Using Bid Design to Measure the Boundaries of WTP

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Abstract

We examine the extent to which bid design provides an informative anchor that influences the context in which individuals evaluate willingness to pay questions. We postulate that agents who are uncertain over possible states of nature that may arise when consuming a good use bid design as a means to resolve such uncertainty. Furthermore, we hypothesize that the impact of bid design on estimated WTP is less pronounced for experienced agents that have observed more draws from nature. We use three measure of bid design to evaluate our conjectures; (i) the mean of bid amounts, (ii) the absolute value of the difference between bid amounts, and (iii) the ratio of the mean to the spread. We interact proxies for individual experience with our measure of bid design to evaluate if such characteristics attenuate the impact of bid design on WTP estimates. We find the likelihood an individual says "Yes" to a given bid systematically varies with measures of bid design. This suggests that bid design provides an informative anchor and can be used to identify probabilistic boundaries for WTP.

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1. Introduction

Most explanations suggested for bid design anchoring effects presume that the responses to multiple bid amounts indicate different underlying distributions for willingness to pay. The anchoring induced by bid design is viewed as spurious, without information useful to estimation of WTP, and a methodological liability. However, we suggest that at least a part of the anchoring induced by bid design is due to unobserved preferences over context and uncertainty over which context applies for valuation of the good in question. Analysis of systematic components of bid design anchoring effects can provide valuable information that may enhance reliability and applicability of WTP estimates.

We consider circumstances in which individual preferences are stable, but systematically vary with the context in which the individual is ultimately likely to consume (or participate in) the good. For example, an individual might be willing to pay a given amount for a bottle on wine in the context of an evening at home over a casual dinner, and another amount for the same wine in a restaurant setting. An individual might be willing to pay a given amount for the same wine to be presented as a house gift purchased just before a visit as a dinner guest, but not willing to pay the same amount for the same wine for themselves while planning the weekly grocery run because in this context, price consciousness might be a larger factor than knowledge about the particular wine in question. Similarly, a consumer who has just tasted a wine under a relaxing and attractive winery environment may be willing to pay an amount that they would not have been willing to pay if they did not have the associated context to provide memories about the experience. These contextual environments affect valuation of both market and non-market goods, and are arguably a strategic component of advertising campaigns. Since the variety and types of contexts under which an individual might consume a good are potentially innumerable, the framing of valuation questions in non-market valuation has become an important issue. Any amount of uncertainty on the part of an individual over context that is unobservable to the researcher would induce random error in WTP estimates that would be systematically related to preferences related to context. This type of uncertainty is different from anchoring bias induced by underlying uncertainty over preferences or unstable preferences.

We postulate that, for some cases, bid design serves as a proxy for context effects in non-market valuation. That is, some part of the anchoring that occurs is a function of the context in which an individual could see himself or herself actually paying the specified amount for the good. Schkade and Payne (1994) note that in a verbal protocol analysis, respondents to contingent valuation (CV) questions often were recorded asking themselves “under what circumstances would I pay this amount for this good” as part of their considerations. In this situation, it is not difficult to consider that as the bid amounts specified vary over the sample, the contexts that are considered by respondents also vary. If this is true, then several implications include: (1) we should be able to analyze how bid design and anchoring are systematically related to context, (2) some component of anchoring induced by bid design is consistent with individual preferences and thus valuation of the good, (3) the systematic portion of anchoring should be measurable and related to other variables designed to indicate context, (4) the random component of the anchoring may include yet other context-specific components that are not identified, and (5) increasing context-specific variation in the sample allows for measuring and controlling for this source of measurement error.

Contextual variation is not suggestive of bias induced solely by the investigator's choice of measurement method (non-informative), but rather is induced by the combination of preference structure and uncertainty over the ultimate context in which a good might be consumed. If this is the case, then efforts to correct for anchoring bias in multiple bounded valuation models by attributing differences in WTP distributions solely to uninformative anchoring may be missing important components of individual valuation of the good in question. Standard approaches focus on precisely defining non-market goods to include as much of the context as possible, so that the good and its context are in a sense treated as one in the same. We consider the alternative approach of allowing context to vary so as to model how WTP systematically varies with context. In this way, systematic contextual components are included directly into valuation estimates.

In this paper we use bid design and a contextual variable, experience, to measure how bid design anchoring effects systematically vary with respondents' levels of uncertainty about context in a repeated question contingent valuation format. We illustrate how bid designs generated to induce anchoring effects in multiple question formats can be used to provide information about respondents' bounds of uncertainty over context. Further, individual characteristics which are correlated with respondents' level of uncertainty about context effects, such as past experience, can be used to estimate systematic variations in the boundaries of WTP. We conclude that welfare estimates may be enhanced by using such a model to more completely define the ranges of WTP. We investigate the notion that attempting to estimate WTP as a point estimate may be unnecessary and potentially lead to ambiguous results that are better explained by viewing WTP as a distribution that is conditional on context.

The effects of bid design and anchoring on dichotomous choice contingent valuation results using follow-up question formats are well documented in the literature. Much of this work focuses on how to correct for bias and on measuring the extent to which efficiency gains from double-bounded formats relative to single-bounded formats are eroded by anchoring bias (see for example Cameron and Quiggen, 1994; Herriges and Shogren, 1996; Alberini, Kanninen and Carson, 1997; Alberini, Boyle and Welsh, 2003; Alberini Veronesi and Cooper, 2005).

In an extensive study using simulated data, Alberini, Veronesi and Cooper (2005) conclude that the relationship among bid design, anchoring, and misspecification of the underlying WTP distribution is so complex that in certain cases it may not be possible to distinguish the individual effects of any one of these independent of the others. Using Monte Carlo simulations, they show that bid design dummies commonly used to test for anchoring bias can instead pick up model misspecifications. They conclude that the amount of information that is conveyed by standard diagnostic tests for bid design bias may be overstated, and that "unless one is prepared to make assumptions about the form of the bias, it cannot be corrected for … [and] … without additional information beyond the responses to the bids themselves, econometric approaches to identifying and correcting for response bias do not appear to be fruitful." They conclude that more work needs to be done to investigate the role of bid design and how resulting bias is measured on the impact of starting point bias, and suggest that alternative approaches include using individual characteristics, such as respondents' views on question format (Alberini et al, 2005, p. 28).

Most models assume people know their preferences with certainty and use expected utility to determine a value when there is uncertainty about future demand or supply conditions. Their own values beyond these sources of uncertainty are typically assumed to be known with certainty. Alberini et al (2003) suggest that this assumption is too strong even for market goods, arguing that in many cases, people purchase goods in the marketplace not fully knowing how well that good will fit their needs and preferences. People who have had more experience with a brand or past purchases of a similar item may exhibit less uncertainty over their preferences for a market or non-market good. Thus past experience is a quantifiable variable which would be expected to be a predictor of uncertainty regarding context, and of the probabilistic range within which WTP is likely to be measured. All else equal, people with more experience would be expected to have a tighter range in which estimated WTP falls than people with less experience.

Most models of anchoring assume the anchoring effect is constant over all individuals, and don't vary by personal characteristics (education, familiarity with good in question, etc), but there is no reason to believe this to be the case. Specifically, as Herriges and Shogren point out, people who are more uncertain about their preferences, are likely to be more susceptible to anchoring if they perceive that the bid amounts provide them with information about the value of the good. In this paper we consider the possibility that the degree of anchoring may be systematically related to the bid design in a manner that can be predicted by the experiential context in which the individual relates to the good.

A number of methods of detection and measuring bid-design effects exist, depending on the purpose of the application. Alberini et al (2005) discuss commonly-used diagnostics for detecting bid design effects, and question the reliability and value of the information conveyed by these diagnostics when bid design, anchoring effects and uncertainty about functional form of WTP occur simultaneously. They refer specifically to dummy variables on bid sets; but their concerns are likely to apply to other common diagnostic tests for bid design effects in double bounded formats including the use of the 'other' bid amount as a right hand side variable. More recently, in the context of multiple (more than two) bid formats, Roach and Boyle (2002) and Rowe et al (1996) find that bid range spreads (truncated and non-truncated ranges) affect welfare estimates from multiple-bounded formats, while the means of the bid ranges do not affect WTP.

We use a variety of diagnostic tools to detect bid design anchoring effects and their correlation with context, including the mean and differences in multiple bid formats. If people who are uncertain about context infer additional information from a bid value, then it is not unreasonable to consider that information may also be conveyed by the relation between the bid values presented. For example, a very wide spread might exacerbate the sense of uncertainty and lead to confusion, so that the respondent places less information value on the bids; while a very narrow spread might suggest that there is relevant information in the bid values that are proposed. On the other hand, for a given spread, the location of the mean also provides information. A very wide spread for a very high mean might leave an individual in doubt of the value of the information signaled by the bid values; while a very narrow spread for a very high mean leave an uncertain respondent with the impression that the information value is higher than if the spread were wider. We use mean, spread and the ratio of mean over spread to provide information about the nature of bid design induced anchoring effects. Finally, for people who have more experience with the good, we would expect that all of the bid design parameters would have less influence on WTP, than for less experienced respondents. Figure 1 and Table 1 illustrate these combinations of mean and spread for two different levels of uncertainty, as measured by experience with the good. We aim to test these conjectures in this paper.

2. Model

We consider a model of WTP in which we assume that it is not possible to measure WTP as a point due to respondent uncertainty about context. We instead focus our measurement on the locus within which WTP may fall given a range of unobserved preferences over context. The boundaries of that locus are a function of respondent characteristics, such as experience with the good, which vary by individual. People with more experience are likely to have tighter bounds over which they consider alternative sets of contexts, because they have personally experienced a wider variety of contexts. We assume that bid design provides context, so that bids are proxies for context. We cannot directly observe contexts that people might consider, and this is a source of measurement error. Thus by varying the bid design systematically over means and spreads, we hope to capture systematic changes in the probabilities that 'yes' responses are given to specific bids. This model is similar to that of an electron orbiting a nucleus – where the measurement process itself hinders the ability to precisely determine where the electron lies. Attempts to measure where the electron may be found at a given time can only be accomplished within a range of probabilities, where that range is in part determined by characteristics of the atom. If we accept that in principle we cannot be certain of where 'true' WTP lies, we can instead concentrate on measuring the boundaries of where it lies. Determining how individual characteristics and contexts shape those boundaries becomes important in reducing measurement error.

In this case, there is no reason to believe that bid design would not affect measurement of WTP – it should. One explicit goal of any empirical study would then be to examine to what extent measurement error exists to determine the boundaries for WTP, and how those boundaries might be affected by individual characteristics that are correlated with degree of uncertainty about preferences. More experienced individuals are less likely to be affected by the bids they are presented with, so their locus contracts. If this is true, then instead of estimating a WTP as a point, economists may be able to design data collection to estimate the locus of values within which WTP would be expected to fall, and to determine how that locus varies, probabilistically, with individual characteristics. Such an approach would indicate a bid design that tests the boundaries of where such a locus might fall over a range of experience.

3. The Data

The good is a recreational site visit, with a sample generated from an on-site survey, so all individuals had experience with at least one site visit. Details of the sampling and survey design are provided by Rollins et al (2007). Respondents were asked to indicate the numbers of times they had made similar recreation trips over the previous 4 years. Respondents whose number of previous trips was above the sample mean were defined as "experienced," those below the sample mean were defined as "not experienced." Thus experience is a dummy variable where 1 = experience. The null hypothesis that expertise is independent of the bid design is tested with an interaction term of expertise and bid design parameters.

Data were generated from a bid design based on paired bid amounts randomly and independently drawn from the same distribution, which was based on data from a pilot stated preference survey. The second bid is not drawn conditional on the first bid response. The bids were presented to respondents sequentially in two separate dichotomous choice questions, one immediately following the other. The questionnaire was administered by mail, so the respondents saw both bid amounts at the same time. Means and spreads (the absolute value of the difference between the two bid amounts) were randomly assigned in the bid design according to a design that covered a range with four categories: narrow spreads and wide spreads are combined with high means and with low means. Bid order (high to low or low to high) was also randomized. Bid design diagnostic variables used in the regression model are mean, spread and mean/spread.

A random effects probit specification is used, where the correlation coefficient indicates correlation between WTP in the first and second observations for each respondent in the panel. A number of studies use random effects specifications in multiple-bounded models. In general, a double-bounded specification restricts the two bid responses to be from the same underlying distribution for WTP. A random effects specification relaxes this restriction, allowing the correlation coefficient (ρ) to pick up the degree to which they are related. The double-bounded model is a limiting case of the random effects specification where ρ =1. When the assumption that ρ = 1 is relaxed, "the initial and follow-up responses provide a sequence of two single-bounded intervals around the two WTP values that are more or less correlated." (Alberini et al, 1997, page 318). Alberini, Kanninen and Carson (1997) compare WTP results from random effects probit versus double-bounded specifications for three data sets to demonstrate that WTP estimates from the two specifications tend to converge with increasing correlation coefficients in the random effects specification. In their study based on three different data sets, the correlation coefficients varied from 0.36 to 0.96. As would be expected, the standard errors are lower in the double-bounded specifications in all three cases. Using a random effects model is an effective approach when one does not wish to assume that latent WTP is identical in multiple question formats, including with data from double bounded question.

4. Results

DeShazo (2002) and others find that willingness to pay is affected by bid order (low to high or high to low); however, we were unable to detect any effect of bid order on the model. This is not surprising since each respondent saw the bids presented in an immediate sequence of two questions. Model 2 in Table 2 shows that the probability of a "yes" response tends to increase with the mean and spread associated with the two bids. Model 1 indicates that this increase declines with an increasing ratio of mean to spread. We shall interpret this below in the context of introducing the effect of past experience with similar goods. Model 1 reveals that the action of experience is not independent of the mean and spread; further, experience alone as an independent effect is not significant, but its interaction with the ratio of mean over spread is. Experience is positive and significant at the 5% level in Model 3 when bid design is not taken into account. This does not change appreciably when the mean and spread of the offered bid are included in Model 2, without the interaction term.

This result is more clearly indicated in Figure 2 where median WTP per trip is plotted for the two groups for different levels of means and spreads. Spreads are given by the values listed along the right hand side, and vary in range from s = \$3 to s= \$50. Individuals with experience = 0 are represented in the solid lines while individuals with experience = 1 are shown by dotted lines. Over the entire sample, an individual WTP of approximately \$390 is calculated. Using regression parameters over the sample data, WTP is calculated systematically over the sample for individuals with and without experience for varying levels of mean and spread.

We see that the two groups behave differently with respect to how the bid design affects WTP. Both groups are less likely to be moved from the average WTP as the means of the offered bids increase for the wider categories of spread. The experienced individuals are slightly less influenced by the mean of the bids. Both groups are influenced by the bids as the spread decreases over the range of means, the extent of this influence increasing with the mean, but their behavior moves in the opposite directions. As the spread decreases, those with experience tend to undervalue the good as the mean increases. This may be explained as a tendency to mistrust the entire valuation context as the pairs of bids are seen to be very high relative to their own WTP locus. Those without experience are more likely to be influenced by the bid amounts at narrower spreads and high means, and this influence tends to be an overvaluation. The tendency of the experienced group to be influenced by the mean changes from positive to negative as the spread increases, that is, for spreads of about $7.77, these respondents were not affected by the mean, but for spreads above and below this amount, they were affected by the mean of the bids, but in opposite directions.

Figure 3 shows Krinsky and Robb 95% confidence intervals (using 1,000 draws) for Figure 2 WTPs.

Table 3 provides a systematic breakdown of the predicted probability that a given agent (experienced or inexperienced) responds “yes” to a particular bid amount given the other bid amount that they observe. For example, reading across the row for bids of $150, table 3 indicates that when the other bid amount is $50, the probability of a “yes” from an inexperienced agent is 20.74% and 19.76% for an inexperienced agent. Moving across the row, when the other bid amount is $200, the probability of a “yes” from an experienced agent is 28.33% and 46.17% from an inexperienced agent. When the other bid is $300, the probability of a “yes” increases to 80.87% for the experience agent and 82.66% for the inexperienced agent. The general trend over the Table 3 is increasing probabilities for a “yes” response with increasing “other” bid amounts.

5. Conclusions

The use of both mean and spread to measure anchoring from bid design effects provides information about how uncertainty affects anchoring bias. These results are significant in that the relationship between bid design and individual characteristics may be more complex than previously identified. The idea of “bias” induced by bid design has rested on the notion of a true underlying WTP as a point estimate. We might instead consider WTP as a probability that falls within a clear and measurable set of boundaries. This would imply that data collection for estimating WTP from dichotomous choice data should incorporate contextual variables that help to delineate those boundaries. Further work includes exploring how these results might vary with different assumptions about latent WTP, and use of additional individual characteristics that may be associated with boundaries of WTP.

We conclude that further work to define boundaries of WTP loci by systematically varying context and bid design might be a fruitful area for future work. More information about the boundaries of WTP may result in the current discussions about the extent of anchoring bias to be less relevant than discussions about how to incorporate a variety of contextual variables and more precisely measure boundaries. This would ultimately involve the need to include more information about respondent characteristics and definitions of the contexts in which people value goods. Anchoring bias may not be a deviation from a ‘true’ underlying point estimate of WTP – but rather an indication of the extent to which individuals are unsure of context over preferences.

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Table 1: Categories of Paired Bids for Figure 1

Offered Bid	Mean	Spread	Type 1	Type 2
AA	low	high	YY	YY
BB	medium	medium	YN	YY
CC	high	low	NN	YN

Figure 1: Behavioral Model for Interactions Between Bid Design and Experience

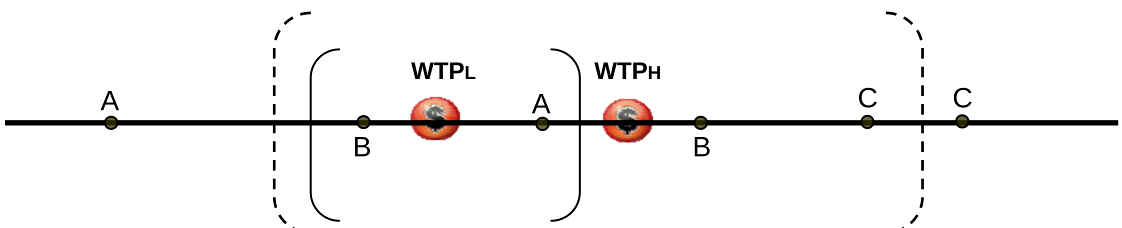


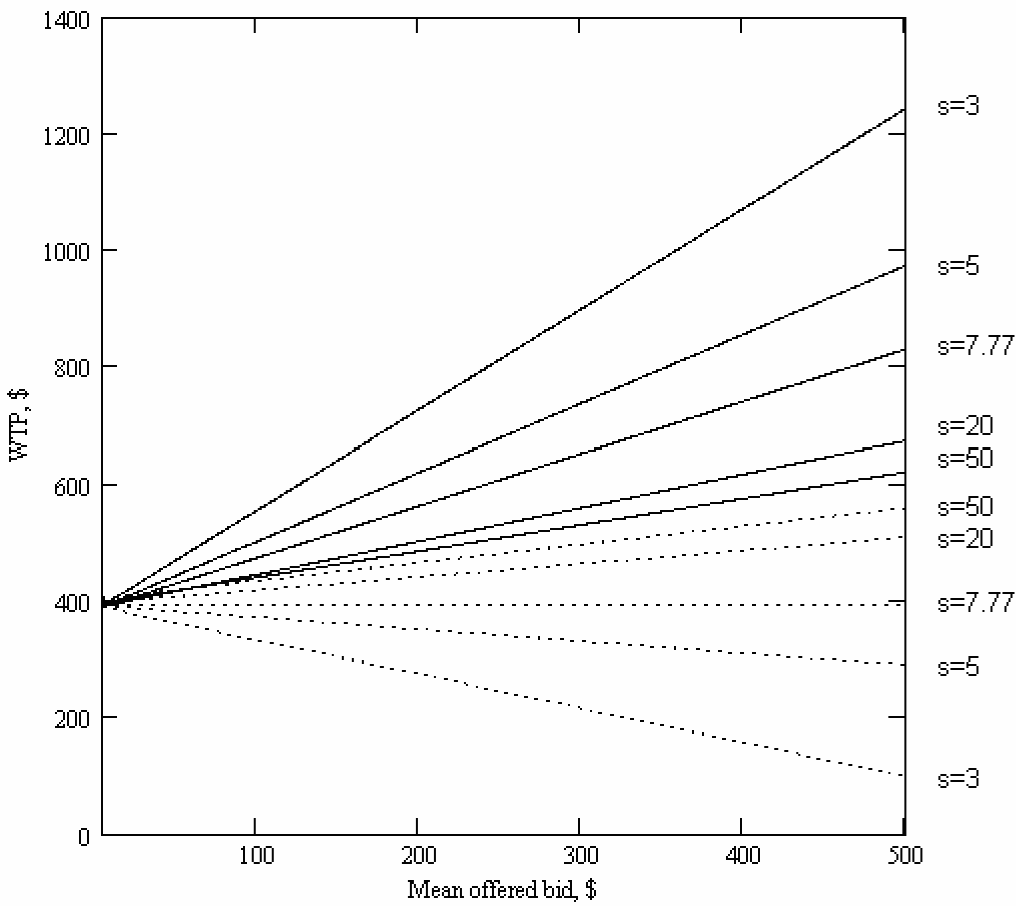
Table 2: Random Effects Probit Model Results [A]

Yes/No Response	Model 1		Model 2		Model 3	
Offered bid	-0.0296	***	-0.0295	***	-0.0207	***
	(0.0018)		(0.0018)		(0.0011)	
Days on site	0.5504	***	0.5591	***	0.5751	***
	(0.1127)		(0.1128)		(0.0994)	
Income	0.0171	***	0.0168	***	0.0155	***
	(0.0033)		(0.0033)		(0.0029)	
Age	0.0167	**	0.0175	**	0.0170	***
	(0.0070)		(0.0070)		(0.0062)	
Experience	0.2393		-0.3058	**	-0.2615	**
	(0.3123)		(0.1738)		(0.1537)	
Mean of offered bids	0.0109	***	0.0133	***		
	(0.0027)		(0.0022)			
Bid spread	0.0073	**	0.0042	**		
	(0.0034)		(0.0021)			
Mean / Spread	0.1198	**				
	(0.0575)					
(Mean/Spread)*Experience	-0.2047	**				
	(0.0975)					
Constant	-1.6536	***	-1.4228	***	-0.4337	
	(0.4790)		(0.4634)		(0.3894)	
Log likelihood	-1533.057		-1537.0101		-1569.2792	
ρ	0.8529		0.8534		0.8157	
	(0.0118)		(0.0117)		(0.0127)	
Number of observations	2996		2996		2996	
Number of groups	1498		1498		1498	
Likelihood-ratio test			7.91		72.44	
(% significance level)			(98.08)		(100.00)	

[a] Standard errors shown in parentheses.
* Significant at or above the 10% level.
** Significant at or above the 5% level.
*** Significant at or above the 1% level.

[A] Table 2 presents a subset of regressors for the estimated models, the full sets of regressors are provided in Appendix A

Figure 2: Mean and Spread impacts on WTP by level of Experience



Dotted lines represent respondents with experience = 1 and solid lines represent respondents with experience =0.

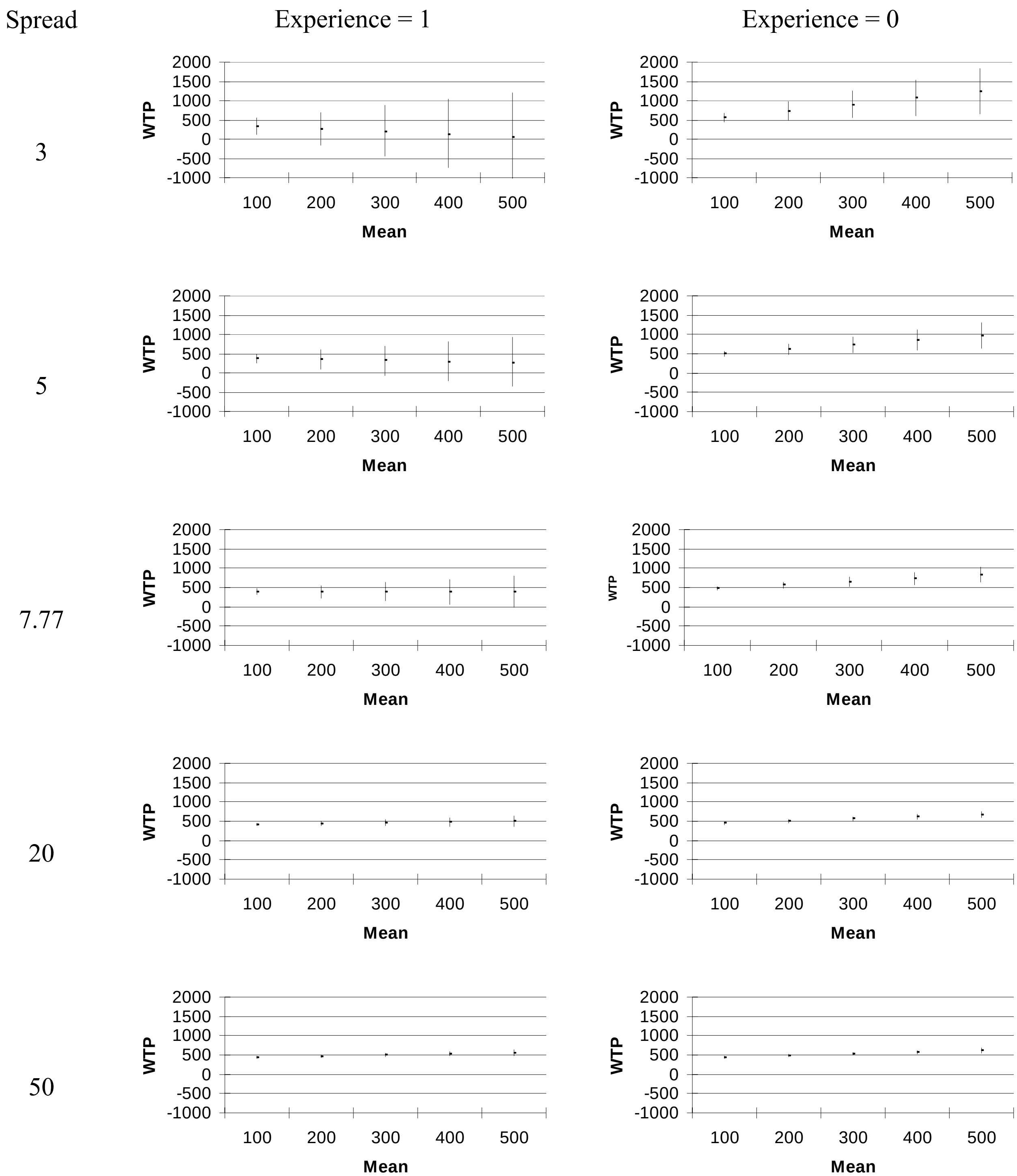


Figure 3: 95% Krinsky and Robb Confidence Intervals for WTP by Level of Experience for Different Spreads

Table 3: The Influence of Bid Design on the Probability of a Yes Response –

	$50 Other Bid Amount		$100 Other Bid Amount		$150 Other Bid Amount		$200 Other Bid Amount		$250 Other Bid Amount		$300 Other Bid Amount	
	Exp Agent	Inexp Agent	Exp Agent	Inexp Agent	Exp Agent	Inexp Agent	Exp Agent	Inexp Agent	Exp Agent	Inexp Agent	Exp Agent	Inexp Agent
$50 Bid			92.79%	93.68%	98.39%	98.24%	99.74%	99.68%	99.97%	99.96%	100%	100%
$100 Bid	49.28%	51.98%			67.13%	76.30%	87.83%	88.15%	96.66%	96.66%	99.35%	99.29%
$150 Bid	20.74%	19.76%	15.04%	22.29%			28.33%	46.17%	57.63%	64.15%	80.87%	82.66%
$200 Bid	5.03%	4.36%	3.67%	4.25%	2.01%	5.77%			5.59%	18.19%	21.71%	30.52%
$250 Bid	0.67%	0.52%	0.46%	0.46%	0.29%	0.47%	0.11%	0.85%			0.46%	4.27%
$300 Bid	0.05%	0.03%	0.03%	0.03%	0.02%	0.02%	0.01%	0.03%	0.002%	0.07%		

Note: Cell entries report the predicted probability that an agent of a given type (experienced or inexperienced) will say yes to a particular bid amount given the other bid amount that they observed. The probabilities are evaluated using the sample means for all model covariates that are independent of the bid amounts and the actual row and column bid amounts to calculate the mean and spread. Cell entries can be read as follows – an experienced agent says yes to a $50 bid approximately 92.8% of the time when the other observed bid amount is $100.

Appendix A: Full set of Variables estimated in Table 2 Models

	Yes/No Response	Model 1		Model 2		Model 3	
	Offered bid	-0.0296	***	-0.0295	***	-0.0207	***
		(0.0018)		(0.0018)		(0.0011)	
	Days on site	0.5504	***	0.5591	***	0.5751	***
		(0.1127)		(0.1128)		(0.0994)	
	Income	0.0171	***	0.0168	***	0.0155	***
		(0.0033)		(0.0033)		(0.0029)	
*Site*1	Canoeing	0.1618		0.1587		-0.2569	
		(0.3685)		(0.3691)		(0.3215)	
	Hunt big game	2.7582	***	2.6333	***	2.7576	***
		(0.6217)		(0.6221)		(0.5411)	
	Rest & Relax	0.8544	**	0.8363	**	0.8748	**
		(0.4267)		(0.4280)		(0.3740)	
*Site*2	Canoeing	1.8876	***	1.8327	***	1.5314	***
		(0.3338)		(0.3344)		(0.2862)	
	Kayaking	1.7101	***	1.6629	***	1.3729	***
		(0.5999)		(0.6006)		(0.5298)	
	Rest & Relax	1.2368	***	1.1907	***	0.9600	**
		(0.4376)		(0.4382)		(0.3823)	
	Hike	1.1994	***	1.1462	***	0.9479	***
		(0.3619)		(0.3623)		(0.3145)	
	Car camping	1.2737	***	1.2302	***	0.9818	**
		(0.4395)		(0.4404)		(0.3841)	
	Back-packing	1.9203	**	1.8320	**	1.5618	**
		(0.9516)		(0.9528)		(0.8388)	
*Site*3	Canoeing	2.0183	***	2.0031	***	2.4778	***
		(0.5461)		(0.5444)		(0.4625)	
	Fishing	1.9904	**	1.8720	**	2.2807	**
		(1.0673)		(1.0434)		(0.9069)	
	Rest & Relax	2.8844	***	2.8858	***	3.1302	***
		(0.9423)		(0.9384)		(0.8269)	
	Age	0.0167	**	0.0175	**	0.0170	***
		(0.0070)		(0.0070)		(0.0062)	
	Expertise	0.2393		-0.3058	**	-0.2615	**
		(0.3123)		(0.1738)		(0.1537)	
	Mean offered bid	0.0109	***	0.0133	***		
		(0.0027)		(0.0022)			
	Bid spread	0.0073	**	0.0042	**		
		(0.0034)		(0.0021)			
	Mean / Spread	0.1198	**				
		(0.0575)					
	(Mean/Spread)*Expertise	-0.2047	**				
		(0.0975)					
	Constant	-1.6536	***	-1.4228	***	-0.4337	
		(0.4790)		(0.4634)		(0.3894)	
	Log likelihood	-1533.057		-1537.0101		-1569.2792	
	ρ	0.8529		0.8534		0.8157	
		(0.0118)		(0.0117)		(0.0127)	
	Number of observations	2996		2996		2996	
	Number of groups	1498		1498		1498	
	Likelihood-ratio test			7.91		72.44	
	(% significance level)			(98.08)		(100.00)	