Revisiting Bid Design Issues in Contingent Valuation

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Abstract: A uniform bid design from a predetermined uniform distribution is proposed as a practical and robust alternative to existing optimal or naïve bid designs. Analytics and simulations show that the uniform design provides efficiency better than naïve designs under ideal conditions and outperforms optimal designs with poor initial information.

I. INTRODUCTION

Statistical properties of willingness to pay (*WTP*) estimate due to the bid design in the dichotomous choice contingent valuation (CV) have received much attention as CV studies have become the predominant technique for valuing nonmarket goods and services. Since the dichotomous choice question in CV results in binary observations of whether individual willingness to pay for a good or service exceeds some randomly assigned, exogenous bid value (Is willingness to pay for G greater than $b?), the pressing question becomes, what is the optimal set of bids offered to subjects so as to get the most information about the population *WTP* for the good or service of interest?[1] Unfortunately, a simple logic of the optimal design in the linear regression model cannot be applied to the dichotomous choice CV studies because the binary response function in the CV is usually nonlinear and the variance of parameter estimates depends on both of bid points and unknown true parameters.

To solve the difficulty of designing the referendum points in the binary data, numerous optimal criteria have been proposed in a series of literatures in the statistical and experimental studies. Among others, for examples, are A-optimality (Sitter and Wu 1993a, Mathew and Sinha 2001), C-optimality (Wu 1988, Ford et al. 1992), D-optimality (Abdelbasit and Plackett 1983, Minkin 1987, Ford et al. 1992, Nyquist 1992), Fiducial interval (Finney 1971, Abdelbisit and Plackett 1983, Sitter and Wu 1993a b, Alberini 1995), and Mean Squared Error (MSE, Cooper 1993). Each optimal criterion aims to minimize or maximize the criterion function which is related to the variance of estimator

[1] In the contingent valuation, exact values of willingness to pay are not available due to incentive problems with asking question of the type "How much would you be willing to pay?" The binary observation of the response is common in other experimental studies like biological assay. It is typically impossible to continuously observe the exact level or time of a change in health status of each subject in the experiment.

since the concern is usually on the consistent estimator such as maximum likelihood estimate (MLE). Resulting designs except the MSE-based design usually suggest one, two or three experimental points based on the assumption of the distribution and true parameters of response function and pre-specified statistical criterion.

However, *ALL* optimal designs have a fundamental problem that acquiring the optimality depends on the quality of information of the true parameter in the model, distributional assumption of the response function. It is a contradiction, as noted in Haab and McConnell (2002), to estimate a model with the information of true parameters and distribution in researcher's hand. In other words, all existing optimal designs are not practicable in the sense that the true information is not available but to be estimated. In addition, the optimal design has been known to lose rapidly the efficiency of estimates when it is applied to a specific research with poor information about true parameters and underlying distribution (Abdelbasit and Plackett 1983, Sitter 1992).

In this paper, we propose a practical and viable alternative bid design. The primary goal of the new design is to overcome the serious dependence of optimal designs on the true parameters. The new bid design named a uniform bid design assigns a bid value drawn from a predetermined continuous uniform distribution to a subject randomly. We draw upon the work of Lewbel et al. (2003) which assumes a continuous bid design to solve an identification problem in nonparametric estimation of *WTP*. When the underlying true distribution and parameters are known, the optimal bid design is expected to outperform the others. But when the optimal or other general designs are constructed upon the poor initial information of true parameters, we expect the uniform bid design to perform favorably.

Both analytically and through Monte Carlo simulations, we compare the performance of the uniform design with existing optimal and robust designs in terms of efficiency and relative efficiency. D-optimality is selected for the optimal criterion since it is the most widely used criterion among optimal designs. In addition to efficiencies, the bias of parameter estimate is empirically compared for the simple case. Even though it is impossible to have a design independent of the poor initial information, we show that the uniform bid design provides higher efficiency than naïve designs does under ideal conditions, and outperforms the optimal design with poor initial information. Based on the result, we conclude that the uniform bid design offers a practical, viable and better alternative of existing bid designs to researchers facing strict budget constraints, or performing a pre-survey to gather better information for the next stage. In addition, and in contrast to the existing bid designs, the uniform design provides a binary data continuously sorted by bid magnitude, enabling the researcher to apply more flexible non- and semi-parametric estimation techniques.

II. OVERVIEW OF BID DESIGNS

Suppose that we want to estimate the population parameters of *WTP* for a nonmarket good or service (*G*) through a dichotomous choice contingent valuation study. For tractability, individual willingness to pay (WTP_i) for *G* is assumed to have a constant mean (μ) and an additive *i.i.d.* error component ε_i with mean zero and constant variance (σ^2): $WTP_i = \mu + \varepsilon_i$. Let $F(\cdot)$ be the cumulative distribution function of the error term ε. Information about *WTP* is revealed to the researcher through a dichotomous choice question of the stylized form: Would you be willing to pay $\$ b_i$ for *G*?

A dichotomous choice CV study requires the researcher to choose the total number (J) and value (b_i) of bid points and the number of observations at each point (n_i)[2]. The bid (b_i) is randomly assigned to a subject to ensure independence from the idiosyncratic error. The subject then indicates whether b_i is acceptable: i.e., whether her *WTP* is greater than the offered bid. The binary response variable for the dichotomous choice question is an indicator variable equal to one if WTP_i is greater than b_i, and zero otherwise. The parametric estimation of *WTP* assumes an underlying error distribution and runs the maximum likelihood method using the probability of binary response; $\Pr_i(yes) = \Pr_i[\mu + \varepsilon_i > b_i] = F[\beta(\mu - b_i)] = F[\alpha - \beta b_i]$ where α and β or μ and β are parameters of our interest[3]. While the MLE is consistent when the model is correct, the efficiency of estimates depends on the selected bid set and true value of parameters. Thus the main concern in designing bid is to choose optimally bid set $\{J, b_i, n_i\}$ in order to get the more efficient estimate under some statistical criteria.

A number of strategies have emerged for designing bid set, from very simple, naïve bid assignments based on limited information about the underlying distribution of *WTP*, to very complex approaches which often require complete knowledge of the underlying distribution of *WTP*. The naïve (but most popular in practice) approach is to simply choose an arbitrary set of J bids and assign each bid to J/N subjects. Often these bids are equi-spaced over a pre-determined range. Despite its simplicity and lack of

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[2] The final observation at each bid, n_i, can not be decided by the researcher when the study utilize a mail survey format. Instead, the researcher can decide how many survey letters will be distributed at each bid. In other survey formats such as phone interview, it is possible for us to decide n_i.

[3] Parameterization of the model by either (μ, β) or (α, β) does not change the properties of the estimates, so we focus on the parameterization of the model with (μ, β).

informational requirements, the naïve approach has been shown to be inefficient and the estimate of mean *WTP* is sensitive to an arbitrary design. At the opposite end of the design spectrum are a group of designs referred to as optimal bid designs. Each of the optimal bid designs are derived from the goal of achieving some optimality criterion related with the efficiency of estimates or of a function of estimates.

A-optimal design minimizes the summation of the variances of all parameter estimates by minimizing the trace of the inverse of information matrix, i.e., trace of variance-covariance matrix. The trace of the variance-covariance matrix is the sum of its diagonal entries and the diagonal entries of the variance-covariance matrix are individual variance of corresponding parameter estimates. Thus, minimizing the trace of the inverse of the information matrix implies minimizing the summation of lower bound variances of estimates. Sitter and Wu (1993a) and Mathew and Sinha (2001) show that A-optimality results in a two-point design in the class of symmetric designs; two bids ($b_{1,2} = \mu^* \pm \Delta$) are placed around the true mean (μ^*) at symmetric interval (Δ) defined by the objective function for minimizing the sum of the variances.

C-optimal and Fiducial designs minimize the variance or the asymptotic variance around the summary statistic of interest, such as mean or median. The mean or median of *WTP* is a nonlinear function of parameter estimates; recall that they are estimated as a ratio of parameter estimates when α and β are parameters of response function. C-optimality suggests single design point equal to the true population statistics (Wu 1988, Ford et al. 1992). While C-optimality allows for potential non-linearity in the function of parameters, the C-optimal design cannot identify individual parameters if *WTP* function includes a constant. Instead of the asymptotic confidence interval, Fiducial design minimizes the length of the fiducial interval proposed by Finney (1971) using Fieller's theorem. Fieller's theorem shows the exact confidence set (parabola) of a ratio of normal random variables given desired confidence level and the roots of the parabola are the endpoints of the confidence set. Sitter and Wu (1993b) show that the fiducial interval is generally superior to the asymptotic confidence interval. Fiducial design consists of two or three points depending on the sample size and confidence level (Abdelbasit and Plackett 1983, Alberini 1995).

When multiple parameters are of interest in the estimation, D-optimality has been the most widely used criterion. D-optimality aims to minimize the volume of the confidence ellipsoid of parameter estimates. Remind that the determinant of a matrix represents the volume of the matrix in *k*-dimensional space. Therefore, D-optimality reduces to maximizing the determinant of the Fisher's information matrix because the covariance matrix is the inverse of the information matrix. In contrast to A-optimality focusing on the sum of variances of individual parameter estimates, D-optimality considers the entire volume of the confidence ellipsoid which includes the covariance between the estimated parameters. Similar to A-optimality, the D-optimality results in a symmetric 2-point design around the true mean (Rosenberger and Kalish 1978 Technical Report 33 Department of Statistics in Pennsylvania State University, Abdelbasit and Plackett 1983, Minkin 1987, Ford et al. 1992, Nyquist 1992, Mathew and Sinha 2001).

Usually optimal design points consist of symmetric two or three bid points which are determined by unknown true parameter values and assumed model specification. Thus, if we have poor information about the true parameter values, optimally designed bid points won't generate the optimum targeted. One obvious solution for preventing efficiency loss is to implement a sequential design using the consistency of MLE (Abdelbasit and Plackett 1983, Minkin 1987, Nyquist 1992). Sitter (1992) also introduces a robust design using the minimax procedure to solve the problem due to the uncertain poorness of initial parameter values. Despite their intuitive appeal, however, the practicality of a sequential method in CV studies is still open to the question, and Sitter's robust design is seriously reliant on the researcher's confidence level about her information.

Moreover, all optimal designs assume implicitly or explicitly an unbounded symmetric error distribution for the population. The properties of optimal designs based on asymmetric error distributions are not well known; exceptions are Ford et al. (1992), Cooper (1993), Alberini (1995) and Crooker and Herriges (2004). While the goal of the optimal design is usually to achieve the optimal efficiency of estimate, the bias of the estimate in the small sample has also received a lot of interest from researchers. In specific application to CV studies, Cooper and Loomis (1992) demonstrate that the estimate of mean *WTP* is sensitive to the arbitrary sample design. Their simulation also shows that an incorrect assumption about the underlying distribution exacerbates the sensitivity of *WTP* to bid design in small samples. Kanninen (1995) suggests a general rule-of-thumb that places bids within 15^{th} and 85^{th} percentiles of true *WTP* to avoid obviously excessive bids.

III. UNIFORM DESIGN AND ANALYTICAL RESULTS

To alleviate the requirement of assumptions about the true distribution of *WTP* prior to assigning bid values to subjects, and to alleviate the potential efficiency loss due to poor initial information in the optimal design, we propose the use of a simple uniform bid design. The implementation of the uniform bid design is straightforward. The researcher determines a closed support for the distribution of willingness to pay $[L,U]$ utilizing the prior information. Bids are then represented by draws from the uniform distribution with the predetermined support. Each subject in the sample receives a bid based on an independent draw from the uniform distribution.

The uniform bid design draws upon the work of Lewbel et al. (2003) which assumes a continuous bid design to solve an identification problem in the nonparametric estimation of *WTP*. A continuous design is also suggested in Boyle et al. (1988), which is known as the method of complementary random numbers. They use prior information to construct an empirical cumulative distribution function (c.d.f.) and select probabilities and their complementary probabilities in the empirical c.d.f. using random number from uniform distribution. Our uniform design, however, selects bid points from a uniform distribution thereby alleviating the need for pre-estimating the empirical distribution. The only task of a researcher in the uniform design is to decide the support of the uniform distribution under the prior information.

Kim and Haab (2004, unpublished manuscript, Department of AED Economics, The Ohio State University) investigate the analytical properties of the D-optimal, robust and uniform bid designs[4]. Under ideal circumstances (known distributional form and correct parameter values), the D-optimal design provides the most efficient parameter estimates of *WTP* function in the sense of the smallest confidence ellipsoid of estimates.

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[4] A robust design introduced by Sitter (1992) guarantees the maximum efficiency given the range of uncertainty of the information. The robust design consists of equi-spaced J design points being wider spread out with more design points than optimal designs. Roughly, the robust design represents the most efficient naïve design. Although Sitter's design is robust to poor initial parameter estimates and the implementation for a specific application is straightforward, the robust design is still reliant on the initial estimate of the parameters and more importantly on the researcher's confidence about his information as initial estimates.

This is not surprising at all since the D-optimal design is proposed to maximize the determinant of information matrix given true parameters. The maximum determinant of the D-optimal design is used as the benchmark for comparison of the efficiency of a design. In addition to the efficiency of a design, the relative efficiency of a design is defined as the ratio of determinant of a design to the determinant of D-optimal design evaluated at the same poor initial estimates.

Selecting one example of the robust design with four bid points and length of 2.23 from Sitter (1992), Kim and Haab (2004) show the efficiency loss of the robust design against D-optimum and the relative efficiency gain compared with D-optimal design. When the efficiency is calculated as the ratio of the determinant of the robust design to D-optimum, it represents the efficiency loss by employing more bid points. The efficiency loss due to more bid points is not much serious. More importantly, the relative efficiency, i.e. the ratio of determinants evaluated at the same poor initial estimates, shows that the robust design generally has enormous relative efficiency gain.

Kim and Haab (2004) provide the asymptotic determinant, efficiency and relative efficiency of a uniform design as a function of true parameters and initial estimates. The asymptotic determinant is $\frac{1}{\beta^2}\left[\left\{\int_L^U w(t)\,dt\right\}\left\{\int_L^U w(t)t^2dt\right\}-\left\{\int_L^U w(t)\,tdt\right\}^2\right]$ where $w(t)$ is the weight function, $\exp[t]/\{1+\exp[t]\}^2$, of the logit model and the normalized point *t* is $\beta(\mu-b_i)$. They find analytically and through simulation that the optimal bid range of the uniform distribution is $[-2.72,\ 2.72]$ corresponding 6.2^{th} and 93.8^{th} percentile in the normalized logistic distribution and the maximum efficiency of the uniform design is 84 percent of D-optimum under the ideal situation. In fact, the uniform bid design suggests a wider range than optimal designs and the Kanninen's general rule-of-thumb. The poor initial information of parameters disturbs the optimal upper and lower bound to be $U = \beta^*\left(\mu^* - \mu_0\right) + 2.72\beta^* / \beta_0$ and $L = \beta^*\left(\mu^* - \mu_0\right) - 2.72\beta^* / \beta_0$ where μ^* and β^* represent true parameters, and μ_0 and β_0 are the initial information about the parameter. By substituting the disturbed support into the asymptotic determinant of the uniform design, the efficiency loss due to poor information can be expressed in terms of β^* / β_0 and $\beta^*\left(\mu^* - \mu_0\right)$.

Figure (1) shows the efficiency of D-optimal design. The poor initial information about parameters leads to rapid efficiency losses for the D-optimal design even when the distribution form is correctly specified. Figure (2) shows the asymptotic efficiency of the uniform design with the support of $\left[-2.72,\ 2.72\right]$. As can be seen in figure (1) and (2), the asymptotic efficiency of the optimal uniform design has relatively flatter space than D-optimal design. Thus, the effect of poor initial estimates is not so much serious in the uniform design as in the D-optimal design. Comparing figure (1) and (2) at the same poor initial estimates yields the asymptotic relative efficiency loss of the uniform design in figure (3). The minimum efficiency of uniform design is 84 percent at the point of $\mu_0 = \mu^*$ and $\beta_0 = \beta^*$ where D-optimal design has the maximum determinant. To any direction from the point of 84 percent, the uniform design has relative efficiency gain. However, we cannot gain much advantage from the uniform design when μ_0 is not so much different from μ^* or β is small enough to make $\beta^*\left(\mu^* - \mu_0\right)$ close to zero or approximately less than one. Note also that poor initial estimate of μ has a symmetric effect on the efficiency while the effect of poor β is asymmetric.

IV. SIMULATIONS RESULTS

While the analytical results of Kim and Haab (2004) provide insight into the potential usefulness of the uniform design, tractability requires assuming a known distributional form and investigating simple parameter misspecification. In this section, we use a series of Monte Carlo simulations to investigate the relative performance of the D-optimal, robust and uniform bid designs with poor parameter information and distributional misspecification. The simulation scenarios cover the asymptotic properties, poor initial estimates and flexible error distributions like beta distribution. The basic model is a constant willingness to pay; $WTP_i = \mu + \varepsilon_i$, where $\mu = 100$ and ε_i is logistically distributed with mean of zero and standard deviation (σ) of 30. The parameters in the estimation model are μ and β (= 1/σ) in simple probability equation; $\Pr_i\left(yes\right) = F\left[\beta\left(\mu - b_i\right)\right]$. The D-optimal design consists of two bids as $\mu_0 \pm 1.54 \cdot \sigma_0$. The robust design allocates four bid points at $\mu_0 \pm 3.345\sigma_0$ and $\mu_0 \pm 1.115\sigma_0$. Finally, the optimal uniform design draws the bid from the uniform distribution of $\left[\mu_0 - 2.72\sigma_0,\ \mu_0 + 2.72\sigma_0\right]$. The simulation is conducted using Gauss 5.0 of Aptech Systems Inc. with CML Version 1.0.35.

Table 1 shows the result of basic model with 1000 observations. The true parameters are assumed to be known as $\mu_0 = 100$ and $\sigma_0 = 30$. The second column of "Actual" reports the actual mean and the inverse of standard error (β) in the sample. Parentheses show the standard error of estimates reported in the Gauss program. As can be expected, every parameter estimates are statistically significant. In this ideal situation with large number of observations, the uniform design has the best result followed by D-optimal and robust designs in terms of standard error and *RMSE* (root mean squared error) of μ. Note that only standard error of β in the uniform design is worst even though the difference is very small. *Eff* represents the efficiency calculated as the ratio of the determinant of each design to the determinant of D-optimum. As shown in analytical comparison, D-optimal design has the maximum determinant under the correct initial estimates, followed by the uniform and robust designs. The efficiencies of uniform and robust design are 83.23 and 62.86 percent of D-optimal design, respectively, which are close to the analytical results of 84 percent for the uniform design and 65.43 percent for the robust design.

Table 2 reports the 100 iteration results of the simple model with various sample sizes. The sample size includes 80, 160, 320 and 640 to cover from the small sample to large sample. Hereafter, the parenthesis reports the standard error of point estimates in 100 iterations. As can be expected, the simulated standard error of estimates decreases in all designs when the sample size increases. For the estimate of μ, the uniform design usually is the best in the sense of small standard error and lowest *RMSE*. On the contrary, the robust design has the smallest standard error in estimating σ. The sum of standard errors for μ and σ is smallest in the uniform design except N = 640, which intuitively suggests that the uniform design performs well too under the A-optimal criterion. The efficiency is calculated using the average of the determinant in iterations. Analytically, the efficiency of the robust design does not depend on the sample size and the maximum efficiency is 65.43 percent. The efficiency of the uniform design is 83.38 ~ 86.28 percent which is around the asymptotic efficiency of 84 percent.

The estimation results of D-optimal, robust and uniform designs in table 1 and 2 are conducted assuming that the true parameters are known. Interestingly, the uniform design performs well in terms of *RMSE*: in fact, both of bias and variance of estimate for the mean in this simulation. In contrast with C-optimal design suggesting one bid points, the result supports more bid points is better in estimating the mean of *WTP* even when the true parameters are known.

The next scenario of simulation is to investigate the performance of three bid designs with poor initial estimates. Table 3 and 4 show the estimation results with poor initial estimates and sample size of 320. The true value of μ is 100, and poor initial estimate of μ varies from 55 to 145 corresponding -1.5 to 1.5 of $\beta^*\left(\mu^* - \mu_0\right)$. Likewise, the poor initial estimate of σ varies from 10 to 60 corresponding 0.3 to 2 of β^* / β_0 with true value of 30. *REff* represents the relative efficiency calculated as the ratio of the determinants of robust and uniform designs to the determinant of D-optimal design at the same poor initial estimates.

The effect of poor initial estimate of μ is reported in Table 3, assuming that the true standard error is known. Actual value of μ in simulation is 100.0989 and σ is 29.9176. Among 100 iterations, 1 iteration step is reported to fail in calculating function of D-optimal design with μ_0 = 145. Both directions of deviation of μ have symmetric effect on the relative efficiency of the robust and uniform designs, which is consistent with the analytical comparison. *RMSE* also shows that the uniform design performs well at poor initial estimate of μ except $\mu_0 = 55$. Table 4 shows the effect of poor initial estimate of σ with assumption of the correct μ. Actual μ in the simulation is 100.2090 and actual σ is 30.0047. As can be seen in the figure 2, poor initial estimate of σ affects the relative efficiency asymmetrically. For the robust design, the relative efficiency is less as β / β_0 is higher, i.e. σ_0 is larger. The uniform design has the lowest relative efficiency at the correct initial estimate of σ_0 and the relative efficiency increases as the poorness increases. Furthermore, the uniform design outperforms D-optimal and robust designs in terms of *RMSE*, as σ_0 is larger than the true.

One of interesting question about the previous designs is how they perform when the true distribution is unknown and asymmetric. Optimal designs can be optimal only when the prior assumptions are correct. The optimal bid point should be changed when the assumption is different, but so far the optimal point with asymmetric error distribution is hardly known yet. The reliance on the prior assumption is also serious in the robust design. For comparing the performance of bid designs in the case of unknown asymmetric error distribution, the true error distribution is assumed to be a beta distribution with various shape parameters. When the shape parameters *a* and *b* are not same each other, the distribution is either right- or left-skewed. The estimation model is specified as logit, thus this simulation includes the misspecification problem of the error distribution. The true mean and standard error are assumed to be known for initial estimates.

Table 5 shows the simulation result of shape parameter (2, 3), (2.5, 2.5) and (3, 2). In this simple simulation, D-optimal design has the largest determinant far from our expectation. The efficiency of the uniform design shows almost 87 percent of the D-optimal design and the efficiency of the robust design is slightly higher than 72 percent. D-optimal and uniform designs show that when the distribution is left- (right-) skewed, they under- (over-) estimate the mean, while the robust design performs in the opposite way. The properties of estimation result with asymmetric error distribution are analyzed more in the next section with actual survey data.

V. AN APPLICATION TO ALBEMARLE AND PAMLICO SOUNDS DATA

This section compares D-optimal, robust and uniform designs as well as the original design in the study by simulating true *WTP* from the original data. The focus of comparison is on the performance of different designs when we have covariates of nonnegative *WTP* function and the error distribution is asymmetric. Huang, Haab and Whitehead (1997) studied the *WTP* for the water quality improvement in the Albemarle and Pamlico Sounds in eastern North Carolina. The original data consisted of double bounded dichotomous questions. However, in this section, only responses to the first question were considered for design comparison. The first two observations were also dropped to be able to conduct the robust design of $J = 4$ in this simulation since the original data includes 726 observations.

First, under the assumption of nonnegative *WTP* (i.e., the exponential *WTP* function) and log normal error distribution, a probit model was implemented to estimate parameters of *WTP*. *WTP* for the water quality improvement in Albemarle and Pamlico Sound was estimated as $WTP = \exp\left(3.8623 + 0.1034 \cdot INC - 0.3580 \cdot D + \varepsilon\right)$ and $\varepsilon \sim Normal\left(0, 0.3047^{-2}\right)$ where *INC* is income level and *D* is a dummy variable for Pamlico only. The expected *WTP*, $E\left(WTP\right) = \exp\left(\bar{x}'\beta + .5\sigma^2\right)$, was estimated $12340.51 in the sample. Note that the median of *WTP* was $56.60 and the mean of the expected log *WTP*, $E\left(x'\beta\right)$, was $3.99. Next, the true individual *WTP* was simulated by multiplying an unexpected error from log normal distribution to the deterministic *WTP*, assuming that the estimation result in the first step is true parameters. The sample average of *WTP*, $Average\left(WTP\right)$, was $4682.27. The simulated true *WTP* was used to generate the sample dichotomous response for each bid design. The response is one if $\ln(WTP) > \ln(bid)$, and zero, otherwise.

Bid values of D-optimal, robust and uniform designs were derived assuming that the true parameters were known. Initial estimates used in designs were mean and standard error of log *WTP*; the mean of the expected log *WTP* is 3.9941 and the standard error is 0.3047^{-1}. Also, optimal points or range for designs except D-optimal design were adjusted for normal distribution by multiplying $\sqrt{3}/\pi$ to those of logit model. Thus, the robust design with J = 4 had bid points of $\mu \pm 0.61\sigma$ and $\mu \pm 1.84\sigma$, and the support of the optima uniform design was $[\mu - 1.50\sigma,\ \mu + 1.50\sigma]$, where μ is 3.9941 and σ^{-1} is 0.3047. The D-optimal bid point consisted of $\mu \pm 1.14\sigma$ for the normal distribution following previous literatures. Those optimal points and range of uniform design can be transformed to nonnegative dollar amount by taking exponential to the bid point. Finally, the dollar value of bids in the D-optimal design was $1.29 and $2288.12. For the robust design, bids are randomly selected from {$0.13, $7.22, $408.14, $23077.07}, and the uniform design had a uniform distribution of [$0.40, $7448.07]. The original design in the Huang, Haab and Whitehead (1992) consists of {$100, $200, $300, $400}, which corresponds from 4.6052 to 5.9915 of the expected log *WTP*. Note that log value of bids in the original design is higher than the mean of the expected log *WTP*.

Table 6 shows the estimation results of simulation with Albemarle and Pamlico Sounds data. Criteria for comparison are the determinant of information matrix, bias of mean and median of expected *WTP* and *RMSE*. First, surprisingly, the uniform design has the largest determinant of information matrix, followed by D-optimal, the original and robust designs. It is interesting that the determinant of the uniform design is larger than that of D-optimal design, because true parameters were assumed to be known in designing the bid set. The original design has also higher determinant than the robust design even though the original design is a one-sided design (i.e., all bids are greater than the mean of expected log *WTP*). The result strongly supports that the uniform design outperforms other designs in D-optimal criterion when the error distribution is asymmetric.

Uniform design outperforms in this simulation not only in terms of the efficiency but also in terms of median *WTP* and *RMSE*. For the bias of mean of the expected *WTP*, the robust design has the closest result to the true value. However, the mean of the expected *WTP* of uniform design is closest to the sample average of *WTP*. Other interesting features in simulation result are that only estimates of constant and bid are statistically significant in all designs. D-optimal and uniform designs have a negative sign for parameter estimates of *INC* even though the estimate is insignificant. Consequently, the uniform design generates the best results under three criteria (the size of the determinant, median and *RMSE*) and performs well in all other criteria.

VI. CONCLUSIONS

Bid design has been known to affect seriously the bias and efficiency of *WTP* in CV studies. However, unknown true parameter values and uncontrollable response rate of survey make it difficult to apply optimal designs in the actual survey. Other practical bid designs like a naïve approach are unknown about the efficiency loss and bias due to poorly designed bids. Based on previous accomplishments and problems, this paper introduces a new bid design using a predetermined continuous uniform distribution. The new design assumes continuity and randomness of bid points. Analytically, the uniform design provides efficiency no less than other practical design in the ideal situation and optimal designs in the realistic poor information. Practically, the uniform design is easy for researcher to implement for any specific application.

We contend that the uniform bid design represents a practical and viable middle ground between the naïve bid designs and the optimal bid designs. By significantly reducing the dependence of the estimation result on specific bid points, the uniform design reduces the potential biases and efficiency losses from basing optimal bid designs on poor information. In addition, the uniform design reduces the likelihood of biases and efficiency losses from the naïve design. While it is inevitable that the optimal bid designs will outperform the uniform bid design when the optimal design is based on the true distribution of willingness to pay, the uniform design performs favorably when faced with poor information about the true distribution.

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FIGURE 1: The Efficiency of D-optimal Design with Poor Initial Estimates

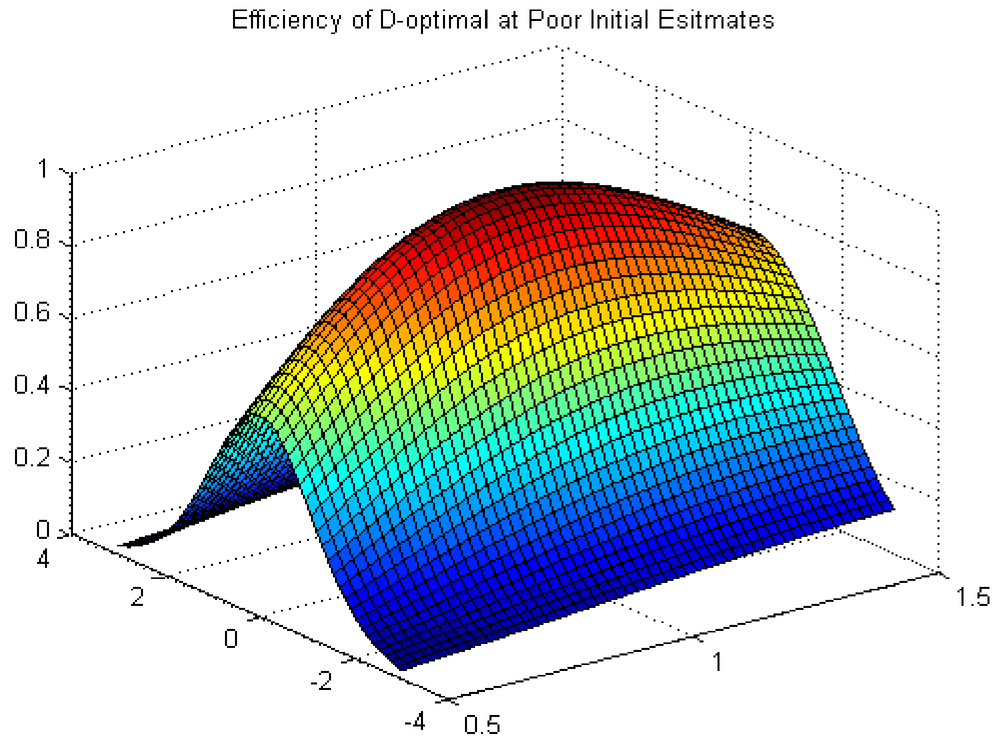


FIGURE 2: The Asymptotic Efficiency of the Optimal Uniform

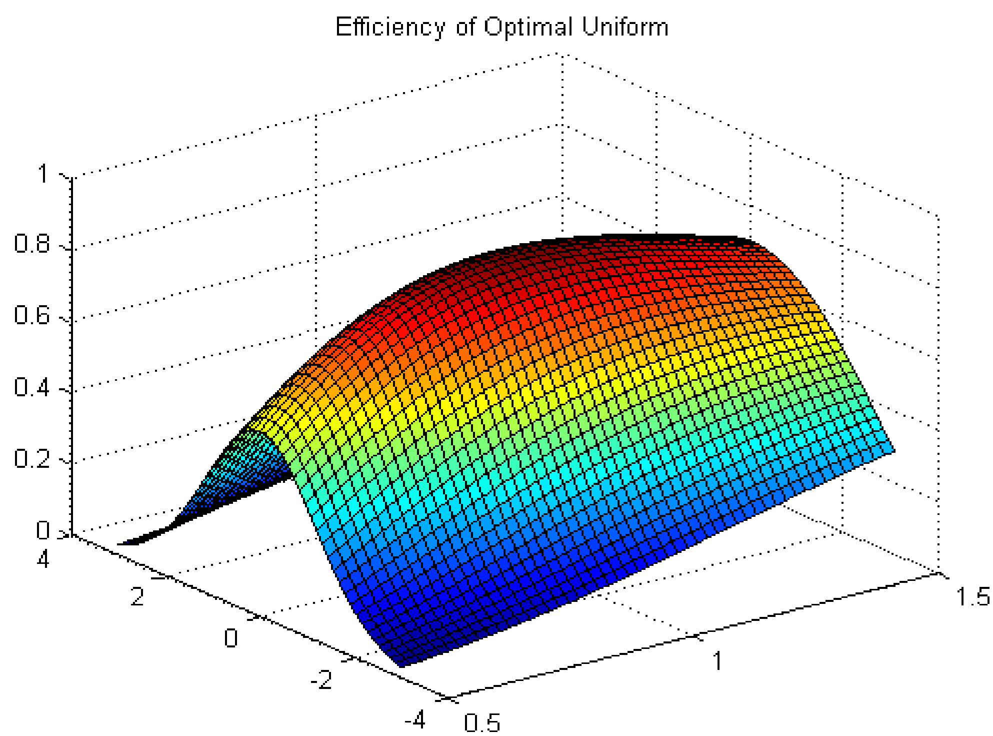
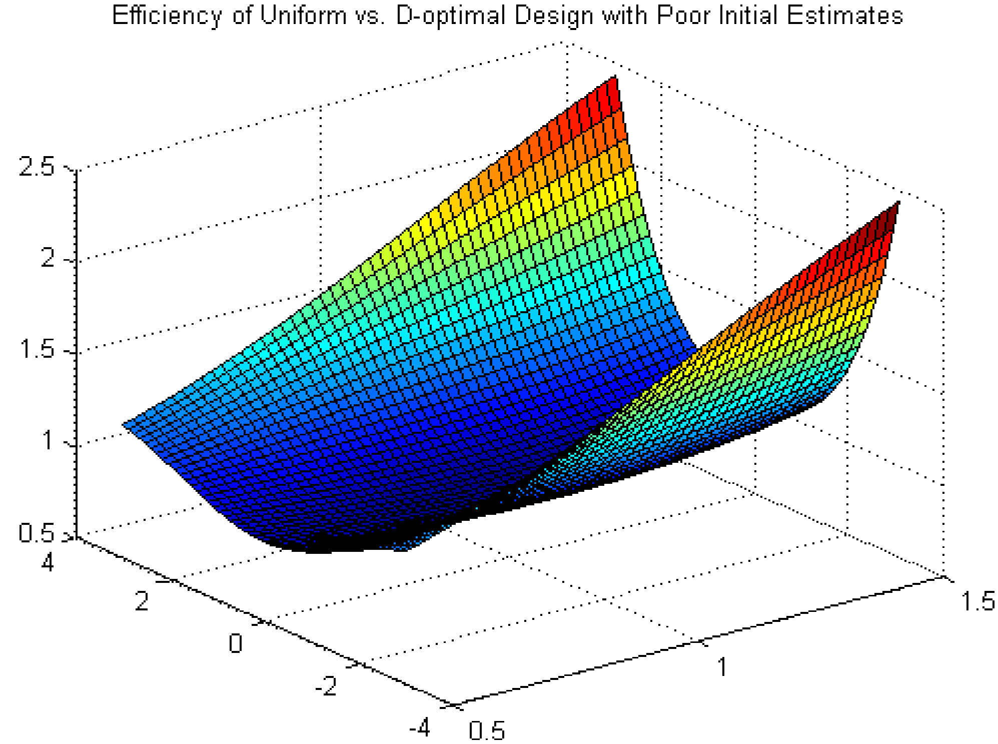


Figure 3: The Asymptotic Relative Efficiency of the Optimal Uniform



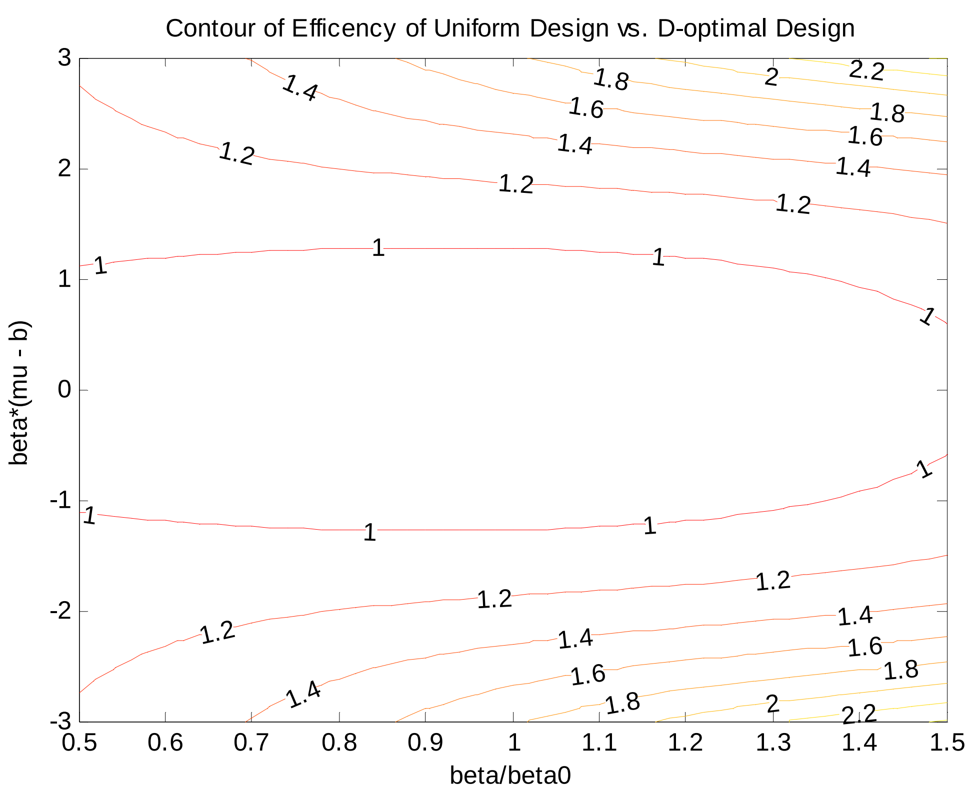


TABLE 1: D-optimal, Robust and Uniform Designs with $N = 1000$

	Actual	D-optimal		Robust		Uniform	
μ	99.3460	97.9300	(2.5669)	97.2631	(2.8061)	98.9095	(2.3491)
β	0.0333	0.0314	(0.0017)	0.0348	(0.0020)	0.0331	(0.0021)
Eff		100		62.8604		83.2300	
RMSE		54.4952		54.5166		54.4786	

TABLE 2: 100 Iterations of Simple model with $N = 80$, 160, 320 and 640

	Actual	D-optimal		Robust		Uniform	
	$N = 80$						
μ	99.4097	99.1955	(9.1829)	99.2402	(10.8442)	98.6798	(8.5866)
σ	30.2086	31.2072	(6.4858)	29.3343	(5.9843)	20.2926	(6.2882)
Eff		100		66.9077		83.3844	
RMSE		55.1554		55.3460		55.0535	
	$N = 160$						
μ	99.7602	99.9925	(5.9714)	99.1349	(7.0857)	99.5768	(5.8555)
σ	30.1389	30.3131	(4.9260)	29.5214	(4.0622)	29.6650	(4.3637)
Eff		100		66.1130		85.6703	
	$N = 320$						
μ	99.9744	99.9537	(4.7597)	99.8970	(4.8828)	100.1410	(4.7288)
σ	29.9883	30.6379	(3.3750)	29.5047	(2.9103)	29.9610	(3.0482)
Eff		100		65.2646		86.2760	
RMSE		54.4653		54.4988		54.4770	
	$N = 640$						
μ	100.0564	100.0261	(3.1681)	100.2129	(3.3033)	100.1940	(3.0738)
σ	29.8866	29.9448	(1.9328)	29.8000	(1.8732)	29.9058	(2.3439)
Eff		100		65.3181		85.0355	
RMSE		54.2470		54.2615		54.2374	

TABLE 3: 100 Iterations with Poor Initial Estimates of μ

	D-optimal		Robust		Uniform	
	$\mu_0 = 55$					
μ	100.3421	(4.3694)	100.3697	(5.8708)	100.2821	(5.2056)
σ	29.2950	(4.0077)	30.1820	(3.0038)	29.9249	(4.0637)
REff	100		113.7679		110.5209	
RMSE	54.3777		54.4384		54.4259	
	$\mu_0 = 75$					
μ	100.5234	(4.2747)	100.0102	(5.3408)	100.1249	(4.2405)
σ	29.7526	(2.9618)	29.9169	(3.4280)	30.1654	(3.1692)
REff	100		76.6577		92.2807	
RMSE	54.3500		54.4036		54.3387	
	$\mu_0 = 100$					
μ	100.0832	(4.3723)	99.8898	(4.9126)	99.9065	(4.3130)
σ	29.7660	(2.5358)	30.0528	(3.3509)	30.2802	(3.2124)
REff	100		65.9432		83.9492	
RMSE	54.3474		54.3878		54.3360	
	$\mu_0 = 125$					
μ	100.4928	(4.6248)	100.2123	(4.4947)	98.9705	(4.8026)
σ	29.9357	(2.9464)	30.2059	(3.5096)	30.2015	(3.6458)
REff	100		76.2574		89.3220	
RMSE	54.3433		54.3787		54.3811	
	$\mu_0 = 145$					
μ	98.4429	(10.9916)	99.6627	(5.0660)	100.1229	(5.2359)
σ	30.9991	(15.0630)	30.0419	(3.5605)	29.8914	(3.3762)
REff	100		113.6570		113.0370	
RMSE	55.2745		54.4147		54.4067	

1 function calculations failed

TABLE 4: 100 Iterations with Poor Initial Estimates of σ

	D-optimal		Robust		Uniform	
	$\sigma_0 = 10$					
μ	99.9413	(3.5821)	100.1924	(3.2139)	100.2011	(3.3338)
σ	31.0174	(7.4705)	30.2099	(4.6208)	29.9297	(7.7508)
Eff	100		188.2141		102.9199	
RMSE	54.4542		54.4497		54.4528	
	$\sigma_0 = 20$					
μ	100.2520	(3.7448)	100.0511	(3.9763)	100.2147	(3.8841)
σ	30.0553	(3.6172)	29.7537	(2.9083)	30.1323	(4.5760)
Eff	100		106.0529		88.1675	
RMSE	54.4621		54.4779		54.4660	
	$\sigma_0 = 30$					
μ	100.4169	(4.1858)	99.8175	(5.3151)	100.0356	(3.4741)
σ	29.9782	(2.9953)	29.6584	(3.0420)	29.9387	(3.4376)
Eff	100		65.2806		84.1582	
RMSE	54.5028		54.5577		54.4695	
	$\sigma_0 = 40$					
μ	100.5465	(4.9207)	99.6000	(6.4361)	99.7180	(3.9807)
σ	30.0485	(2.6084)	29.4623	(3.3248)	29.9082	(3.0037)
Eff	100		51.8393		89.4349	
RMSE	54.5438		54.6527		54.5005	
	$\sigma_0 = 50$					
μ	100.5412	(5.8683)	99.3532	(7.4830)	100.5217	(5.3780)
σ	30.0761	(2.5784)	29.1542	(3.3584)	29.8827	(3.0294)
Eff	100		51.4139		106.9764	
RMSE	54.6406		54.7920		54.5640	
	$\sigma_0 = 60$					
μ	99.9107	(8.0184)	99.2053	(8.2823)	99.7317	(5.1448)
σ	29.6054	(2.7518)	29.2356	(3.7721)	30.0000	(3.4945)
Eff	100		63.6623		150.8424	
RMSE	54.8710		54.9194		54.6104	

TABLE 5: Flexible Beta for Error Distribution

	Actual	D-optimal		Robust		Uniform	
	*(2, 3) (120, 33.0797**)						
μ	120.3063	119.0280	(5.1557)	121.1151	(5.4924)	118.6580	(5.0230)
σ	33.1084	41.3910	(4.4445)	33.6435	(3.0979)	39.4347	(4.5767)
REff		100		72.2039		87.1280	
RMSE		60.1123		60.1492		60.1171	
	*(2.5, 2.5) (150, 33.7618**)						
μ	150.1951	150.3924	(5.4428)	150.8241	(6.0330)	150.1364	(5.2994)
σ	33.6002	41.7015	(4.8726)	34.6713	(3.0551)	39.3621	(5.0721)
REff		100		72.4775		87.2118	
RMSE		60.9814		60.0449		60.9943	
	*(3, 2) (180, 33.0797**)						
μ	179.8880	180.2808	(5.2549)	179.6522	(5.0183)	182.1175	(5.1080)
σ	33.1867	40.2857	(4.0691)	34.4068	(3.0565)	38.8170	(4.4010)
REff		100		72.8120		86.3334	
RMSE		60.2527		60.2417		60.2774	

* The first parenthesis represents the shape parameter (a, b) of beta distribution and the second shows the true mean and standard error. ** The standard error is normalized as that of logistic distribution by multiplying $\sqrt{3}/\pi$ to the standard error of beta distribution.

TABLE 6: Albemarle and Pamlico Sounds Data

	True	D-optimal	Robust	Original	Uniform
Constant	3.8623	4.1112 (10.405)*	3.4456 (7.332)*	4.0511 (11.070)*	4.1953 (12.045)*
INC	0.1034	-0.0458 (0.513)	0.0511 (0.497)	0.0877 (1.516)	-0.0266 (0.336)
D	-0.3580	-0.2909 (0.785)	-0.1640 (0.398)	-0.1708 (0.723)	-0.4584 (1.381)
ln(Bid)	0.3047	0.3424 (19.632)*	0.2968 (16.311)*	0.4179 (4.666)*	0.3249 (14.936)*
det(I)		9.1766e+7	4.2038e+7	5.4386e+7	11.2556e+7
Mean	12340.508 (4682.269)**	3256.792	9943.707	1235.814	5576.139
Median	56.603	45.802	34.027	70.588	48.944
RMSE		46946.280	47209.224	47040.178	46943.929

* t-statistics is statistically significant with 95% confidence level. ** the sample average of WTP