Implementing and Testing Risk Preference Induction Mechanisms in Experimental Sealed Bid Auctions*

by

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Abstract

Risk preference inducing lottery procedures can serve as valuable tools for experimental economists. However, questioning their effectiveness, experimenters may avoid them even when predictions and conclusions depend crucially on risk preferences. Here, I review risk preference induction attempts in sealed bid auctions, discussing factors that promote or hinder success. Making the procedure very transparent and having subjects learn about it in simple environments promote success. Hysteresis resulting from switching between monetary payoffs and lottery procedures in one environment hinder success. Thus, lottery procedures appear sensitive to the implementation. However, implemented carefully, they can generate behavior consistent with the intended preferences.

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*I thank James Cox, Vernon Smith and James Walker for their data. An appendix giving all the estimates referred to in the text is available from the author on request.

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Roth and Malouf (1979) and Berg, Daley, Dickhaut and O'Brien (1986) develop procedures for controlling experimental subjects' risk preferences based on lottery mechanisms. While these procedures are potentially valuable tools, their success appears sensitive to how they are implemented and tested. For example, Walker, Smith and Cox (1990, hereafter WSC) use such a procedure in four person, first price, sealed bid auction experiments.[1] They conclude it does not curtail apparently risk averse behavior in this market environment. They state that "the lottery procedure does *not* induce risk-neutral behavior...[it is] a poor generator of risk-neutral behavior in the context of the first-price auction environment." (WSC, p. 21, italics theirs.) Contrary to their findings, Rietz (1992, hereafter simply Rietz) finds that, when carefully implemented and appropriately tested, such procedures *can* induce behavior consistent with the intended risk preferences in sealed bid auctions. These mixed results may make experimenters hesitate to use this procedure even when assumptions about risk preferences are crucial to their predictions and conclusions.

Here, I discuss the differences between how I implement and test the procedures and how WSC do. I show that using appropriate econometrics on their data leads to fewer, less extreme rejections of risk neutrality. Nevertheless, the tests often reject the hypothesis that their risk preference induction procedure "worked" at the individual behavior level. The methods I use to make the procedure more transparent and easier to learn reduce the rejection rate further. Thus, attempts to make risk preference induction procedures as simple and as easy to learn as possible appear important in determining whether they succeed.

1 Risk Preference Induction

Assuming that subjects maximize expected utility, experimenters use various lottery procedures to induce risk preferences. To see how a lottery procedure works, consider how expected utility maximizing subjects view a two prize, monetary lottery. As long as subjects value only monetary income, each subject will display preferences linear in the probability of winning the higher lottery prize. Further, if subjects can affect only the probability of winning the high prize, subjects who prefer more money to less will try to maximize this probability.

Risk preferences are induced by conducting experiments in two phases: the usual subject interaction phase and a lottery phase. In the first phase, subjects receive "point" payoffs for participating in the environment under study (instead of the usual monetary payoffs). In the second phase, these points determine each subject's probability of winning the high value lottery prize. Linear transformations from points to probabilities should induce subjects to behave as if they had risk neutral preferences over the first phase's point payoffs. Strictly convex or concave transformations should induce behavior corresponding to risk-loving or risk-averse preferences, respectively.

While straightforward, experimenters can implement such procedures in many ways. See Berg, Dickhaut and McCabe (1990) for a summary of research using such procedures.

WSC pay subjects in "PLATO Dollars" in the first phase. While subjects must submit positive bids, they can bid above their own value and, thus, enter phase two with negative phase one earnings. In phase two, subjects pick ranges of lottery ticket numbers corresponding to the number of PLATO dollars they earned. Finally, each subject with positive points picks a lottery ticket and wins the lottery if the ticket number falls within the chosen range.[2] They often introduce this procedure after subjects have participated in auctions using PLATO dollars which convert directly into cash. Further, they introduce it in first price auctions directly. Since optimal strategies depend on the perceived actions of other participants, this environment is relatively complex.

In contrast, subjects in Rietz earn generic "points" in phase one. While subjects can easily bid above the predicted bids, they cannot bid more than their value. This eliminates the possibility of negative point profits and any associated framing effects. In phase two, they draw a lottery ticket and win if their phase one points exceed the ticket number. In more successful treatments, subjects never participate in first price auctions for monetary payoffs directly. Further, in the most successful treatments, subjects first encounter the procedure in second price auctions. Since each bidder has a dominant strategy, independent of all other bidders' strategies, second price auctions are less complex than first price auctions.

2 Sealed Bid Auction Theory

Sealed bid auctions are a logical place to study risk preference induction. While simple, they involve both random draws by nature (values for the auctioned objects) and uncertainty about other bidders' strategies. Further, the tendency for subjects to bid "as if risk averse" appears robust and well documented (see WSC and Kagel (1990)).

2.1 First Price Auctions

In single unit, first price, sealed bid auctions, N bidders (indexed by $i=1,2,\ldots,N$) each submit a sealed bid (b^i, $i=1,2,\ldots,N$) to purchase a single object that has a random value for each bidder (v^i, $i=1,2,\ldots,N$). Each v^i is drawn independently from a known uniform distribution on the interval $[0,\bar{v}]$. The high bidder wins the object and pays a price (P) equal to his or her bid.

Optimal bids in such an auction depend on the probability of winning the auction for each possible bid, the subject's value and the subject's utility function. For symmetric Nash equilibria, Vickrey (1961), Harris and Raviv (1981), Cox, Smith and Walker (1985) and Cox, Smith and Walker (1988) respectively find optimal bid functions for risk neutral bidders, homogeneously risk averse bidders, heterogeneously risk averse bidders and heterogeneously risk averse bidders with income thresholds and premiums on winning the auctions.[3] Assuming subjects can not or will not bid above their own value or below zero, all of these result in linear optimal bid functions of the form:

(1) $$b_t^i = \beta_0^i + \beta_1^i v_t^i,$$

where b_t^i is the subject's bid, v_t^i is the subject's value and β_0^i and β_1^i parameterize subject i's bid function. Risk neutral preferences will result in $\beta_1^i=(N\text{-}1)/N$ for all subjects. Bid function slopes will be higher for risk averse subjects. Except in Cox, Smith and Walker (1988), which assumes subjects place an independent value on winning the auction or have income thresholds, optimal bid functions will have $\beta_0^i=0$ for all subjects. For example, in four person auctions, the Vickrey prediction is $\beta_1^i=0.75$ and $\beta_0^i=0$ for all i. This gives a testable prediction about price distributions. Conditional on known (or induced) risk preferences, each version gives testable predictions about bid function slopes. While optimal bid functions appear independent of other bidders' behavior, it is crucial. Specifically, these bid functions are *only* optimal against other bidders who are using linear bid functions over the same range.

2.2 Second Price Auctions

Second price, sealed bid auctions, differ from first price auctions in that the winning bidder pays a price equal to the second highest bid. In these auctions, bidders can only affect the probability of winning the auction and not the price. Optimizing, non-cooperative bidders without income thresholds will bid their own value regardless of risk preferences. Bidders with income thresholds will bid their own value if the expected value of winning the auction exceeds the income threshold and zero otherwise. The optimal bid function is independent of what other bidders do.

3 Implementation and Testing Procedures

3.1 Implementation

For the lottery procedure to succeed, subjects must understand how the procedure transforms the auction outcomes into payoffs. Further, they must be able, and sufficiently motivated, to develop optimal bidding strategies under the procedure. Here, I describe differences between implementations in Rietz and WSC that may affect how the lottery procedure performs.[4] Specifically, Rietz implements two sets of features intended to foster success. The first set promotes common knowledge and helps make the experimental procedures more transparent. The second controls for the hysteresis effects of switching from monetary payoffs to the lottery procedure. Both appear important to the lottery procedure's success.

Several common knowledge features were common to all treatments in Rietz. I ran each experiment in one room with all bidders present. Both oral and written instructions explained that all bidders used the same instructions and were paid using the same lottery procedure. Finally all values, prices and profits from the auction were quoted in generic "points" which translated directly into the probability of winning cash in the lotteries. In contrast, WSC's instructions appear on the terminal screen before the experiment begins. They do not say whether they include common knowledge statements in the instructions or read them aloud. They quoted all values, prices and auction payoffs in PLATO dollars (which translated into probabilities of winning high or low cash prizes in the lottery phase).

In the most successful treatments in Rietz, an additional feature helped make the lottery procedure transparent. I introduced it in a very simple, dominant strategy game: a set of twenty second price auctions in which bidders could not bid more than their value. The dominant strategy is for all bidders to bid their own value regardless of risk preferences. Limiting bids from above should vastly simplify the decision problem since, up to that point, increasing the bid increases the probability of winning the auction without affecting profits or introducing possible losses conditional on winning. In contrast, WSC introduce the lottery in more complex, unconstrained first price auctions.

Finally, in the most successful treatments in Rietz, I do not switch from monetary payoffs to point payoffs using the lottery. Bidders never receive monetary payoffs directly. Instead, they use the lottery after every auction. This does not require subjects to re-evaluate their bidding strategies after the lottery procedure is introduced. If this re-evaluation requires effort and the benefits from it are small, subjects may suffer from hysteresis, continuing with the strategy they developed without the procedure. In their first set of experiments, WSC switch from monetary payoff first price auctions to first price auctions using the lottery procedure. They also use subjects that had been in previous monetary payoff first price auction experiments <u>and</u> conformed well to CRRAM and, generally, to the risk averse predictions. Bidder behavior changes little after introducing the procedure, showing that hysteresis may be an important factor.

3.2 Testing

"Success" or "failure" of risk preference induction can be tested at the market level using prices or at the individual behavior level using bids. WSC only discuss individual behavior. At the aggregate level, I use Kolmogorov-Smirnov tests to determine whether the observed price distributions differ significantly from the price distribution predicted using the actual bidder values and the Vickrey risk neutral bid functions for all bidders.[5] I also ask whether the price distributions differ significantly across the various treatments.

While, at the individual level, testing for risk neutrality appears simple, it is actually quite difficult. The predictions of all models can be tested using a regression on each bidder's ordinary bid function or their transformed[6] bid function:

(2) $$\frac{b_t^i}{v_t^i} = \frac{\beta_0^i}{v_t^i} + \beta_1^i + \eta_t^i,$$

where η_t^i is an error term. Estimating and testing this equation proves difficult for two reasons. First, bids must be in the range $[0, v_t^i]$ in Rietz and above 0 in WSC. This censors the data and biases ordinary least squares estimates.[7] In addition, the sizes of the regression residuals correlate highly with the regressors causing heteroskedasticity problems.[8] Thus, appropriate testing procedures must be robust to both censoring and heteroskedasticity. WSC use Ordinary Least Squares (OLS) which is sensitive to both.

For estimating and testing individual bid functions, I use a version of Powell's (1984) Least Absolute Deviations (LAD) Estimator. Specifically, for every bidder i, the LAD estimator solves:

(3) $$\min_{\beta_0^i,\, \beta_1^i} \sum_{t=1}^{T} \left| \frac{b_t^i}{v_t^i} - \frac{\hat{b}_t^i}{v_t^i} \right| ,$$

where t indexes the observations, v_t^i is bidder i's value, b_t^i is bidder i's observed bid and $\frac{\hat{b}_t^i}{v_t^i}$ represents the predicted normalized bid using equation (2).[9] LAD estimates are consistent and asymptotically normal under general conditions.[10] The errors must have median zero and the probability of censoring the observation corresponding to the median error must approach zero as the number of observations increases to infinity. Since LAD estimates depend only on the median deviation, they should be robust to bidders who deviate significantly from their bid functions at very high or low values and to those who self-censor bids near their own value or zero. To estimate the variance of the parameter estimates, I use a bootstrapping technique that redraws observations from the original sample. Re-sampling from the observations (and not from the original regression errors) overcomes problems associated with heteroskedasticity.[11]

4 Results

The data is from the first 12 of the 15 experiments reported in WSC and the 8 experiments reported in Rietz. See these papers for details of the experiments.

The label WSC-I denotes experiments from WSC's first set of five experiments. In experiments 1, 2 and 3, subjects participated in 20 monetary payoff auctions followed by 20 auctions using the lottery procedure. All subjects had participated in previous monetary payoff first price auction experiments. Further, only subjects who conformed highly to their constant relative risk aversion model (CRRAM) and, thus, generally to the risk averse predictions, were chosen. In experiments 4 and 5, a subset of subjects from the first three experiments returned for a second set of 20 auctions using the lottery procedure. These experiments correspond roughly to the "CK" treatment in Rietz. In experiments labeled CK, inexperienced subjects participated in 20 monetary payoff first price auctions followed by 60 auctions using the lottery procedure. In these experiments, risk preference induction performs poorly at best.

The label WSC.II denotes experiments from WSC's second set of seven experiments. In experiments 1 through 4, subjects without previous experience in auction experiments participated in 20 auctions using the lottery procedure. In experiments 5, 6 and 7, a subset of subjects from the first four experiments returned for a second set of 20 auctions using the lottery procedure. These experiments correspond roughly to the "CKH" treatment in Rietz. In experiments labeled CKH, inexperienced subjects participated in 20 first price auctions using the lottery procedure followed by 60 more first price auctions continuing to use the lottery procedure.[12] In these experiments, risk preference induction performs somewhat better than in the above experiments which expose subjects to hysteresis effects.

Finally, the labels TCKH-RN and TCKH-RA denote the "full" treatment experiments from Rietz.

In these experiments, inexperienced subjects participated in 20 second price auctions using the lottery procedure followed by 60 first price auctions continuing to use the lottery procedure. In TCKH-RN experiments, I attempted to induce risk neutrality. In TCKH-RA experiments, I attempted to induce the constant relative risk aversion utility function that gives a bid function slope of 0.825. Risk preference induction performs the best under these treatments.

Table 1 gives Kolmogorov-Smirnov test statistics for differences between actual and predicted price distributions for all sessions. It also gives rejection frequencies for each group of experiments. Under the

Insert Table 1 about here.

"full" treatments from Rietz, the price distributions *never* differ significantly from the predictions generated by assuming the induced risk preferences. In contrast, price distributions lie significantly to the right of the predictions in *all* of the sessions without risk preference induction. The null is rejected in four out of seven experiments (57.14%) that switch from monetary payoffs to the lottery procedure (CK and WSC.I experiments). The results are also mixed when inexperienced subjects first encounter the lottery mechanism in first price auctions (CKH and WSC.II experiments). In these experiments, the null is rejected in four out of eleven experiments (36.36%).

Figure 1 shows price distributions aggregated within types of experiments. Table 2 gives Kolmogorov-Smirnov statistics for differences between these distributions. The price distribution from

Insert Figure 1 about here.

experiments without risk preference induction does not differ significantly from the price distribution from experiments in which risk preferences were induced following auctions without risk preference induction. Thus, price distributions do not change significantly when switching from monetary payoffs to using the

Insert Table 2 about here.

lottery procedure. However, the price distribution from experiments using the lottery procedure from the beginning lies significantly to the left of these distributions. The price distribution from the "full" treatment experiments lies significantly further to the left. Thus, eliminating hysteresis effects moves prices much closer to the risk neutral prediction. Allowing subjects to accustom themselves to the lottery procedure in relatively simple second price auctions moves the prices even closer to the predictions.

Table 3 gives rejection rates for the hypothesis that the bid function slopes correspond to the induced risk preferences.[13] OLS, subject to biases because of censoring and heteroskedasticity, generally results in

Insert Table 3 about here.

rejection under all treatments regardless whether risk preferences are induced. However, results using LAD estimates are consistent with the price distribution results. When subjects first encounter the lottery mechanism in first price auctions after already participating in monetary payoff first price auctions (CK and WSC.I experiments), bid function slopes frequently exceed predictions significantly. Figure 2 shows the distribution of the differences between the slope point estimates and the predictions. Relative to other

Insert Figure 2 about here.

treatments, these point estimates are distributed tightly above the predictions. This corresponds to more risk averse preferences than predicted. Again, results are mixed when inexperienced subjects first encounter to the lottery procedure in first price auctions (CKH and WSC.II experiments). The null is often rejected.

However, point estimated sometimes exceed the predictions and sometimes fall short of the predictions. In CKH experiments, differences between the predicted and estimated slopes are distributed relatively evenly around zero. In WSC.II experiments, they are distributed above zero. However, both are relatively diffuse. Finally, the most successful induction occurred when inexperienced subjects first encountered the lottery procedure in second price auctions and proceeded to first price auctions later (TCKH-RN and TCKH-RA experiments). Rejection rates again fall and estimates are relatively tightly distributed around a mean near the predicted values. Further, according to Kolmogorov-Smirnov statistics in Table 4, the deviations from

Insert Table 4 about here.

the predicted bid function slopes under this treatment are distributed significantly to the left of (i.e. closer to zero than) those from the experiments in which risk preferences were not induced or induced after subjects participated in monetary payoff auctions.

Thus, results agree both at the aggregate and individual behavior levels. Risk preference induction moves outcomes toward those predicted. Risk preference induction is least successful in attempts to change behavior already learned in monetary payoff auctions. It is most successful when subjects can assimilate to it in a simple environment and they do not switch from monetary payoffs to the lottery mechanism.

5 Conclusions

Lottery procedures can induce risk preferences in sealed bid auctions with varying degrees of success. They have difficulty changing behavior learned in previous monetary payoff auctions. Further, when used in first price auctions with inexperienced subjects, they are only moderately successful. However, applied with sufficient care, they can generally succeed.

Three factors appear important in promoting success. First, making the procedure as transparent as possible promotes success. Second, the procedure performs better when applied to subjects without experience in similar, monetary payoff environments. Hysteresis noticeably affects subjects who have participated in similar, monetary payoff environments. Finally, allowing subjects to accustom themselves to the lottery procedure in simple environments promotes success. Here in particular, allowing subjects to participate in repeated (dominant strategy) second price auctions using the lottery procedure before having them participate in first price auctions using the procedure improved the procedure's performance significantly.

Thus, risk preference induction procedures can perform well in complex market environments such as sealed bid auctions. However, they should be implemented carefully. The implementation should fit the environment and make the procedures simple enough for subjects to understand their implications completely.

Notes

* I thank James Cox, Vernon Smith and James Walker for their data. An appendix giving all the estimates referred to in the text is available from the author on request.

1. They report preliminary results and reach similar conclusions in Cox, Smith and Walker (1985).

2. It is not clear how WSC deal with the possibility of negative phase one profits.

3. Harris and Raviv (1981) and Cox, Smith and Walker (1985) assume constant relative risk aversion utility functions and Cox, Smith and Walker (1988) assume a similar utility function with arguments for an income threshold and a value for winning the auction that are independent of v_t^i.

4. See Rietz and WSC for detailed discussions of the designs.

5. Conover (1971) discusses Kolmogorov-Smirnov statistics and gives tables of critical values. Results using Cramer-von Mises and Wilcoxon Rank Sum tests differ little from the Kolmogorov-Smirnov results.

6. When subjects are not allowed to bid above their value, this transformation gives constant censoring limits at 0 and 1 instead of variable censoring limits at zero and v_t^i. This makes the problem conform to standard censored regression models. If bids are not censored from above, the ordinary bid function conforms to standard censored regression models.

7. Powell (1984) discusses how censoring biases OLS estimates. Dropping censored observations does not eliminate this bias.

8. White's (1980) correction is not a sufficient adjustment for this problem because censoring will still bias estimates.

9. In the single limit case,

$$\min_{\beta_0, \beta_1} \sum_{t=1}^{T} \left| b_t^i - \hat{b}_t^i \right| ,$$

where comes from (1) can as easily be used. In the estimation, I use all of the observed bids including those over 750. This is valid under the null. While the risk neutral bid function does not predict bids over 750 and the model with heterogeneous risk aversion may have not have a closed form solution in this range, there is nothing in the theory with errors or risk aversion that implies that bids must not exceed 750. With homogeneous risk aversion, bid functions are even linear in this range. Further, when subjects can bid in this range, they have high values and high expected payoffs. This should motivate subjects to be more accurate when placing high bids (as evidenced by the smaller than proportional increase in variance of higher bids).

10. Asymptotic normality of this estimator follows from Pakes and Pollard (1987).

11. Bootstrapping gives a more powerful small sample estimator than using Powell's method of estimating the variance which requires estimating the density function of the errors at 0. I thank Gary Chamberlain for suggesting the bootstrapping technique using samples drawn from the original data.

12. Values in the last 60 auctions were the same as in the last 60 auctions in the other treatments.

13. An appendix giving all the estimates referred to here is available from the author on request.

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Table 1: Kolmogorov-Smirnov Statistics for Differences in Actual and Predicted Price Distributions (Data from Rietz (1992) and Walker, Smith and Cox (1990))

Sessions without Risk Preference Induction		Sessions with Risk Preference Induction Following First Price Auctions without Risk Preference Induction		Sessions with Risk Preference Induction without Previous Auction Experience		Sessions with Risk Preference Induction Following Second Price Auctions with Risk Preference Induction	
Session	Stat.	Session	Stat.	Session	Stat.	Session	Stat.
CK.1 S.I	.700[a]	CK.1 S.II	.483[a]	CKH.1 S.I	.200	TCKH-RN.1 S.II	.150
CK.2 S.I	.700[a]	CK.2 S.II	.417[a]	CKH.2 S.I	.300	TCKH-RN.2 S.II	.117
WSC-I.1 (Baseline)	.500[a]	WSC-I.1 (First Test)	.350	CKH.1 S.II	.233	TCKH-RA.1 S.II	.233
WSC-I.2 (Baseline)	.350[a]	WSC-I.2 (First Test)	.250	CKH.1 S.II	.317[a]	TCKH-RA.2 S.II	.150
WSC-I.3 (Baseline)	.600[a]	WSC-I.3 (First Test)	.500[a]	WSC-II.1 (First Test)	.200		
		WSC-I.4 (Second Test)	.350	WSC-II.2 (First Test)	.240		
		WSC-I.5 (Second Test)	.450[a]	WSC-II.3 (First Test)	.360[a]		
				WSC-II.4 (First Test)	.280		
				WSC-II.5 (Second Test)	.360[a]		
				WSC-II.6 (Second Test)	.520[a]		
				WSC-II.7 (Second Test)	.200		
Rejection Frequency:	4/4 (100%)	Rejection Frequency:	4/7 (57.14%)	Rejection Frequency:	4/11 (36.36%)	Rejection Frequency:	0/4 (0.00%)

[a]Significant at the 95% level of confidence.

Table 2: Kolmogorov-Smirnov Statistics for Differences in Aggregate Actual Price Distributions Across Treatments (Data from Rietz (1992) and Walker, Smith and Cox (1990))

	Sessions Aggregated		
Sessions Aggregated	CK.1 S.II, CK.2 S.II, WSC-I.1, WSC-I.2, WSC-I.3, WSC-I.4 and WSC-I.5 (220 Obs)[b]	CKH.1 S.I, CKH.2 S.I, CKH.1 S.II, CKH.1 S.II, WSC-II.1, WSC-II.2, WSC-II.3, WSC-II.4, WSC-II.5, WSC-II.6 and WSC-II.7[c] (335 Obs)	TCKH-RN.1 S.II TCKH-RN.2 S.II[d] (120 Obs)
CK.1 S.I, CK.2 S.I and Baselines of WSC-I.1, WSC-I.2 and WSC-I.3[a] (100 Obs)	0.0927	0.3973[e]	0.5050[e]
CK.1 S.II, CK.2 S.II, WSC-I.1, WSC-I.2, WSC-I.3, WSC-I.4 and WSC-I.5[b] (220 Obs)	.	0.3846[e]	0.4432[e]
CKH.1 S.I, CKH.2 S.I, CKH.1 S.II, CKH.1 S.II, WSC-II.1, WSC-II.2, WSC-II.3, WSC-II.4, WSC-II.5, WSC-II.6 and WSC-II.7[c] (335 Obs)	.	.	0.1852[e]

[a]Sessions without Risk Preference Induction
[b]Sessions with Risk Preference Induction Following First Price Auctions without Risk Preference Induction
[c]Sessions with Risk Preference Induction without Previous Auction Experience
[d]Sessions with Risk Preference Induction Following Second Price Auctions with Risk Preference Induction
[e]Significant at the 95% level of confidence.

Table 3: Risk Neutral Hypothesis Rejection[a] Frequencies Using Individual Session II Bids

Treatment Summarized	Ordinary Least Squares						Least Absolute Deviations					
	$\beta_0^i=0$			$\beta_1^i=0.75^b$			$\beta_0^i=0$			$\beta_1^i=0.75^b$		
	Total	< 0	> 0	Total	< .75	> .75	Total	< 0	> 0	Total	< .75	> .75
CK Session I	25.0%	25.0%	0.0%	87.5%	0.0%	87.5%	0.0%	0.0%	0.0%	62.5%	0.0%	62.5%
CK Session II (All Periods)	37.5%	25.0%	12.5%	75.0%	25.0%	50.0%	50.0%	37.5%	12.5%	87.5%	0.0%	87.5%
CK Session II (Last 30 Periods)	62.5%	25.0%	37.5%	62.5%	25.0%	37.5%	37.5%	37.5%	0.0%	62.5%	0.0%	62.5%
CKH Session I	12.5%	12.5%	0.0%	37.5%	12.5%	25.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
CKH Session II (All Periods)	50.0%	37.5%	12.5%	87.5%	25.0%	62.5%	37.5%	12.5%	25.0%	75.0%	37.5%	37.5%
CKH Session II (Last 30 Periods)	62.5%	25.0%	37.5%	75.0%	0.0%	75.0%	37.5%	12.5%	25.0%	25.0%	12.5%	12.5%
TCKH-RN Session II (All Periods)	75.0%	50.0%	25.0%	62.5%	12.5%	50.0%	25.0%	0.0%	25.0%	12.5%	12.5%	0.0%
TCKH-RN Session II (Last 30 Periods)	62.5%	50.0%	12.5%	37.5%	0.0%	37.5%	0.0%	0.0%	0.0%	12.5%	0.0%	12.5%
TCKH-RA Session II (All Periods)	50.0%	12.5%	37.5%	75.0%	37.5%	37.5%	25.0%	25.0%	0.0%	25.0%	0.0%	25.0%
TCKH-RA Session II (Last 30 Periods)	50.0%	0.0%	50.0%	50.0%	25.0%	25.0%	25.0%	25.0%	0.0%	25.0%	0.0%	25.0%
WSC-I (w/o Induction)	16.7%	8.3%	8.3%	66.7%	0.0%	66.7%	8.3%	8.3%	0.0%	50.0%	0.0%	50.0%
WSC-I (First Test)	41.7%	0.0%	41.7%	41.7%	0.0%	41.7%	0.0%	0.0%	0.0%	25.0%	0.0%	25.0%
WSC-I (Second Test)	12.5%	0.0%	12.5%	75.0%	0.0%	75.0%	12.5%	0.0%	12.5%	50.0%	0.0%	50.0%
WSC-II (First Test)	18.8%	6.3%	12.5%	56.3%	0.0%	56.3%	12.5%	12.5%	0.0%	56.3%	0.0%	56.3%
WSC-II (Second Test)	50.0%	8.3%	41.7%	66.7%	25.0%	41.7%	16.7%	8.3%	8.3%	33.3%	0.00%	33.3%

[a]Using regression equation (2), at the 95% level of significance.

[b]$\beta_1^i=0.825$ for Treatment TCKH-RA

Table 4: Kolmogorov-Smirnov Statistics for Differences in Distributions of LAD Point Estimates of Bid Function Slopes
(Exact Critical Values for Two Sided Tests at the 95% Level of Confidence in Parentheses Below Statistics)

	Sessions in Second Distribution					
Sessions in First Distribution	WSC-I, Baseline[a] (Obs. = 12)	CK, Session II[b] (Obs. = 8)	WSC-I, First and Second Test[b] (Obs. = 20)	CKH, Sessions I and II[c] (Obs. = 16)	WSC-I, First and Second Test[c] (Obs. = 28)	TCKH-RN and TCKH-RA, Session II[d] (Obs. = 16)
CK, Session I[a] (Obs. = 8)	0.2500 (0.5833)	0.2500 (0.6250)	0.3000 (0.5689)	0.5625[e] (0.5625)	0.3571 (0.5452)	0.6250[e] (0.5625)
WSC-I, Baseline[a] (Obs. = 12)	.	0.3333 (0.5833)	0.2333 (0.4667)	0.5208[e] (0.4792)	0.2976 (0.4692)	0.64583[e] (0.4792)
CK, Session II[b] (Obs. = 8)	.	.	0.4000 (0.5689)	0.7500[e] (0.5625)	0.4643 (0.5452)	0.8125[e] (0.5625)
WSC-I, First and Second Test[b] (Obs. = 20)	.	.	.	0.4125 (0.4250)	0.2143 (0.3982)	0.4750[e] (0.4250)
CKH, Sessions I and II[c] (Obs. = 16)	.	.	.	.	0.2857 (0.4262)	0.3125 (0.4275)
WSC-I, First and Second Test[c] (Obs. = 28)	.	.	.	.	.	0.3571 (0.4262)

[a]Sessions without Risk Preference Induction
[b]Sessions with Risk Preference Induction Following First Price Auctions without Risk Preference Induction
[c]Sessions with Risk Preference Induction without Previous Auction Experience
[d]Sessions with Risk Preference Induction Following Second Price Auctions with Risk Preference Induction
[e]Significant at the 95% level of confidence.

Figure 1: Aggregated Cumulative Price Distributions for Sessions without Risk Preference Induction (-), Sessions with Risk Preference Induction following First Price Auctions without Risk Preference Induction (-+-), Sessions with Risk Preference Induction without Previous Auctions (-⊖-) and Sessions with Risk Preference Inductions following Second Price Auctions with Risk Preference Induction (-◇-)

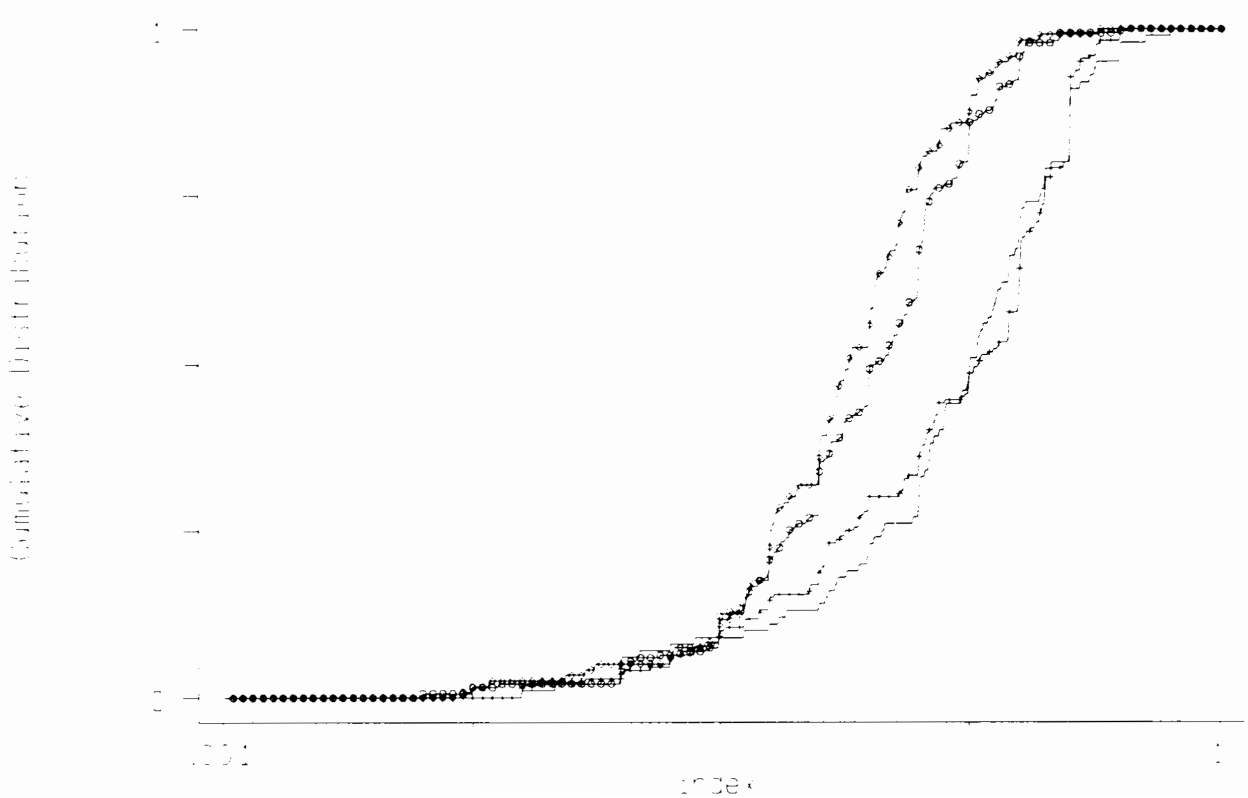

Figure 2: Distributions of Differences Between LAD Estimated Slope Coefficients and Predictions

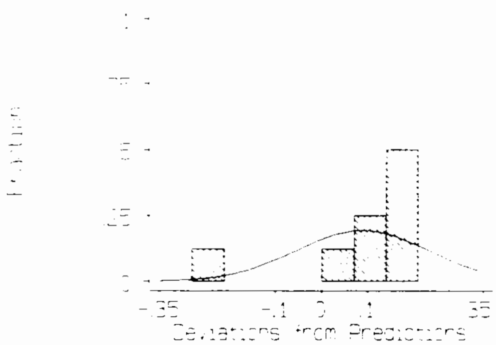

Figure 2.a: CK Experiments, Session I
(No Risk Preference Induction)

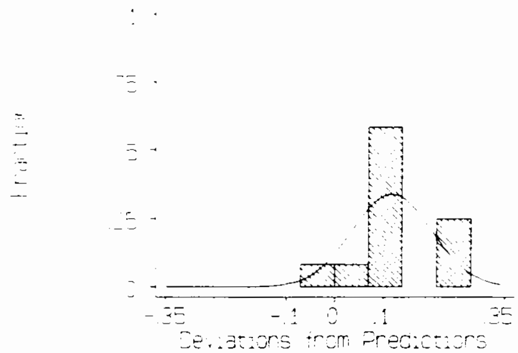

Figure 2.b: WSC.I Experiments 1-3
(No Risk Preference Induction)

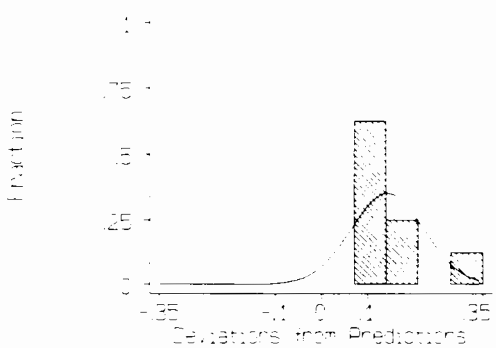

Figure 2.c: CK Experiments, Session II
(Risk Preference Induction after 20 1st Price $ Auctions)

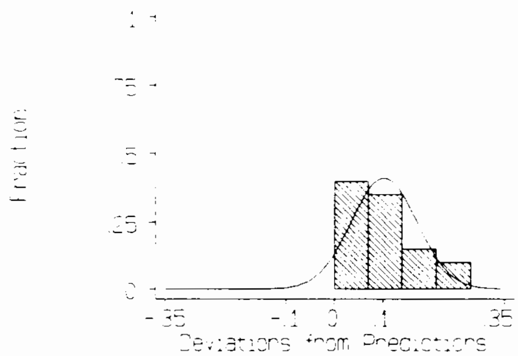

Figure 2.d: CSW.I Experiments
(Risk Preference Induction after 20 1st Price $ Auctions)

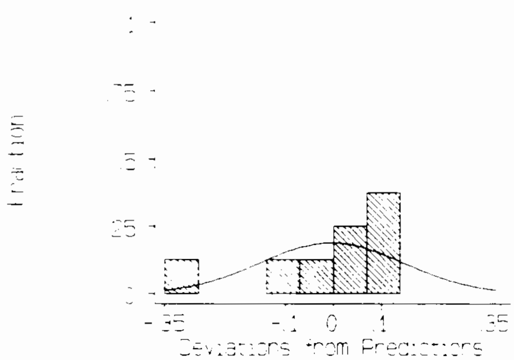

Figure 2.e: CKH Experiments, Both Sessions
(Simple Risk Preference Induction)

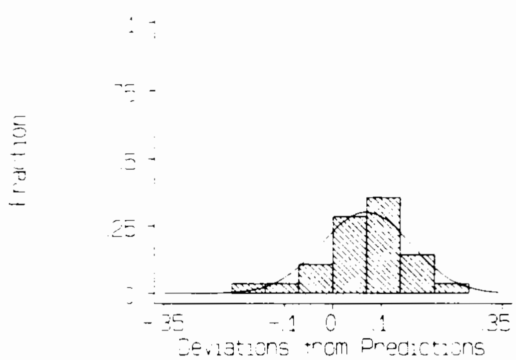

Figure 2.f: WSC.II Experiments
(Simple Risk Preference Induction)

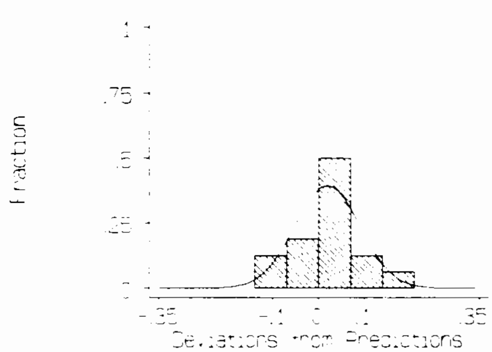

Figure 2.g: TCKH-RN & TCKH-RA Experiments
(Risk Preference Induction after 20 2nd Price Lottery Payoff Auctions)