. Thus to scrutinize different visual stimuli, the eyes must move between such stimuli, to allow the focus of the fovea for information handling (Duchowski 2003). The eye movements have two components: fixations and saccades. The rapid movement, usually between 20-40 ms, to shift attention between one visual stimulus and the next one is the saccade. Fixations last longer, around 200-500 ms, representing the times when the eyes are relatively affixed on a contiguous area. The fixations are the moments when the focus on the area is projected on the fovea (Wedel and Pieters 2008). Eye tracking devices are basically a set of high resolution cameras that follow the subject's eyes and gather their position on the computer screen, distance to the screen and, depending on the device being used, other measures such as pupil dilation and luminosity levels. The eye tracker then captures the fixations and saccades within the visual field of the subject, which in this case is the computer screen.

The use of eye tracking in economics is novel and gaining traction as the technology becomes more accessible. For the interest of ANA, it provides a great tool, as the eye tracker monitors the fixations and time spent on each of the attributes, without eliciting any information from the subjects, providing a less biased measure than stated ANA (Balcombe et al. 2015). Though subjects in settings with eye tracking are generally aware that they are being monitored and the possibility of experimenter demand effects cannot be ruled out, it is a safe assumption that the search dynamics for a most preferred good would not be manipulated due to experimenter demand effects by a subject deemed a utility maximizer. With this in mind examining the eye movements could potentially be important to understand decision making (Reutskaja et al. 2011).

METHODOLOGY

Data Collection

A total of 60 subjects from the general population (non-students) were recruited through email to participate in the study at a university campus in a small-sized city in the southern United States. Participants were presented with 12 choice sets with four alternatives each, one of them representing the possibility of not purchasing any of the products offered, the so called opt-out option. The product used in the experiment was one pound of fresh fish fillet. Each alternative had four attributes to be considered: fish type, production method, price and origin. Every alternative was also accompanied with a photograph of the corresponding product. The fish attributes and attribute levels for the CE are described in table 1.

Table 1: Available Attributes and Attribute Levels

Attribute	Attribute Levels			
Fish	Catfish	Pacific Cod	Mahi Mahi	Flounder
Production Method	Wild	Farm		
Price	$1.5	$2.5	$3.5	

Using these attributes, the choice sets were designed in Ngene (ChoiceMetrics 2014) using the Fedorov algorithm. A D-efficient fractional factorial experimental design was done in a multinomial logit framework with no priors (Kuhfeld 2013). Following the general practice in CE, the opt-out option was placed last in each slide (Louviere, Hensher, and Swait 2000, Hess and Daly 2010). Responses were incentivized by making one of the choice sets binding. The binding round was randomly determined by rolling a twelve sided die. The number rolled indicated the binding round and the subject's selection in that choice set was given to them along with their participation payment of $30 minus the price of their selection.

Alternatives were presented in a 1920 x 1200 pixel computer screen while a Tobii TX-300 eye tracker collected information about the subjects' eye movements. Data were collected at a rate of 120 data points per second. CAL. The areas on the screen where each attribute was located were defined as "areas of interest" using the software Tobii Studio (TobiiAB 2015). This setup allows for several eye-tracking metrics to be segregated for each attribute. One of these metrics is total visit duration (TVD): the measurement in seconds of how long the subject spent focused in a particular attribute. Counting the number of fixations and re-fixations is another common measure (Orquin and Mueller Loose 2013). The absence of fixations on a particular stimulus implies that subjects did not tend to it and therefore did not consider it when making their choices (Orquin and Mueller Loose 2013). This point of view excludes the possibility that subjects may be recalling the information from memory, which is a valid assumption in situations the subjects are familiar with. Low or zero TVD could also have the same implications and drawbacks. However, higher counts of fixations versus higher time spent focusing on a particular stimulus could have different repercussions. As subjects spend more time on a stimulus, they may be limiting the amount of information going to the fovea and the brain (Duchowski 2003). The same needs not to apply to the number of fixations on the stimuli as the time for each fixation may vary and serve different purposes from a data gathering strategy standpoint, though the two are highly correlated. The rate of decay of TVD over time may indicate potential learning and fatigue effects. Khushaba et al. (2013) found that learning and fatigue effects reduce the overall time spent per alternative and choice set as a subject progresses through a CE. Thus comparing the absolute values of TVD, or any other eye tracking metric for that matter, disregarding the choice set number would not be appropriate. The weighted TVD provides a comparable measure of attention across choice sets and alternatives, since it is relative to the total time spent per choice situation for each attribute, alternative and subject.

The weighted TVD allows for identification of attendance and non-attendance for an attribute by choice set and alternative for each subject. The classification is based on a minimum attendance threshold. This study uses 10% as attendance threshold: if a subject spent 10% or less time on the attribute it is taken to be revealed as non-attended[1]. Revealed ANA indicator variables were used for estimation purposes.

Econometric estimation

The econometric specifications used begin with the most parsimonious model fit, the standard logit assuming full attribute attendance, moving to the panel logit specification and finally estimation of a logit model where the attention to the attributes is modeled endogenously. The responses on selections by subjects are evaluated through a random utility framework (McFadden 1974) where the utility that individual i receives from selecting good j has the form of $U_{ij} = \beta(x_{ij}) + \varepsilon_{ij}$. Here the second component is a stochastic error term independent and identically distributed that follows an extreme value distribution. This error is independent of x_{ij} and is uncorrelated across individuals i and j goods. The first component is deterministic and

[1] Robustness checks were conducted with 5% and 15% thresholds. The general results of the segregation hold. Results are available upon request from the authors.

describes the behavior of the *i*-th individual with respect to the *j* attributes being evaluated. Then if alternative is chosen, it must maximize utility for that subject. In this case the dichotomous response of product *j* being selected or not can be modeled with a standard logit conditioned on the available alternatives.

Given that the subjects face T choice sets, where they make selections assumed to be independent for each choice situation t, a time dimension can be added to the utility function: $U_{ijt} = \beta\left(x_{ijt}\right) + \varepsilon_{ijt}$. This utility now describes a panel model, where the time series element is the choice set and the cross-sectional portion are the individuals. What this framework entails in terms of preference is that if alternative *j* is chosen, then it must maximize the utility for that choice set, not the entire decision experience of all selections during the CE. Both model applications described so far assume subjects use all the available product attributes to make their choices. Using the revealed ANA indicators, relaxes this assumption and the assumption that all subjects pay the same level of attendance to all the attributes.

A third approach used is to econometrically model the endogenous attribute attendance (EAA) (Hole 2011, Hole et al. 2013). This approach considers the choice process and the outcome. It provides the joint probability of choosing an alternative, given an attribute processing strategy selected: i.e. the marginal probability that a given attribute processing strategy is used multiplied by the probability of the product being selected given the choice of the attribute processing strategy. Respondents have K attributes to choose from, thus the model assumes respondents only choose a subset C_q of information to make their decision. The entire set of attribute subsets is defined by $Q = 2^K$, which includes the set where all attributes are considered (C_Q) and an empty set where all the attributes are ignored (C_1). The first set represents the common assumption in CE that subjects use all the information available to make their choices. The second set denotes decision making following a random procedure where all the attributes are ignored.

The random utility function described previously can then be conditioned on the subset of information begin used: $U_{ijt} = \sum_{k \epsilon C_q} \beta^k x_{ijt}^k + \varepsilon_{ijt}$. The choice probabilities for this utility function specification would still follow the logit framework described in the previous two models. The EAA model has one critical assumption: that ANA probability of each attribute is independent of each other (Hole et al. 2013). The output of the model is reported in two stages: the fit of the model for the selection given the attribute processing strategy selected and the probabilities that the attributes were non-attended as part of the attribute processing strategy. In this case, using indicators for revealed ANA could also be useful for comparison of model fit and prediction power.

RESULTS AND DISCUSSION

In line with previous findings in CEs with eye tracking such as Khushaba et al. (2013) the absolute TVD for each choice set and each attribute declines as the subjects advance in the CE. A description is shown in Figures 1(a)-(d). In Figure 1(a) the total amount of seconds spent on each alternative by choice set is shown. It can be seen that although not monotonically, the TVD decreases over time. Figure 1(b) shows TVD for fish type, 1(c) for price and 1(d) for production method. This breakdown by attribute also shows the same trend as 1(a): over time subjects are learning and becoming more fatigued with the task and spend less time attending to each attribute. In terms of attribute attention, weighing TVD for revealed ANA allows accounting for this decreasing trend. The summary statistics for TVD are shown in table 2.

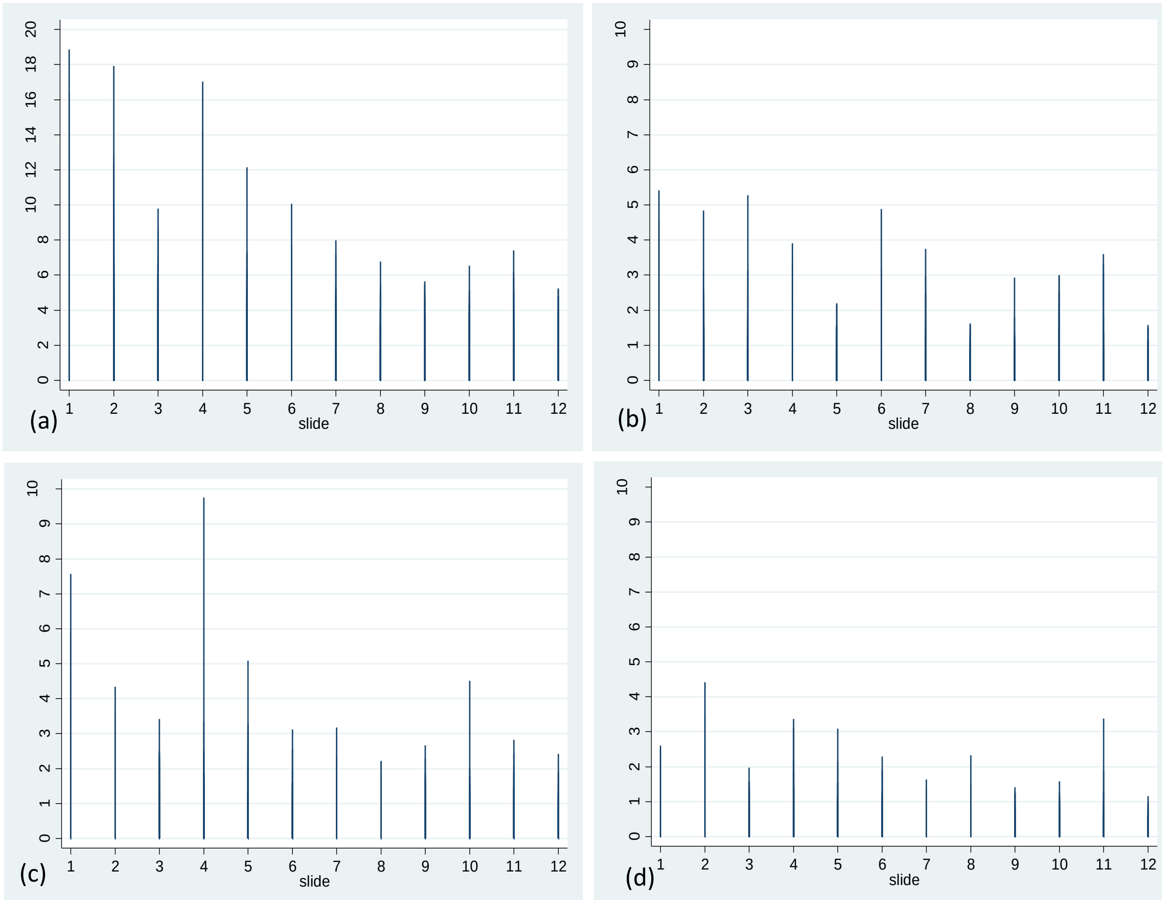

Figure 1: TVD for each alternative and attribute broken down by slide.

Table 2: Summary statistics for TVD by choice set

Choice Set	Alternative			Fish Type			Price			Production Method		
	Mean	Max	SE	Mean	Max	SE	Mean	Max	SE	Mean	Max	SE
1	3.223	18.860	0.187	0.644	5.420	0.057	0.748	7.570	0.060	0.457	2.600	0.036
2	2.196	17.930	0.154	0.433	4.840	0.041	0.530	4.340	0.045	0.316	4.420	0.034
3	1.828	9.800	0.111	0.389	5.280	0.039	0.406	3.420	0.033	0.236	1.970	0.023
4	1.673	17.030	0.137	0.355	3.910	0.035	0.405	9.760	0.052	0.205	3.370	0.028
5	1.571	12.150	0.104	0.260	2.200	0.025	0.374	5.090	0.039	0.240	3.090	0.026
6	1.490	10.060	0.104	0.349	4.880	0.038	0.320	3.120	0.029	0.214	2.290	0.023
7	1.305	7.990	0.083	0.300	3.750	0.030	0.299	3.180	0.028	0.157	1.640	0.018
8	1.207	6.770	0.076	0.245	1.620	0.023	0.315	2.220	0.027	0.165	2.320	0.019
9	1.173	5.640	0.070	0.241	2.930	0.023	0.299	2.670	0.027	0.170	1.410	0.017
10	1.191	6.530	0.076	0.301	3.000	0.032	0.314	4.510	0.030	0.135	1.580	0.016
11	1.155	7.420	0.079	0.259	3.600	0.031	0.319	2.820	0.030	0.152	3.380	0.022
12	0.965	5.250	0.063	0.190	1.580	0.019	0.289	2.420	0.025	0.138	1.160	0.014

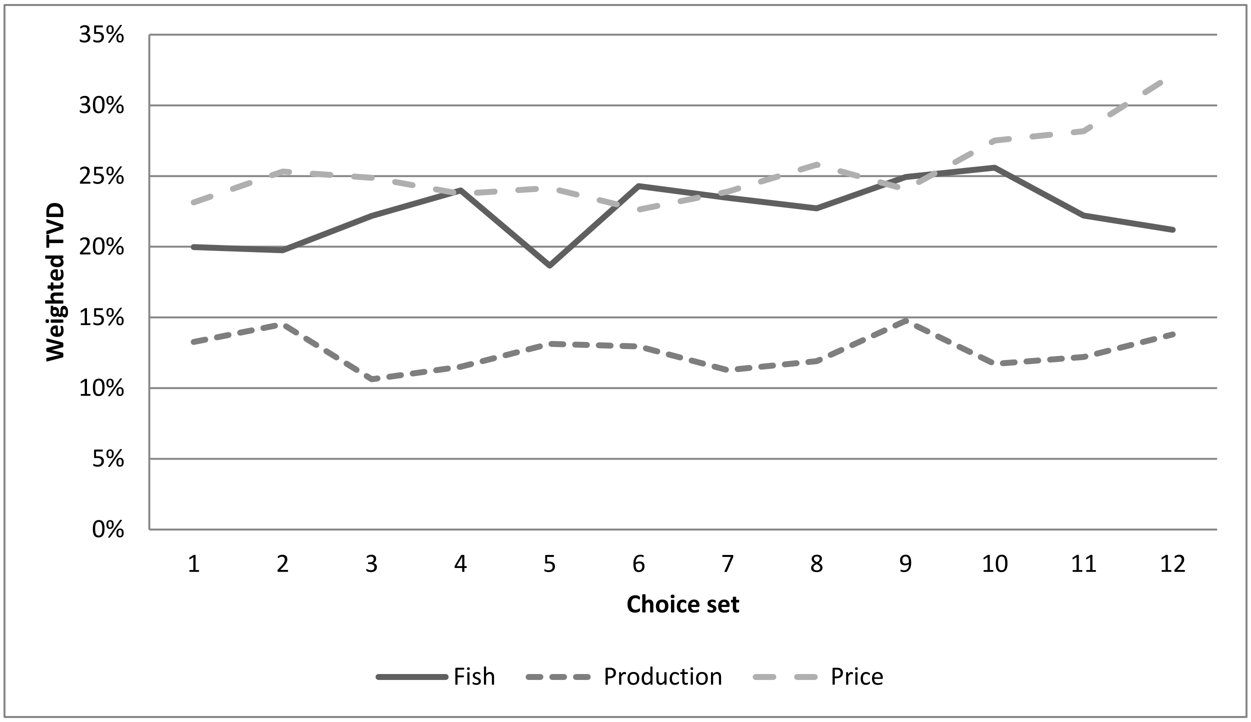

Figure 2: Weighted TVD for each attribute by slide

Weighted TVD for each attribute by slide is shown in figure 2. The weighted TVD is not statistically different between slides in a Wilcoxon rank test[2]. It can be seen in Figure 2 that the weighing procedure helps account for the decreasing trend in TVD for attribute attention. For the sake of being able to make comparisons and identify the effects of using revealed ANA, results are presented for the most parsimonious model, the standard logit framework, then for the panel logit specification and finally for the EAA logit model. The estimates of the logit model are presented in table 3.

[2] Wilcoxon test results not reported but available upon request from the authors.

Table 3: Standard Logit Model

	Full Attendance	Revealed Attendance
Fish	0.236356***	0.33553*
	(0.07816)	(0.17182)
Price	-0.68758***	-0.72402***
	(0.07376)	(0.16465)
Prod	0.03417	0.33337*
	(0.08632)	(0.18217)
N Obs	2880	758
Log-Likelihood	-1729.9190	-474.1296
AIC	3465.8380	954.2593
BIC	3483.7340	968.1513
Tjur	0.0156	0.0151

Note: Significance is indicated by *, ** and *** for the 10%, 5% and the 1% level or less respectively. Standard errors in parentheses.

The model includes the three attributes that were described in the methodology section as part of the specification. The first column of parameters describes the estimates assuming participants use all available attributes to make their choices. The estimates show that production method is not statistically significant; price has a negative and significant effect; and the type of fish has a significant and positive effect on choice. Several model fit measures are reported: log-likelihood (LL) and the information criteria, Akaike (1974) (AIC) and Bayesian (Raftery 1995) (BIC) and additionally the Tjur (2009) discrimination coefficients (pseudo R^2). An advantage of the Tjur statistic is that it is not affected by sample size or maximization technique. It is obtained by calculating the means of predicted probabilities of the events (*y=1*) and non-events (*y=0*), then taking the difference between those two. If the model is an accurate predictor, the absolute value of the difference should be higher.

Indicator variables for revealed ANA are used to select the data of attributes revealed as fully attended to. A likelihood ratio test (significant at 0.01)[3] reveals that the full data assuming subjects use all available attributes produces different parameter estimates than the model using only the attributes that were revealed as attended (Greene 2012). For this reason all results in this study are reported for the models with the traditional assumption of full attention to all attributes and the models with data of revealed attendance. The results described in the second column of parameters of table 3 are the estimates for a standard logit regression using the data with revealed attendance. The parameter estimates have a higher mean and variance for the revealed attendance model than for assumed full attendance. This result goes in line with previous literature on consumer heterogeneity: as the attribute is being considered, subjects decide different action paths with respect to the information it provides (Greene and Hensher 2013). The larger sample size of the model with assumed full attendance data can account for lower variance in the parameters. Complementary to this, using only the attributes that have been revealed as attended reduces the noise in the data, which in turn produces estimates with lower variances. It is also noteworthy that for the revealed attendance data, all the attributes seem to play a role in their decision making, if at least marginally. All the parameters in the revealed attendance model are significant, at least at the 10% level. As for the model fit, likelihood based tests are not comparable due to the differences in sample sizes. The Tjur's R^2 is comparable but shows that separating the data by revealed attendance does not improve the predictive power of the model.

Table 4 provides the results for a panel logit model with random effects. The LL in both models is higher than their non-panel structured counterparts presented in table 3. We also see an increase in the magnitude of the mean for the parameters for fish type and production method.

[3] Results of LR test not reported but available upon request from the authors.

This increase implies significance at a higher degree for the production method. The largest improvement however can be captured by the Tjur statistic, which shows that the fit of the models improves greatly by accounting for the panel structure.

Table 4: Panel Random Effects Logit Model

	Full Attendance	Revealed Attendance
Fish	0.57538***	0.81899***
	(0.08706)	(0.20171)
Price	-0.60814***	-0.69244***
	(0.07652)	(0.17951)
Prod	0.31602***	0.76101***
	(0.09516)	(0.21669)
N Obs	2880	758
Log-Likelihood	-1685.6790	-427.6176
AIC	3379.3590	863.2353
BIC	3403.2210	881.7580
Tjur	0.1306	0.1753

Note: Significance is indicated by *, ** and *** for the 10%, 5% and the 1% level or less respectively. Standard errors in parentheses.

The EAA model provides a great tool to be able to improve the fit of the models and provide better estimates and prediction power to the models (Hole et al. 2013). The results in the first column of Table 5 show the application of such model assuming full attention to attributes and modeling the non-attendance endogenously. The second column presents the results of the EAA model by using revealed ANA. The parameter estimates for the attributes considered in the CE carry the same interpretation as with the previous two models shown. The following three estimates are the endogenously determined probabilities of the model. These represent the portion of the sample that would have been non-attended for each attribute in the decision making in order for the selections in the sample to happen.

Table 5: Endogenous Attribute Attention Logit Models

	Assumed Full Attendance	Revealed Attendance
Fish	1.19837***	2.51017***
	(0.09955)	(0.61519)
Price	-0.98155***	-1.34832***
	(0.10366)	(0.48395)
Prod	1.59866***	3.28579***
	(0.14320)	(0.76553)
ANAFish	0.31348***	0.24819***
	(0.08129)	(0.10264)
ANAPrice	0.22109***	0.08152
	(0.08469)	(0.38432)
ANAProd	0.65836***	0.51441***
	(0.07055)	(0.12325)
N Obs	2880	266
Log-Likelihood	-820.3046	-65.44444
AIC	1652.6090	142.8889
BIC	1688.4020	164.3899
Tjur	0.1689	0.6936455

Note: Significance is indicated by *, ** and *** for the 10%, 5% and the 1% level or less respectively. Standard errors in parentheses.

The estimates for each attribute in the EAA specifications have the same direction as in the previous models described. The means of the parameters are higher in all the arrangements of the EAA model, indicating that the marginal effect of each attribute is stronger. In model with the data of revealed attendance, the probabilities of non-attendance to price are not statistically different than zero. In this same specification around half of the times, production method was not considered decisive for product selection, and one in four occasions fish types would not be pondered on to choose the preferred option. Endogenously estimating attribute attendance on the data increases the mean effect of each of the attributes considered. In line with the work of Hole et al. (2013), the fit of the models calculating the attribute attendance endogenously is superior than the previous models. The use of revealed ANA to segregate data improves goodness of fit even more than in the previous models. The prediction of selections for the revealed attendance data is 0.69 (Tjur's), which is the best predictive power of all the results presented in this paper.

CONCLUSIONS

All of the models presented in this paper suggest that using revealed ANA as a criterion to refine subject behavior in CE can be advantageous for both explanatory and predictive purposes. In all cases the use of revealed attendance using the objective measures from the eye tracker improves the log likelihood, information criteria, Akaike and Bayesian, and Tjur statistics for model fit and relevance of the parameter estimates. The best single improvement however, is achieved by allowing for an endogenous estimation of the probabilities of non-attendance to the attributes inferred from the decisions taken with the EAA model. The EAA model fit and prediction is further enhanced by using revealed ANA indicators. Eye tracking technology is not ubiquitous and the practicality of its use can have its caveats. The results indicate is that if only to segregate the data by revealed attendance, the use of this technology helps explaining and predicting selections in CEs even in the most parsimonious model. In the absence of this technology though, using the EAA model provide the best results. A logical expansion of this research would be to enhance the experiment by asking subjects their level of attendance *post facto* as the stated ANA literature has done. Visual attention and stated attention could be tested as complementary or divergent measures of attendance and be used to further explain behavior.

Using stated and revealed ANA in a framework of inferred and endogenously estimated ANA might provide even better fit of the models and higher explanatory power.

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