Off the Reservation: Pushing the Bounds of Rationality in Experimental Auctions

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"*Choices are the hinges of destiny*"

Pithagoras c430 B.C.

Abstract

The use of experimental economics in valuation of market and non-market goods has grown considerably over the past few years. The ability of experimental auctions (EAs) to reveal consumer preferences and their malleability have been greatly praised by researchers across the profession. Because of the high cost of conducting EAs, researchers have a vested interest in extracting as much information as possible from the research sample, usually presenting multiple products or product alternatives to participants. In the last decade large amounts of work has been done to improve the methodology and design of EAs. However, choosing how many products or product alternatives to use has no clear guideline. Findings of this study support a "choice overload" phenomenon even with a relatively small number of products used for auction. Mean willingness to pay was found to be a decreasing function of the number of alternatives presented to participants. A heteroscedastic error variance scaler was estimated and it was found to be a decreasing function of the number of alternatives presented, implying more variance across responses as the number of alternatives increases.

Key words: Choice Overload, Experimental Economics, Heteroscedastic Error Variance, Willingness to Pay

JEL codes: C91, C18

Introduction

Choice is defined by Merriam-Webster (2014) as the power to make a decision or the act of deciding between two or more possibilities. This carries a very potent message: power and possibility through decisions. The importance of evaluating choices reveals as paramount to economic research. The complexity of the choice task and the ability of people to choose play an important role on the validity of the results (Levitt and List 2007). Louviere (2006) states: “I am not convinced that…subjects placed in strange tasks…tell us much about real behavior”. Cason and Plott (2014) propose that the complexity of current experimental valuation techniques produce a “failure of game recognition” where subjects do not make the connection between their acts and the consequences, rendering choices that are not reflections of preferences. Complexity is an issue for subjects, especially those with low mathematical skills, something often neglected by economists (Dave et al. 2010). Burton and Rigby (2012) show that almost unambiguously, increasing the number and complexity of choices increases the error variance in discrete choice experiments (DCE). However, when subjects are permitted to self-select the number of options to choose from, they revealed their preferences more accurately, considerably reducing the variance in the results.

The scientific concern about subjects’ behavior when facing many alternatives is not new. In the mid-20th century experimental psychology findings by Miller (1944) revealed what he called the *double avoidance-attraction conflict*. Conflict as defined by Miller (1944) is produced when an individual must decide between two competing responses that are incompatible and it arises more frequently when a subject has strong tendencies towards approaching and avoiding a goal. In one of his studies, subjects who were classified as “timid” using psychometric tests were charged with asking for a raise in the participation fee in the study. Timid participants had incentives to ask for a higher payment, but strong tendencies, due to their personal traits, to avoid the confrontation of asking for the raise. The concept developed in the results of this experiment is that having to let go of an attractive option or status quo for a potentially better alternative, could lead to conflict in individuals and procrastination in the choice decision. Lewin (1951) expanded this idea further by proposing that options that are not only incompatible but also mutually exclusive lead to more conflict; this situation is enhanced as the differences between competing alternatives appears to be smaller. Lipowski (1970) proposed that the struggle to decide increases with the number of options available, leading to anxiety and failure to choose. Contrary to the common assumption that more options are better, the concept of *choice overload* (Iyengar and Lepper 2000), describes that an extensive array of alternatives reduces the desire for goods or at least the likelihood of purchase. Iyengar and Lepper (2000) conducted a field experiment placing a promotional tasting booth in an upscale grocery store, which displayed either 6 different flavors of jam or 24 flavors. The flavors of jam that are common in the market (i.e. strawberry, blueberry, etc.) were excluded to avoid strong preference for a particular flavor that could influence the results. After subjects approached the booth they tasted as many jams as they wanted to, as many times as they wanted to and they were given a coupon towards the purchase of any jam of their choosing from the preserves section of the grocery store. Iyengar and Lepper (2000) found that subjects presented with 24 different jams were much more curious about what was going on than those presented with 6 jams for tasting. Around 60% of the subjects who walked by the booth with 24 different flavors stopped to taste the jams, while only 40% of the shoppers walking by paused when there were only 6 alternatives. However, from those who stopped at the booths to taste the jams, the ones that sampled from the larger number of alternatives were less likely to purchase (3% of them did) than those presented with a relatively smaller set (30% bought a jam after visiting the booth). This counter-intuitive result that more options of a good decrease the probability of purchase is what they define as the *choice-overload effect*. A possible explanation described by the authors (Iyengar and Lepper 2000) is that with simple choices, namely limited options, subjects engage in a search for an optimal solution but not with larger sets of options. Heiner (1983) suggests that individuals resort to simplifying decisions they find complicated, which could be the case if more alternatives offered increases the complexity of the decision.

Most research on choice overload compares large sets of alternatives, i.e. 16-30 (up to 300) with relatively small ones, i.e. 6-8 (Scheibehenne, Greifeneder, and Todd 2010). This article evaluates in a non-hypothetical experimental auction (EA) if individuals choosing among similar competing products manifest choice overload even with few alternatives, reducing the ability of subjects to effectively make market valuations. As EA have become crucial in marketing (Lusk and Shogren 2007) choice overload effects could be problematic if they manifest in small sets of alternatives. Due to the cost and time consuming nature of EAs, securing a large sample is always a challenge (Lusk et al. 2001). Hence, researchers conducting EAs have a vested interest in trying to extract as much information as possible and usually include multiple products to be evaluated by participants. In the last couple of decades, research to improve the methodology of EA has gained considerable attention (Lusk and Shogren 2007, Rousu and Kosa 2005, Corrigan and Rousu 2006, Lusk, Alexander, and Rousu 2007, Drichoutis, Lazaridis, and Nayga 2008). However, there is no clear guideline on how many alternatives should be presented in an EA. Is there a breakpoint where confusion overcomes subjects?

Economists designing EAs are most of the time interested with broader empirical and policy questions, such as: What would be the effect of having more alternatives? How many alternatives are too many? One of the several aspects to consider is the increased search cost associated with a larger set of options. Stivers and Tremblay (2005) define search costs as the loss in utility for each additional unit in the set being considered. Based on this definition a larger set to choose from increases these search costs, thus diminishing utility for all alternatives. There is also another issue to be considered with the change in probabilities of finding the "right" alternative. Norwood (2006) argues that in a choice situation greater variety increases the probability of individuals finding a "new" more preferred option. However, he also points out that if subjects only peruse a subset of options chosen randomly, the probability of finding a most preferred option is lower with a larger set than a smaller set. This study has as main objective: to answer if having more options in an EA is helping or hindering the research agenda of economics? The analysis questions can be broken down into two main areas: 1) About the WTP means: does the number of products available in an EA affect WTP values? Is WTP a non-increasing function in the number of alternatives? Is such function monotonic?; and 2) About the variance of the estimates: does a relatively small number of alternatives add enough complexity for a choice overload effect to manifest in an EA? Can subjects differentiate products among competing alternatives in experimental auctions? Does increasing the number of alternatives hinder respondents' ability to differentiate between products?

Answers to these questions would help improve the design of EAs, providing criteria for tradeoffs between number of products offered, cost of running the EA and quality of the data gathered through EAs. Tackling these questions could also shed some light on the product offering in more complex settings, such as real markets, where the laboratory rigor of experimental economics does not hold.

Theoretical framework

In its simplest form the expected utility of selecting a product can be expressed as the maximum, **U***, of a utility function $\mathbf{U}(\mathbf{X}_1)$, where $\mathbf{X_1}$ is the vector of all available alternatives for product $\boldsymbol{X_1} = \{x: x_{11}, x_{12} \ldots x_{1n} \in \boldsymbol{X_1}\}$ varying in different attributes and attribute levels. This maximization is subject to a budget constrain $\boldsymbol{P_{X1}X_1} \leq \boldsymbol{I}$, where $\mathbf{I}$ is the set of resources for the decision, i.e. time, cognitive effort, money, etc. Under such model, $\boldsymbol{P_{X1}}$ represents the relative prices of the resources available for the decision and is a function of the monetary cost of the resources themselves. Additionally, the utility maximization is also subject to constrains on the use of resources to examine $\mathbf{X}_1$ denoted by $\boldsymbol{s} = f(\boldsymbol{n}) \leq \boldsymbol{S}$ where $\boldsymbol{n}$ is the number of alternatives of $\mathbf{X}_1$. The cost of searching is a monotonically non-decreasing function of the size of $\mathbf{X}$: as $\boldsymbol{n}$ increases, so does the number of comparisons that need to be performed, increasing the complexity of the choice, $\mathbf{s}$, yielding an indirect utility function $\boldsymbol{V}(\boldsymbol{P_{X1}}, \boldsymbol{I}, \boldsymbol{S})$. Now to take this model further consider a two distinct goods case, $\boldsymbol{U}(\boldsymbol{X_1}, \boldsymbol{Y_1})$ where $\boldsymbol{Y_1} = \{y: y_{11}, y_{12} \ldots y_{1m} \in \boldsymbol{Y_1}\}$ is a different good from $\boldsymbol{X_1} = \{x: x_{11}, x_{12} \dots x_{1n} \in \boldsymbol{X_1}\}$, but still a close substitute (there is elasticity of substitution between goods $\boldsymbol{X_1}$ & $\boldsymbol{Y_1}$), and constrains $\mathbf{I}$, $\mathbf{S}$ exist. Under these conditions, basic microeconomic intuition suggests that with relative prices and resource limitations constant, if the number of alternatives in $\boldsymbol{X_1}$ increases ($\boldsymbol{n}$ grows larger), while the size of $\boldsymbol{Y}$ is fixed ($\mathbf{m}$ is constant), consumers would substitute x for y to maximize utility. As the number of alternatives increases, so does the complexity of the choices and with it the use of resources to examine the options. The effect on the indirect utility $\boldsymbol{V}(\boldsymbol{P_{x1}}, \dots \boldsymbol{P_{xn}}, \boldsymbol{P_{Y1}}, \boldsymbol{I}, \boldsymbol{S})$ would be that the resources (including search costs) spent for each good would have to decrease as the number of products increases in order to remain in the same level of utility. What this implies in the practical sense is that with a higher degree of complexity, decision makers can resort to heuristics such as reducing the portion of **X** being evaluated, search only for lower priced goods, inspecting only goods they are familiar with or the ones they have a strong preference for, use more time to make their selection, and also the possibility they may not be able to reveal their true preferences due to cognitive load resulting from the increased number of comparisons the decision carries.

Let us take into consideration that economic theory dictates different revealed preferences through willingness to pay (WTP) would come from individuals perceiving products as being different (Von Neumann and Morgenstern 2007). If consumers do not perceive products as dissimilar or if they lack the ability to discern, they would be indifferent between alternatives (Debreu 1959, Samuelson 1983). This may be important for any market with a large amount of substitutes. The relevance of this to economic experiment design is crucial. If the ability of subjects to discriminate between alternatives is affected by the number of available alternatives or if the dissimilarities amid products being evaluated are not perceived as significant, WTP would not be a true reflection of preferences. An increase in the number of alternatives would increase complexity under this model, which confuses subjects and as Cason and Plott (2014) propose: confusion makes subjects fail to recognize the connection between their actions and consequences.

In this study the traditional theoretical framework of utility maximization is augmented to account for the factors described above. A number of models can be used in the analysis of the data from of EAs. The choice of which model to use is mainly driven by the data produced in the EA. Data in most EAs is coming from the same subject over multiple rounds or it is aggregated for multiple products, providing a panel structure for the data. To incorporate this panel structure different models are typically used, including linear and non-linear fixed effects regressions (List and Shogren 1999) and random effects models (Corrigan and Rousu 2006). Since in EAs the WTP can be zero, yielding a distribution censored at zero, a censored approach may be used. For these kind of data it is common to use a Tobit (Tobin 1958) model to estimate WTP: $y^* = \boldsymbol{\beta_0} + \boldsymbol{\alpha\beta} + \varepsilon$ where $y = 0 \; if \; y^* \leq 0$ and $y = y^* \; if \; y^* > 0$.

In order to account for consumer heterogeneity in responses, a factor (or several) can be assumed to have heterogeneous effects on the responses across individuals and a random parameters approach (McAdams et al. 2013) can be used. Under such model the parameters assumed to be random are allowed to vary with a specified distribution, usually a normal or log-normal with a mean $E[\beta_i|z_i] = \boldsymbol{\beta} + \Delta z_i + \Gamma v_i$, where $\boldsymbol{\beta}$ is the constant means in the distributions, z_i is the set of observed variables, Δ is the coefficient matrix, v_i

is the unobservable latent random terms and Γ is the diagonal matrix that produces the covariance matrix of the random parameters. The probabilities are based on the conditional density $f(y_{it}|x_{it}, \beta) = f(\beta_i', x_{it})\ where\ i = 1, \ldots N\ and\ t = 1, \ldots T_i$. The model assumes then that Δz_i is the variation in the responses to the parameters across individuals (Greene 2012). Therefore, the estimation of the censored data described previously is now modified to: $y^* = \boldsymbol{\beta_0} + \boldsymbol{X\beta} + \boldsymbol{Z}\Delta + \varepsilon$.

In the model used in this study $\boldsymbol{X}, \boldsymbol{Z}$ are the explanatory variables assumed to influence WTP, $\boldsymbol{\beta}$ is the vector of coefficients for those explanatory variables with fixed effects, Δ the vector of coefficients following a distribution (usually a normal) and ε is the error term accounting for unobserved factors influencing WTP. In this general form, the model (as well as almost all of the models used for EAs) assumes a normal distribution of mean zero and variance σ^2 of the error terms (Greene 2012). The other assumption about the error term is that it has the same variance across all levels of the attributes (x_i) being used for evaluation (homoscedasticity). However, if the changes in WTP are not only due to the explanatory variables but also an effect of unobserved heterogeneous factors across individuals, these unobserved factors can produce heteroskedastic error terms (Hess and Rose 2012).

If differentiating between alternatives becomes too complex (Swait and Adamowicz 2001) or increasingly costly by enlarging the set of alternatives (Stivers and Tremblay 2005, Norwood 2006) there could be several consequences on the WTP estimates following the theoretical framework of utility maximization described previously. First, if the number of alternatives presented is used as an explanatory variable in the vector **X**, it can be determined if it has an effect on the WTP and its direction. Second, since search costs and perceived complexity are both unobservable processes, the variance of the error term could depend on the number of alternatives. In this case, a scale parameter can be used to account for the heteroscedasticity of the variance as a function of the number of alternatives. The Tobit model presented before can be modified to include a scaler for the error term:

(1) $$y_i^* = \beta_0 + \boldsymbol{X\beta} + \frac{\varepsilon}{\lambda} \quad where$$

(2) $$\lambda = \boldsymbol{s} + u, \quad with\ \boldsymbol{s} = f(n)$$

Where the scale of the error terms (λ) is 1 when the errors are assumed to be identically distributed across attributes (α) and attribute levels (i) that determine the WTP in the usual homoscedastic model. When incorporating heteroscedastic errors the scaler is used to adjust the influence of the parameters:

(3) $$y_i^* = \beta_0 + \lambda\boldsymbol{\alpha\beta} + \varepsilon$$

The scaler captures the influence of unobserved traits on the decision, by adjusting the weight of the coefficients (β). The scaler in this study is a function of the number of alternatives. If the scaler function is non-decreasing as the number of alternatives (n) increases (i.e. λ has a positive sign) there is a smaller variance: more homogeneous effect of unobserved characteristics with each additional product being considered. If the scaler function decreases (negative λ) with increases in (n), the variance in responses is higher due to the heterogeneous effect of uncontrolled variables with each additional unit presented. A higher magnitude of the scaler implies a stronger effect of the non-observed features mentioned above (search costs and complexity) in the responses.

In order to measure differences across treatments in EAs Lusk, Feldkamp, and Schroeder (2004) propose calculating the implied differences: $DeltaWTP_{itj} = WTP_{itj} - WTP_{i(Base)j}$ where $t \neq Base$. These differences are not censored at zero as subjects can choose to increase or decrease their bids in an EA from one round to the next. Thus there is no need for a censored approach to measure differences and a random parameter linear model can be used (Searle, Casella, and McCulloch 1992).

Experimental Procedures

Subjects were recruited from a mid-sized city located near a large university campus in the Southern United States through advertisements in local newspapers and in the weekly supplements for grocery shopping coupons. A total of 197 subjects participated in the experiment. Each subject only participated in one session. A total of 10 sessions were carried out with a range of 12-28 participants per session. A compensation of $35 was paid at the end of the session, minus any purchases incurred during the experiment.

To measure revealed preferences an EA was used, namely a second price auction. The second price Vickrey auction (Vickrey 1961) was selected due to its incentive compatibility, manipulability and efficiency (Lusk and Shogren 2007) as well as being the predominant method in non-hypothetical value elicitation mechanisms (Lusk, Feldkamp, and Schroeder 2004). The auction product was one pound of strawberries. The reason to use strawberries is that they are highly heterogeneous within each variety, i.e. one pound of the same variety can have an array of sizes, color tones, textures and shapes. Another advantage of using strawberries is they are commonplace: it is safe to assume participants in the experiment are familiar with strawberries.

Seven different varieties of strawberries were offered for auction. The most popular variety available in local grocery stores was chosen as baseline for comparison. All varieties were coded in cyphers of three alphabetic characters to avoid ordinal bias (Meilgaard, Civille, and Carr 2007). These cyphers were not related with the names of the varieties, so subjects would reveal their preferences on the sample presented and not bring their perceptions from the market into the lab. Not all varieties were offered at the same time. The baseline variety was the only strawberry available for bidding in all rounds. The only difference between the rounds was the number of strawberry alternatives available in the auction. Each round had a different number of strawberry varieties available that ranged from one to eight. Each session had a randomized order of the bidding rounds. The randomization controls for subject fatigue and ordering effects in the auction procedure.

To measure changes in subject´s ability to discern, a duplicate of the baseline variety was included in all rounds except for the control round, where only the baseline variety and a substitute were presented. This duplicate has a different code than the base variety, but was in fact the same. If subjects´ ability to differentiate is unaltered by the number of other options presented, the gap (if any) in the WTP between the baseline variety and its duplicate should remain the same regardless of how many other varieties are offered. In order to avoid deception (Cooper 2014) no information about any of the products was provided. To be able to measure independence of alternatives and consistency in decisions a substitute product was included in all rounds of the auction along with the baseline strawberry variety. This control product was one pound of grapes, which have been regarded as substitutes for strawberries in the literature (Henneberry, Piewthongngam, and Qiang 1999, Lin et al. 2009). If independence of alternatives holds, the revealed preference for the substitute is independent of the number of non-preferred alternatives, i.e. the WTP for grapes should remain unchanged by the number of strawberry varieties presented.

Results

The sample consisted mostly of females (65%) with an average age of 46 years, yearly annual income around $54,000 and expenditures on food of $130 per week. In comparison, the study sample is representative of the population according to data from the US Census Bureau (2015). The main objective of the study was to find if the number of alternatives has a non-trivial effect on the WTP in an EA. Figure 1 shows a graph of the mean WTP for the baseline variety on the left axis and the standard error of the WTP with different number of alternatives (1-8) on the right axis. With a simple eyeball test, the graph shows a drop in WTP for the baseline variety as more alternatives are added until four strawberry alternatives are offered. At this point, the mean WTP appears to be more "stable" when 5, 6 and 7 different varieties are available[1]. WTP finally drops to when the maximum number of alternatives offered. Although the mean WTP in this EA is a non-increasing function of the number of alternatives, the pattern it is not always monotonic for all levels, only until four alternatives are presented. There is also indication of an increasing variance in the WTP in the graph of the standard error as the number of alternatives

[1] There are no statistically significant differences in a Wilcoxon rank-sum test in the mean WTP when 2-8 alternatives are offered. The mean WTP is only statistically different from all the other scenarios at the 0.05 level in the control round, when only the baseline variety is presented.

increases, which leads into the next set of research objectives: the effects of the number of alternatives on the variance of WTP in EAs.

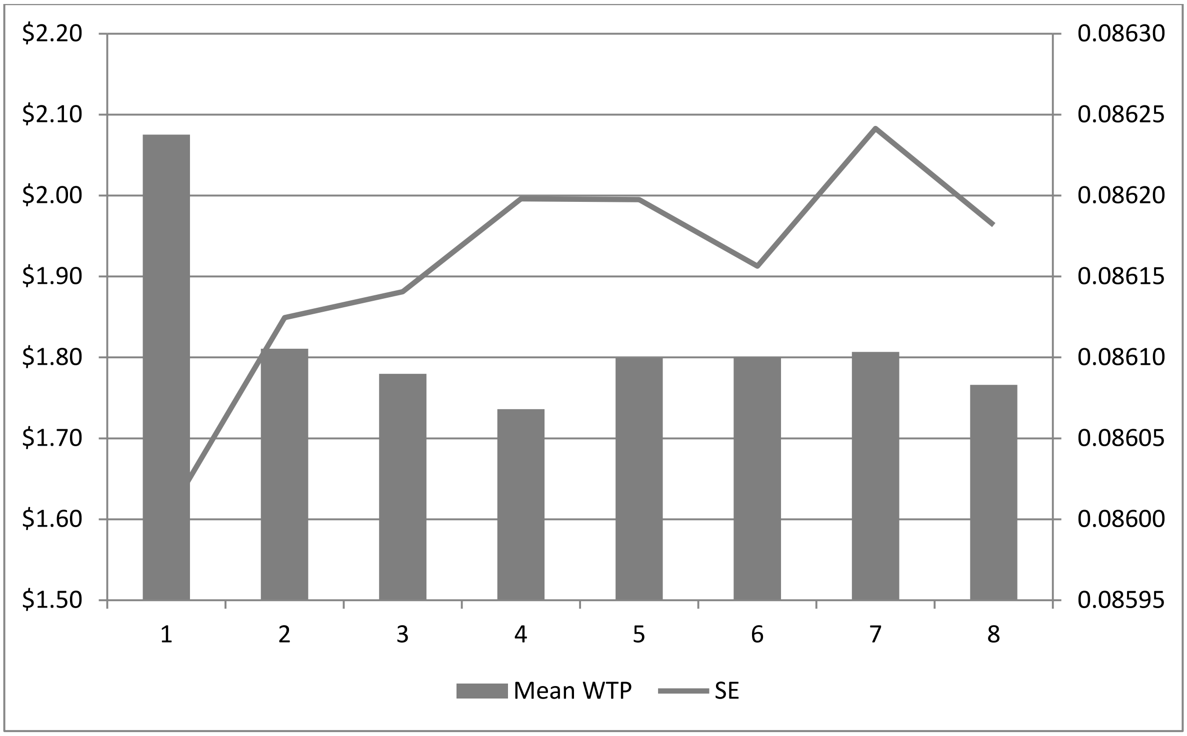

Figure 1: Mean WTP and SE for base variety with different number of alternatives

This behavior of the WTP led to explore the possibility of structural differences (Wooldridge 2010) in the models across the number of alternatives presented. A comparison was done between the likelihood ratio of the full model and the likelihood of separate models ran for different number of alternatives. It was found that there are structural differences in the models when splitting the results by number of alternatives presented. Nevertheless, when the results are evaluated in the groups 1-4 and 5-8 there are no structural differences from the full model. Therefore, the analysis was done evaluating the full model and contrasting it with the two separate models for 1-4 alternatives and 5-8. The results are not presented here but are available from the authors upon request.

The outcomes of the experiment can be best described by answering the questions that motivated this research. The first question is whether the number of alternatives presented has an effect on the WTP estimates in an EA:

Hypothesis 1: The number of alternatives available has no effect on the WTP

Can there be choice overload with a small set of alternatives? We evaluate the WTP of the base variety to test this hypothesis since it was the one strawberry variety present in all rounds of the auction. The results for a random parameter Tobit estimation of the WTP of the base variety are described in Table 1. A random parameter Tobit using the number of alternatives following a normal distribution was used to account for the diversity in cognitive ability, which can be challenged by the complexity of the choice with more alternatives being presented, thus yielding a different response in each subject.

In the model, the number of alternatives offered in each round is included as a random parameter assumed to have a normal distribution. The coefficient for this variable is non-zero, statistically significant and negative. Therefore, the number of alternatives does have an influence on WTP: for each additional alternative offered the WTP decreases $0.04 as shown in the second column describing the marginal effects of each parameter. When evaluating the model when only 1-4 alternatives are offered the significance of the number of alternatives is increased and the WTP decreases $0.12 for each additional alternative presented. In contrast, the model of WTP if 5-8 alternatives are shown also has a negative and significant effect of the number of alternatives shown, but it is smaller than when 1-4 alternatives are presented.

Table 1. Random Parameter Tobit Model of WTP for base variety

	Full Model		1-4 Alternatives		5-8 Alternatives	
	Nonrandom parameters	Marginal Effects	Nonrandom parameters	Marginal Effects	Nonrandom parameters	Marginal Effects
Constant	2.66355*** (0.08699)		2.82800*** (0.1503)		3.33393*** (0.15902)	
AGE	-.01410*** (0.00115)	-.01399***	-.01237*** (0.00188)	-.01205***	-.02052*** (0.00153)	-.02052***
EDUC2	.09910* (0.05057)	.09833**	0.13596 (0.08508)	0.13246	-.18949*** (0.06681)	-.18944***
EDUC3	0.05655 (0.05325)	0.05611	-0.01314 (0.09005)	-0.0128	-.20832*** (0.07204)	-.20827***
HHSIZE	-.03362** (0.01491)	-.03336**	-.04390* (0.02445)	-.04277*	-0.00574 (0.01913)	-0.00574
FEM	-.20080*** (0.03493)	-.19924***	-.15774*** (0.05675)	-.15367***	-.35576*** (0.04469)	-.35567***
MARRIED	0.01226 (0.02232)	0.01217	-0.02398 (0.03689)	-0.02336	.08829*** (0.02815)	.08826***
RACE1	.10235** (0.044)	.10156**	.19291*** (0.07311)	.18794***	-0.011 (0.0582)	-0.011
RACE3	-.27988*** (0.04273)	-.27771***	-.30545*** (0.071)	-.29757***	-.32018*** (0.05876)	-.32009***
INCOME	.00527*** (0.00053)	.00522***	.00462*** (0.00088)	.00450***	.00501*** (0.00069)	.00501***
WFV	-.06583*** (0.02182)	-.06532***	-0.0537 (0.03542)	-0.05232	-.15028*** (0.02905)	-.15024***
	Random parameters		Random parameters		Random parameters	
N ALT	-.04218*** (0.00663)	-.04186***	-.12835*** (0.02492)	-.12504***	-.03942** (0.01756)	-.03941**
Std.Dev.	.72815*** (0.00708)		.75549*** (0.0133)		.53327*** (0.00885)	
Log-Likelihood	-1704.1131		-930.39952		-770.78007	
N Obs	1368		684		684	

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

What this implies is that in experimental design it is a non-trivial task to determine the number of products being auctioned. Outside of the laboratory an argument can be made that not only the overwhelming set of 24 jams compared to the 6 jam set in the

Iyengar and Lepper (2000) study can have effects on the intent to purchase in the audience, but a movement within the range of 1-8 alternatives can also have an impact on WTP.

Hypothesis 2: There is a constant error variance across the number of strawberry alternatives presented. [This means that in the model $\mathrm{WTP}^{*}_{\mathrm{Base}} = \lambda\mathbf{X\beta} + \varepsilon$ where λ is a scaler of the variance and it is a function of the number of alternatives, $\lambda = 1$]

Choice overload was observed in the results of Hypothesis 1: a reduction in the WTP as the number of alternatives increases. The next question is if the responses are consistent: whether the variance in responses is constant over the number of alternatives. Do the unobserved factors increasing complexity and search costs changes as the number of alternatives presented increases? When more unobserved processes impact WTP as the array of products increases, this reflects in higher variance of the error term. The results of a heteroscedastic Tobit (hTobit) model for the WTP of the baseline variety using a scale parameter from a function of the number of alternatives for variance are described in Table 2. The hTobit accounts for unobserved differences in the conditional variance of the WTP estimates but not the effect on the WTP means themselves.

In Table 2 only the heteroscedasticity scaler and the intercept of the regression are statistically different than zero. For the full model and the one where 1-4 alternatives are shown the variance scaler is negative. This implies that the variance in the responses is not only dependent on the number of alternatives presented, but that it increases as the size of the array of options increases. With a limited allowance of resources such as time and cognitive ability, individuals making purchasing decisions have to push themselves to maximize these resources.

Table 2. Heteroscedastic Tobit model of WTP of the baseline variety

	Full Model		1-4 Alternatives		5-8 Alternatives	
	Nonrandom parameters	Marginal Effects	Nonrandom parameters	Marginal Effects	Nonrandom parameters	Marginal Effects
Constant	-3.14854*** (0.13363)		-2.57122*** (0.14468)		-5.02753*** (0.30055)	
AGE	0.00046 (0.00058)	0.00008	-0.00002 (0.00068)	0	0.00127 (0.00116)	0.0001
EDUC2	0.02726 (0.05607)	0.00454	0.00586 (0.06794)	0.00016	0.02868 (0.08266)	0.00221
EDUC3	-0.02733 (0.05608)	-0.00456	-0.00594 (0.06795)	-0.00016	-0.02871 (0.08267)	-0.00221
HHSIZE	-0.00048 (0.00152)	-0.00008	0.00022 (0.00182)	0.000006	-0.00165 (0.00236)	-0.00013
FEM	0.00028 (0.00081)	0.00004	0.00015 (0.00098)	0.000004	0.00042 (0.00117)	0.00003
MARRIED	0.00009 (0.00073)	-0.00002	-0.00007 (0.00087)	0.000002	-0.00013 (0.00104)	-0.00001
RACE1	0.08605 (0.0792)	0.01435	0.04192 (0.09643)	0.00112	0.08027 (0.11583)	0.00618
RACE3	-0.08596 (0.07916)	-0.01433	-0.04203 (0.09639)	-0.00112	-0.07994 (0.11578)	-0.00615
INCOME	0.00021 (0.00035)	-0.01433	0.00015 (0.00044)	0.000004	0.00021 (0.00052)	0.00002
WFV	-0.00017 (0.00021)	0.00003	-0.00014 (0.00025)	0.000004	-0.00012 (0.00032)	-0.00001
	Het. Scaler	Sigma	Het. Scaler	Sigma	Het. Scaler	Sigma
N ALT	-.06540*** (0.00703)	-.06540*** (0.00703)	-.33640*** (0.0277)	8.30988*** (0.90598)	.11939*** (0.01403)	1.82134*** (0.15422)
Log-Likelihood	-6188.22486		-2942.61565		-3529.43926	
N Obs	1576		788		788	

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

This pressure to achieve a result can lead to confusion and a suboptimal performance (Ariely et al. 2009, Cherry et al. 2004). With suboptimal decision making with a larger number of alternatives to choose from, what the model shows is that the revealed preferences are not clean cut: no single factor can be traced to have an effect on the WTP for the base variety when accounting for heteroskedastic variance. The model when 5-8 alternatives are presented on the other hand has a positive variance scaler as a function of the number of alternatives. This implies that the variance in WTP decreases as more alternatives are shown: the decision making process when 5-8 alternatives are offered becomes less heterogeneous. Subjects may be simplifying their decision making process past the four alternatives threshold and using heuristics that allow more efficient decision making. Nevertheless, the results of the EA when 1-4 alternatives are presented are different from the ones when 5-8 alternatives are offered. Therefore, as EAs and other experimental techniques have become stalemates in research, conclusions drawn from them could be tarnished by the confounding effect of having too many options to evaluate.

Hypothesis 3: There is no difference in the WTP of the duplicate variety across the number of alternatives. [In the utility model $\mathbf{U}(\mathbf{X_i}, \mathbf{X_j}), \mathbf{V}\left(\mathbf{P_i}, \mathbf{P_j}, \mathbf{I}, \mathbf{S}\right)$ if $\mathrm{x}_\mathrm{i}^{(1)} = \mathrm{x}_\mathrm{i}^{(2)} \in \mathbf{X_i}$ it implies that $\mathrm{p}_\mathrm{i}^{(1)} = \mathrm{p}_\mathrm{i}^{(2)} \in \mathbf{P_i}$; Then if the size of $\mathbf{X_i}$ increases, $\mathrm{p}_\mathrm{i}^{(1)} = \mathrm{p}_\mathrm{i}^{(2)} \in \mathbf{P_i}$ should still hold. If this is true the WTP for two identical products is unaffected by the number of alternatives presented. So, if the number of alternatives does not impact the ability to differentiate between products, the gap (if any) between the WTP of two identical products should be the same across all different number of alternatives presented].

Is the ability of subjects to tell differences between products impacted by the number of products they have to evaluate? The ability of subjects to tell differences between products is crucial for all valuations gathered through EA. Since resources to evaluate a decision, such as time to decide and discerning ability are limited, increasing the size of the array to evaluate could have an effect on the capability to tell differences between goods. This effect can be captured by measuring the difference between the WTP of the baseline variety and its duplicate: $\Delta WTP = WTP_{Base} - WTP_{Duplicate}$.

Table 3. Random Parameter Linear Model of WTP differences between base variety and its duplicate

	Full Model	1-4 Alternatives	5-8 Alternatives
	Nonrandom parameters	Nonrandom parameters	Nonrandom parameters
AGE	-.00437*** (0.00114)	-.00380* (0.00197)	-0.00165 (0.00159)
EDUC2	-0.0702 (0.04731)	-0.07096 (0.08597)	0.08087 (0.06722)
EDUC3	-.12880** (0.05006)	-0.10796 (0.09032)	-0.00535 (0.07106)
HHSIZE	-0.00636 (0.01583)	-0.00871 (0.02783)	0.00891 (0.0209)
FEM	-.06597* (0.03479)	-0.04662 (0.06013)	-0.02449 (0.04761)
MARRIED	.04252* (0.0233)	0.0258 (0.03881)	.07234** (0.03082)
RACE1	-0.06849 (0.0466)	-0.04684 (0.08087)	-0.05333 (0.0601)
RACE3	0.06365 (0.04861)	0.09879 (0.08416)	0.08118 (0.06559)
INCOME	.00101* (0.00052)	.00157* (0.00087)	-0.00019 (0.00074)
WFV	0.01433 (0.02358)	0.04757 (0.04029)	-0.01446 (0.03081)
	Random parameters	Random parameters	Random parameters
NALT	0.00346 (0.00831)	-0.04019 (0.02975)	-.03443** (0.01462)
Std.Dev.	.60323*** (0.00556)	.62078*** (0.01155)	.55465*** (0.00793)
Log-Likelihood	-1171.29105	-539.00169	-633.91417
N Obs	1197	513	684

Note: Significance is indicated by *, ** and *** for the 10%, 5% and the 1% level or less.

These implied differences between the base variety and the duplicate can be either positive or negative, as subjects in the EA can choose to increase or decrease their bids for the products offered. This eliminates the need of a censored approach. A random parameter linear regression using the number of alternatives as random parameter is described in Table 3. This table yields two interesting results. First, subjects seem to find differences where technically there aren't any. There should not be any gap between the WTP for the baseline variety and its duplicate since they are identical; nevertheless, the number of available alternatives affects WTP. The second result is that as the number of alternatives increases the gap between the WTP of the base variety and its duplicate decreases. This entails that subjects that once perceived two goods as being different, no longer consider them distinct when they have more items to choose from. The number of alternatives in the model of 5-8 alternatives is statistically significant and the variance of the parameter is lower than the model with 1-4 alternatives. A possible explanation is that the ability to discern of an individual is limited, so if other resources such as time and required effort to perform an evaluation are constrained, it would imply that a smaller portion of the resources will be dedicated to each comparison as the set to peruse from grows larger. With fewer resources devoted to make comparisons, less attributes of the products may be used for the evaluation, a subset of the array may be selected to evaluate or any other heuristic can be used to maximize the use of resources. In any case, the evaluation process of a small array is different than the process to make such evaluation when the size of the array grows larger.

Hypothesis 4: The WTP for the substitute relative to all products does not change with the number of alternatives of the products. [If the number of elements in $\mathbf{X_n}$ in the utility model $\mathbf{U}(\mathbf{X_n}, \mathbf{Y_m})$ increases, then following the indirect utility $\mathbf{V}(\mathbf{P_{i \ldots n}}, \mathbf{P_j}, \mathbf{I}, \mathbf{S})$ the relative price $\mathbf{P_j}$ will increase. Therefore, in a regression of $\Delta\text{WTP} = \text{WTP}_{\text{Base}} - \text{WTP}_{\text{Substitute}}$ having a statistically significant coefficient for the number of alternatives implies the WTP gap changes as such number increases, i.e. the substitute produce becomes relatively more attractive].

If the preference for a substitute and the preference for a product are independent of which alternatives are presented, the gap between the WTP of the substitute and the base variety should remain the same with different number of alternatives of the strawberries. To measure this relationship a random parameter linear regression of the WTP differences between the baseline strawberry variety and the substitute grapes is estimated. Since the differences can go either way, positive or negative from one round to the next, a random parameter linear approach is convenient and no censoring is needed. To account for the potential effects across individuals of the increase in the number of alternatives, the number of alternatives presented is used as a random coefficient in the regression. The results for such a model are described in Table 4.

The number of alternatives as a parameter of the regression is statistically significant and negative when 1-4 alternatives are presented. This implies that increasing the number of alternatives reduces the gap between the WTP for the baseline variety and the substitute when 1-4 alternatives are presented. As was shown in the results under hypothesis 1, the WTP of the baseline strawberry variety decreased as the number of alternatives increased (up to four alternatives).

Table 4. Random Parameter Linear Model of WTP differences between the baseline variety and the grapes

	Full Model	1-4 Alternatives	5-8 Alternatives
	Nonrandom parameters	Nonrandom parameters	Nonrandom parameters
AGE	-.00380*** (0.00098)	-0.00236 (0.00161)	-.00592*** (0.00153)
EDUC2	.42108*** (0.03933)	.49030*** (0.06343)	.31207*** (0.06561)
EDUC3	.18864*** (0.04272)	.22142*** (0.069)	.19340*** (0.07108)
HHSIZE	0.01872 (0.01445)	0.01408 (0.02335)	.05920*** (0.02085)
FEM	.06548** (0.02971)	.14790*** (0.04817)	-0.00016 (0.04564)
MARRIED	-0.01238 (0.01918)	-0.03018 (0.03148)	.09241*** (0.02874)
RACE1	0.05625 (0.04026)	0.10389 (0.06424)	0.05463 (0.06057)
RACE3	.19301*** (0.04101)	.19528*** (0.06424)	.11927* (0.06197)
INCOME	.00223*** (0.00051)	.00154* (0.00084)	0.00108 (0.00074)
WFV	-0.0322 (0.02191)	-0.01533 (0.03416)	-.08004*** (0.03092)
	Random parameters	Random parameters	Random parameters
NALT	-0.00563 (0.00672)	-.06343*** (0.02253)	0.00377 (0.01457)
Std.Dev.	.69965*** (0.00727)	.71507*** (0.01286)	.58334*** (0.00964)
Log-Likelihood	-1626.07344	-868.07237	-793.17734
N Obs	1368	684	684

Note: Significance is indicated by *, ** and *** for the 10%, 5% and the 1% level or less.

The mean WTP for the control product (grapes) was not statistically different from one round to the next[2]. Then with a decreasing WTP for the baseline variety and a relatively constant WTP for grapes, there is a substitution effect happening between the baseline variety of strawberries and the grapes. In contrast, when 5-8 alternatives are presented, the effect of the number of alternatives on the difference between the WTP of the baseline variety and the substitute is not statistically different. Once the boundary of four alternatives is crossed, the mean and the variance of WTP of both the baseline variety and the substitute are not statistically different across number of alternatives, thus no effect on the differences between them. The implication is that as the cost of evaluating more alternatives of the strawberries increases, the grape substitute whose search costs are constant becomes more attractive and a portion of the market indeed makes the switch and selects the substitute.

Hypothesis 5: The number of alternatives has no effect on the variance of the WTP of the substitute with respect to the WTP for baseline variety. [Therefore, in the model $\Delta\mathrm{WTP} = \lambda\mathbf{X\beta} + \varepsilon$ where $\Delta\mathrm{WTP} = \mathrm{WTP}_{\mathrm{Base}} - \mathrm{WTP}_{\mathrm{Substitute}}$ and λ is a scaler of the variance from a function of the number of alternatives, $\lambda = 1$. Then if the scale parameter in the model is not equal to 1 the variance in the differences in WTP changes, depending on the sign, as the number of alternatives increases].

[2] Wilcoxon rank-sum tests were performed on the mean WTP for the control across all rounds and no statistically significant differences were found. Results are available from the authors upon request.

As shown under hypothesis 5, the gap between the WTP of the substitute and the WTP for base variety decreases as the number of alternatives increases. The array size may also have an unobserved effect on the WTP gap, impacting the error term with each level.

Table 5. Heteroscedastic Linear Regression of WTP differences between baseline variety and the grapes substitute

	Full Model	1-4 Alternatives	5-8 Alternatives
	Nonrandom parameters	Nonrandom parameters	Nonrandom parameters
AGE	-1.92506*** (0.07993)	-2.11967*** (0.08299)	-2.15131*** (0.08346)
EDUC2	-154.883*** (9.74437)	-170.543*** (10.11744)	-173.095*** (10.175)
EDUC3	155.725*** (9.74347)	171.471*** (10.11651)	174.036*** (10.17406)
HHSIZE	0.21582 (0.24764)	0.23752 (0.25713)	0.24095 (0.25859)
FEM	0.22013 (0.13604)	.24241* (0.14124)	.24599* (0.14205)
MARRIED	.60249*** (0.12392)	.66351*** (0.12867)	.67348*** (0.1294)
RACE1	1.73459 (13.99005)	1.9141 (14.52567)	1.94688 (14.60831)
RACE3	-0.89316 (13.98448)	-0.98767 (14.51988)	-1.00655 (14.60249)
INCOME	-.63384*** (0.05803)	-.69786*** (0.06025)	-.70831*** (0.0606)
WFV	.67141*** (0.03803)	.73931*** (0.03948)	.75038*** (0.03971)
	Random parameters	Random parameters	Random parameters
Scaler	.04134*** (0.00729)	-.00025*** (0.00003)	-.00011*** (0.00003)
Sigma	732.950*** (15.60386)	782.668*** (10.50813)	841.113*** (7.68559)
Log-Likelihood	-70460.15938	-70800.8925	-70824.30825
N Obs	1576	788	788

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

The output of a heteroscedastic linear regression using a scaler parameter as a function of number of alternatives is in Table 6. Once again, the implied differences don't have bounds, so there is no need for a censored approach.

With a positive and significant effect, the scale parameter in the full model shows that as the number of alternatives increases, the variance of the gap between the WTP of the baseline variety and the substitute is reduced. As the number of alternatives increases, the unobserved factors account for less of the variability of the differences between the WTP of the baseline variety and the substitute. In contrast, when the results are split into models for 1-4 alternatives and 5-8 alternatives, the scale parameter as a function of number of alternatives is negative and significant. This implies that the variance in the differences between WTP of the baseline variety and the substitute within each group increases with the number of alternatives presented within each group. Therefore, the unobserved and unaccounted effects of having more alternatives to choose from are increasing the variance in the differences in WTP. To check for robustness of the results heteroscedastic Tobit models of the ratios between the WTP of the baseline variety and the substitute and the WTP baseline variety and its duplicate were estimated and the results. Those results have the same direction and similar magnitude as the ones reported here. They are not included in this paper, but are available from the authors upon request.

Conclusions

As the markets for different products grow, so do the number of alternatives presented to consumers in those markets. In an effort to develop new products and marketing strategies, experimental economics and the laboratory have proved tremendously useful. In particular, the use of experimental auctions has become widespread in the marketing and economics literature. Though great lengths have been taken to improve the methodology of EA, the number of products or product alternatives being auctioned on does not have a clear guideline. The intrinsic assumption is that the ability of subjects to evaluate the products is unaffected by the number of alternatives available. If this is not the case, this can be a hazard to the results gathered through EAs.

The results of this study showed that changing the number of alternatives in EA can have non-trivial effects on the WTP gathered from subjects. Furthermore, there is an unequivocal increase in the variance of responses with an increase in the size of the array of options to choose from. This noise, these unobserved effects, are confounding the results of WTP estimates, providing results that are not true reflections of preferences. The results are more than a cautionary note on experimental design regarding number of alternatives. When conducting valuation experiments the cognitive effort demanded from subjects is not negligible and increasing the number of alternatives to choose from exerts even more stress. In the field, the cognitive ability of subjects dedicated to evaluate differences between products remains limited, but time is not always constrained, contrary to most laboratory settings. If time is not under constrains, then more effort can be devoted to each comparison. However, other resources that are also part of the discerning process can be limited and lead to results similar to the ones found in this study.

A logical extension to this work would be conducting field experiments on whether actual purchasing of goods is affected by a relatively small change in the number of alternatives in the same way as it is in the laboratory. Interesting candidates would be products that have a high heterogeneity associated with each alternative, like strawberries used in this study. This would allow for a higher number of comparisons to be made on many different levels. A field experiment of this sort could prove interesting for different areas given that for example in 1997 the amount of fresh produce items carried in the average grocery store were 345 and by 2008 the number of available products in the fruit and vegetable sections in grocery stores had increased to 2,200 (FMI 2015); this increase took place while the consumption of fruits and vegetables per capita has decreased from 311 to 180 pounds per year in the same period of time (ERS 2011).

So, having more products to choose from in EAs is fostering or hindering the research agenda of economics? From the results of this study, the answer would be the latter. The preference revealing features of the second price auction seem to succumb to the lack of recognition of the objective from the participants. The preferred method of non-hypothetical valuation is not immune to a cognitive load effect on subjects. As the number of different alternatives provided increases so does the complexity of the choice, forcing subjects to maximize their resources, sometimes beyond their own abilities to discern between products. Extensive research is needed in this area with other valuation techniques and different products, but so far it seems that at least for subjects in EAs, more is not always better.

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