Risk Preference Instability Across Institutions: A Dilemma*

By

Joyce Berg, University of Iowa
John Dickhaut, University Of Minnesota
Kevin McCabe, George Mason University

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Abstract

In this paper we use laboratory experiments to ask two related questions. First, do individuals behave as if their risk preferences are stable over time within a given institution? Second, do individuals behave as if their risk preferences are stable across institutions? In particular, we study the decisions of cash motivated subjects in the repeated play of three different institutions, the Becker, Degroot, and Marschack (BDM) pricing procedure for the sale of a risky asset (1964); an English clock auction for the sale of a risky asset; and, a first price auction for the purchase of a riskless asset. For each institution we estimate an individual's risk coefficient. We then test the hypotheses that for the same individual the estimated risk coefficient across institutions is the same. We find that these estimates are statistically different. We also perform a more qualitative comparison of a subject's risk preferences across tasks by comparing the individual's decisions to an expected value maximizer. Most subjects acted as if they were risk loving in the English clock auctions and risk averse in the first price auctions. In the BDM procedure behavior was split between risk loving and risk averse bidding.

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1. Introduction

Models of individual behavior under uncertainty play a major role in research on the allocative and informational properties of organizations and markets. In order to interpret empirical studies researchers and policy makers often assume that individuals' risk preferences are relatively stable over time and across institutions. In field studies risk preferences are often assumed to be stable in order to study the impact of information on behavior in different institutions. For example, stability is assumed in order to study issues of market microstructure, such as the differences in price behavior at the opening of an exchange compared to intraday prices on the same exchange. In laboratory studies the assumption of stability is made in order to compare the effect of different institutional treatments. For example, in a within subject design it is assumed that the risk preferences of the subjects in question will remain the same over the length of the experiment and that any change in behavior must be the consequence of stimuli within the laboratory. Furthermore, in the formulation of policy the stability of certain types of preferences is often assumed. For example, if field observations lead us to believe that most of the population is risk averse, then when we propose a new mechanism or a change to an existing mechanism we assume that people will be risk averse in this new institution.

In this paper we use laboratory experiments to ask two related questions. First, do individuals behave as if their risk preferences are stable over time within a given institution? Second, do individuals behave as if their risk preferences are stable across institutions? In particular, we study the decisions of cash motivated subjects in the repeated play of three different institutions, the Becker, Degroot, and Marschack (BDM) pricing procedure for the sale of a risky asset (1964); an English clock auction for the sale of a risky asset; and, a first price auction for the purchase of a riskless asset.

We find large differences in inferred risk preferences across our three institutions. For each task we estimate an individual's risk coefficient assuming that subject's risk preferences are consistent with Constant Relative Risk Aversion. We find that the distributions of risk coefficients are statistically different across tasks. We also perform a more qualitative cross institution comparison of a subject's risk by comparing individual decisions to an expected value maximizer. Most of our subjects acted as if they were risk loving in the English clock auctions and risk averse in the first price auction. . In the BDM auction behavior there was a 50-50 split between risk taking and risk averse behavior. Thus we can claim that regardless of what the utility function might be that risk preferences are not stable across institutions.

2. Experimental Design

Let U(x) be an individual's utility function over monetary wealth x, and, $g = [(x_1, p_1), ..., (x_n,p_n)]$ be a gamble which returns monetary wealth x_i with probability p_i, then expected utility is defined to be $EU(g) = p_1U(x_1) + ... + p_nU(x_n)$. We say that an individual is risk averse if U is concave and risk loving if U is convex where the degree of risk preference is reflected in the curvature of U. Given U for some subjects, the certainty equivalent of a gamble g is an amount of wealth x_g such that $U(x_g) = EU(g)$. If $x_g < p_1x_1 + ... + p_nx_n$, then the individual is risk averse.

Since U is unobservable, in order to infer risk attitudes we must be able to map subjects' messages or choices back to U. Such a mapping depends on our assumptions about how behavior in a given task is modified by different specifications of U. We have chosen three institutions where this mapping is defined by theory.

A. The BDM Procedure

In the BDM pricing procedure subjects are asked to state a selling price for a two state gamble. Once the selling price is chosen, a random number is drawn from a uniform distribution with a support that includes both prizes. If the random number is less than a subject's selling price then the subject plays the gamble and is paid the outcome from the gamble. If the random number is greater than or equal to a subject's selling price, then the subject is paid an amount equal to the random number and does not play the gamble.

The BDM procedure was implemented on a computer as follows. A subject was presented with 20 gambles each with a low prize of zero and a high prize randomly drawn between 1 and 225. We referred to the high prize as the POINT PRIZE and only indirectly referred to the low prize in terms of a zero outcome range. Our instructions stated the following:

> "Each gamble consists of a POINT PRIZE, a PRIZE RANGE, and a ZERO RANGE. If you play the gamble, we will roll a 30-sided die, numbered 1 through 30. If the number rolled is in the PRIZE RANGE, then you will receive the POINT PRIZE. If the number rolled is in the ZERO RANGE, then you will receive zero points."

In constructing our 20 gambles we randomly chose the POINT PRIZE (between 1 and 225) and the cutoff value of the PRIZE RANGE (between 1 and 30) before the first experiment. The gambles presented to subjects are shown in Table 1. The subject was then asked to state the smallest number of points for which he would be willing to exchange his gamble. Once everyone had chosen a selling price a ball was drawn from a bingo cage that contained balls labeled 1 through 225. If the ball had a number larger than or equal to the subject's selling price then the subject exchanged his gamble for the number of points on the ball. If the ball showed a number less than the subject's selling price then the subject played the gamble. Points were immediately converted to cash using the conversion rate of two points per cent.

B. English Clock Auctions

In an English clock auction for the sale of a single unit of an asset an initial clock price is set equal to the largest possible valuation of the asset and sellers then choose to exit the auction. The price is then lowered at a pre-specified rate. Sellers can choose to exit the auction at any time with the understanding that the decision to exit is final. Sellers who exit the auction end up playing the gamble, while the last remaining seller in the auction sells his asset at a selling price equal to the price at which the second to last seller exited. In the English clock auction, an expected utility maximizer has a dominant strategy to stay in the auction until the auction price reaches his certainty equivalent.

We conducted English clock auctions on a computer network with four individuals over 20 periods. At the beginning of each period, each individual was endowed with an identical gamble to either sell, or play. The low prize of each gamble was zero and the POINT PRIZE and cutoff value of the PRIZE RANGE were randomly chosen the same way BDM gambles were chosen. Table 1 lists these gambles. Each auction started at a price equal to the POINT PRIZE of the gamble. All subjects were assumed to be willing to sell, i.e., enter the auction, at this price. The price was then decreased by three points every two seconds. A subject's decision to exit the auction was equivalent to the decision to play his gamble. As soon as three of the four subjects had exited the last subject in the auction was paid the current auction price in exchange for his gamble. The other three subjects played the gamble and received the points indicated by the outcome of the gamble. Points were immediately converted to cash using the conversion rate of two points per cent.

McCabe, Rassenti, and Smith (1990, 1991) have studied the English clock with riskless assets. They find that subjects behave very similarly to the dominant strategy prediction. They also find that the English clock out-performs many other progressive and sealed bid dominant strategy mechanisms in both allocative efficiency and pricing with respect to theoretical price predictions. For these reasons we chose to extend the study of English clock to uncertain assets in order to compare the behavior of English clock auctions with BDM.

C. First price Auctions

In a first price auction N buyers are each given a value drawn uniformly between V_{min} and V_{max}. Buyers each submit a sealed bid simultaneously to the auction which then sells one unit of the good to the buyer with the highest bid at a price equal to his bid. For example, if buyer i has a value v_i and his bid $b_i(v_i)$ is highest then buyer i's payoff is $U_i(v_i - b_i(v_i))$.

ickrey (1961) was the first to show that if we assume risk neutral, noncooperative bidders, who know the distribution of values, then the utility maximizing, symmetric Nash Equilibrium, bid function is given by the linear rule:

(1) $$b_i(v_i) = [(N-1)/N]v_i.$$

In laboratory experiments Cox, Smith, and Walker (CSW) found that most subjects followed a linear bidding rule but they tended to bid higher than the bids predicted by (1). Since higher bidding could be explained by subjects risk aversion over losing the auction to another bidder, CSW looked at the class of constant relative risk averse utility functions, i.e., $U_i(x_i) = x_i^{r_i}$. CSW argue that the utility maximizing, symmetric Nash Equilibrium, bid function, for values below the maximum bid of the least risk averse bidder, is given by the linear rule:

(2) $$b_i(v_i,r_i) = [(N-1)/(N-1+r_i)]v_i.$$

In estimating r_i from individuals bid functions CSW find values of r_i are significantly less than one for most subjects.

Our first price auctions ran on a computer with four subjects. For each of 20 periods a random resale value between 0 and 225 points was drawn independently for each subject. Each value was equally likely to occur. Given their value subjects were then asked to place a bid, i.e., how many points they would be willing to pay to get a good which they could then exchange for their resale value. Once all four bids were collected the highest bidder was announced the winner. This person received points equal to the resale value minus the winning bid. Everyone else in the auction received zero points.

D. Within Subject Design

Given the robustness of subject behavior in the previously reported experiments with first price auctions we felt that these auctions would be unaffected by the sequencing of tasks. In order to minimize the complexity of the experiment to subjects we sequenced the two selling tasks before the first price task. Furthermore, in order to give the English clock auction its best shot we chose to first run BDM to give subjects experience in pricing gambles and then run the English clock auction. A typical experimental session consisting of all three tasks lasted around two and a half hours. While subjects played for points they were told from the beginning that these points would be converted to dollars using fixed exchange rates (2 points = 1 cent in BDM and English clock and 1 point = 4 cents for first price). Exchange rates were chosen to make the expected payoff from each task roughly the same.

3. Experimental Methods

In this section we explain our procedures for running the experiments and our methods for analyzing the data.

A. Experimental Procedures

Subjects in these experiments were undergraduates at the Carlson School of Business at the University of Minnesota. All of our subjects had participated in a paid individual choice experiment. Subjects were recruited by phone to participate in a three hour experiment. A subject received $5 for showing up and an additional $3 if they were bumped due to overbooking. When they showed up each subject choose a numbered chip without replacement from a cup, which indicated which computer terminal they should take. The terminals which were used each were surrounded by a partition which prevented subjects from seeing the data on each other's screens. A no talking rule was strictly enforced. One of the chips, designated M, allowed us to choose a monitor for our randomizing devices. The monitor was paid $15 in addition to the $5 show up fee.

Once everyone had arrived and was seated the instructions were read out loud by an experimenter. During the reading of the instructions the bingo cage was filled from 23 cups. The first 22 cups had ten balls in sequence while the 23-cup had five balls. The subjects were each given two to three cups and asked to examine the contents and once satisfied to put the balls in the bingo cage. We also showed the subjects our 30-sided die and told subjects they were free to examine the bingo cage or the die at any time. At this time we also explained the role of the monitor in using the randomizing devices during the experiment.

B. Data Analysis Procedures

i. Qualitative Assessment Of Risk Preferences

In the first price auction we graph a subject's bids against the value drawn. As a benchmark we graph the 45% line as well as the risk neutral line, i.e., bid = 3/4 value. Intuitively, a risk averse subject will raise his bid above the risk neutral bid in order to improve his chances of winning. However, he will not bid above the 45% line since this means bidding above value, which results in a loss. A risk-loving subject will bid below the risk neutral bid since he is willing to reduce his chances of winning in order to get a larger payoff. Thus, for risk averse subjects we expect to see bids between these two lines, and for risk loving subjects we expect to see points below the risk neutral prediction.

In the BDM and English clock procedures we plot subjects minimum selling price (vertical axis) against the expected value of the gamble (horizontal axis). As a benchmark we plot the 45% line. A risk neutral subject has a certainty equivalent equal to expected value. Intuitively, points above the 45% line reflect risk-loving behavior since a subject must be paid more to give up his gamble. Points below the 45% line reflect risk averse behavior since subjects are willing to take less in order to sell their gamble.

ii. Quantitative Assessment Of Risk Preferences

In the first price auction, if z_t is the actual bid, in period t, by a subject given his resale value v_t, then given the observations $\{(v_1, z_1),..., (v_{20}, z_{20})\}$ the CSW procedure estimates the regression equation,

(3) $$z_t = a + b\, v_t + e_t.$$

If the subject has a constant relative risk averse utility function, then from (2) we know that a = 0, b = $[(N-1)/(N-1+r_i)]$ and our estimate of r_i is $[(1-b)/b](N-1)$. In order to estimate r_i we need to consider values v_t less than or equal to the maximum bid of the least risk averse person. If we assume the least risk averse bidder is risk neutral, i.e., has r' = 1, then we know our subject's bid function is linear for values

(4) $$v_t < [(N-1+r_i)/N]V_{max}.$$

Given (2) and (4), we can then estimate (3) iteratively by first assuming $r_i = 1$ including all (v_t,z_t) such that $v_t < (3/4)/225$. Given our estimate of r_i we then include (v_t, z_t) according to (4) and re-estimate r_i. We continue to iterate until there is no change in our estimate of r_i.

We can also compute a r_i for each subject in the BDM and English clock tasks. Again we assume constant relative risk aversion. If ce_t is the certainty equivalent of a gamble t with high prize H_t and low prize of 0, and the probability of the high prize is p_t, then we know a subject's selling price should make him indifferent between playing the gamble or receiving the selling price. Thus the selling price should equal ce_t, i.e.,

(5) $$ce_t^{r_i} = (1-p_t)0^{r_i} + p_tH_t^{r_i}.$$

Taking the natural logarithm of both sides of (5) gives us a form we can estimate equation (6) using

OLS.

$$\ln ce_t = a + b \ln p_t + c \ln H_t + e_t, \quad (6)$$

where a is required to be 0. From (5) we know b = 1/r and c= 1_i.

4. Experimental Results

Figure 1 graphs subjects' bids in session 1. Each session consists of four subjects. Subjects in the same session participated in the same first price and English clock auctions. Sessions 1 and 2, 3 and 4, 6 and 7, 9 and 10, and 11 and 12 were run concurrently, with inexperienced subjects, in the same room. Session 5 was run with experienced subjects from sessions 3 and 4. Session 8 was run by itself with inexperienced subjects. Subjects mostly behaved as if risk averse in our first price auctions. In particular, a total of 35 of our 48 subjects bid consistently (at least 90% of the time) above the risk neutral bid line. Subjects almost always behaved as if risk loving in our English clock auctions. In particular, a total of 40 of our 48 subjects consistently (at least 90% of the time that they did not win the auction) dropped out of the auction before the price reached the expected value of the gamble. For the BDM auction subjects often behaved as if risk loving but not as strongly as in the English clock auctions. For BDM a total of 19 of our 48 subjects bid consistently (at least 90% of the time) above the expected return for the gamble.

Figure 2 summarizes our regression estimates of subject's risk coefficients. Consistent with previous studies of first price auctions we find over 85% of our subjects are risk neutral or risk averse. In our BDM estimates we find only 45% of our subjects are risk neutral or risk averse, and finally, in our English clock experiments the number of risk neutral and risk averse individuals drops to only 20%. Using a Kolmogorov-Smirnov test to compare these empirical distributions we find significant differences (at the .01% level) between all pair wise comparisons of these three distributions.

Figure 3.a. summarizes the R squared statistics for our estimated equations. In order to test our hypothesis that an individual has stable risk preferences within a task we require an R square above .9. We find that 78% of our subjects have R squares above .9 in first price auctions, 30% of our subjects have R squares above .9 in the BDM auctions, and 82% of our subjects have R squares above .9 in the English clock auctions.

Most of the regression coefficients associated with the calculation of a subject's risk coefficient were significant at the .05 level (Figure 3.b.). Figure 3.c summarizes our consistency checks on these estimates by looking at the distribution of t-tests on the other OLS coefficients not directly used in estimating risk coefficients. In the first price regressions this coefficient is the intercept, a, in equation (3). Note that this estimate should not be significantly different from zero. In the BDM and English clock auctions we have forced the intercept in equation (6) to be 0., BDM E5.

Discussion

Our experimental data supports two main conclusions. First, we conclude that for most of our subjects risk preferences are very stable within the English clock and first price auctions and less stable within the BDM procedure. Second, we conclude that our assessment of risk preferences varies across institutions. Subjects act as if risk loving in the English clock auctions and then act as if risk averse in the first price auctions. This result is even more surprising given the strong consistency of behavior within these two auctions. These results suggest that researchers must be extremely careful in extrapolating a person's, or group of people's, risk preferences from one institution to another. Without appropriate benchmarks on the as if preferences of individuals researchers can mistake changes in behavior due to risk preferences for change in behavior due to other stimuli such as information or rule changes.

After we began this line of research of contrasting individual risk behavior across different institutions Isaac and Jackson compared behavior of the same individuals in the first price auction and in BDM. Their study differed from this study in several respects. To begin with they used only one gamble in their administration of the BDM procedure and based their evaluation of BDM on only two evaluations of that gamble. The gamble was one with a .5 chance of $4.00 and a .5 chance of $0.00. In our own published work we have reported large variability in the pricing choice under BDM. Furthermore in the Isaac and Jackson study, there could possibly be a tendency for subjects to automatically report the expected value of $2.00 since that number was so easy to compute. (Issac and Jackson's estimated average risk coefficient was 1.05, with 1.00 reflecting risk neutrality.) Estimating BDM with only two observations meant that there were no statistical tests of the properties of the estimator of the risk coefficient or the diagnostic properties of the estimation process. In contrast our study not only extended the set of possible gambles used in BDM it also added another institution to study, the English clock auction. The latter auction generally has performed with remarkable consistency in certainty settings so it seemed quite likely that there would be less noise in the data than the BDM approach. Our results bear this conjecture out at both a qualitative level as well as through hypothesis testing. Moreover our ability to categorize behavior in absence of an assumed risk function allows us to claim that differences in risk preferences across institutions holds regardless of any assumptions regarding a specific utility function (Isaac and Jackson did not pursue this generality).

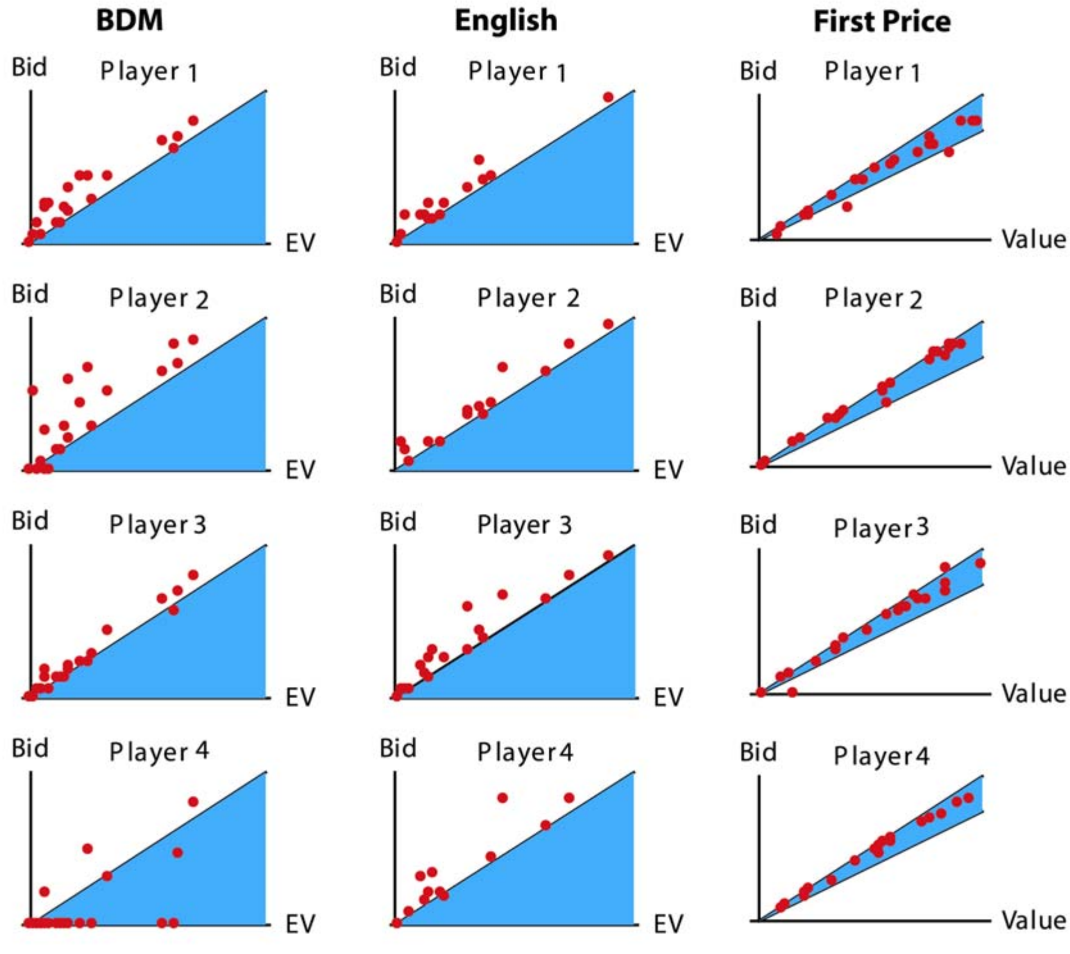
A rallying cry of much of experimental economics is that "institutions matter." (Smith, 1984). Standard propositions in Neoclassical Economics (such as monopolist behavior) are susceptible to the institutions in which the proposition is tested. The current research can be thought of in a similar vein, namely we have shown that even with respect to the revelation of risk preferences, institutions matter. Revealed preferences of individuals are generally believed sufficient for deriving any prediction and/or welfare statement. Yet this paper demonstrates that the preferences revealed are not independent of the procedure (institution) via which they are revealed. Such a result leads to the difficult problem that there simply might not be such things as preferences ("They ain't nothing til we call em") (Tversky and Thaler, 1990) or possibly there is something more to preferences than just observed choices. A substantial amount of work that can be interpreted as part of the study of institutions is on preference reversals. Berg, Dickhaut and Reitz (forthcoming), have demonstrated that the phenomenon of preference reversal itself is sensitive to an institution, the preference induction technique, that attempts to prespecify what preferences will be revealed. Recently researchers have begun to take a more fundamental approach to attempt to try to isolate idiosyncratic differences that we see in preferences that are revealed via subtle changes in the environment.

Attempts are being undertaken to try to develop the proposition that decision processes in the brain are susceptible to very subtle changes in the context in which choice is made. (Dickhaut, et al., 2003, K. Smith et al. 2002). Related work with auctions isolates psycho-physiological processes that can give a more complete picture of how these auctions function (Dickhaut et. al. 2001, and K. Smith and Dickhaut, 2003).

Table 1
Gambles used in English Auction and BDM

Prize Range	Point Range
56	8
188	9
30	29
118	1
115	20
15	26
32	24
167	9
190	25
73	7
147	26
131	9
49	23
65	27
62	16
154	28
34	8
111	5
58	1
187	22

Figure 1
Graphs of Bidding Behavior in the BDM, English and First Price Auctions



Each row in Figure 1 shows bidding behavior in the Becker, DeGroot, and Marschack pricing procedure, the English Auction and the First Price Auctions. Points (in red) show specific bids. For the BDM procedure and English Auction bids are graphed against Expected Value (EV). In the first price the bid of the winning bidder is graphed against value. In the BDM (and English) procedure a bid is associated with the related expected value of the bet to the subject. In the first price auction the bid of the winning bidder is graphed against the value for that subject. Shaded areas denote risk aversion.

Figure 2
Risk Coefficients in Three Different Institutions

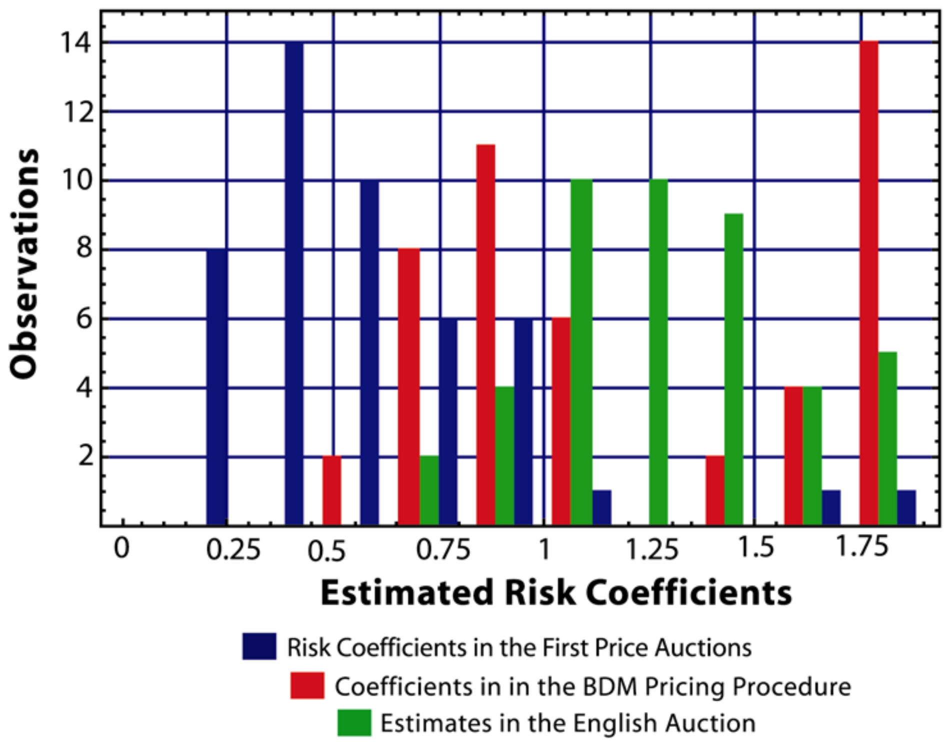


Figure 3

Cumulative Distribution functions of t statistics on risk coefficient estimates, t-statistics on diagnosticity checks, and R^2's.

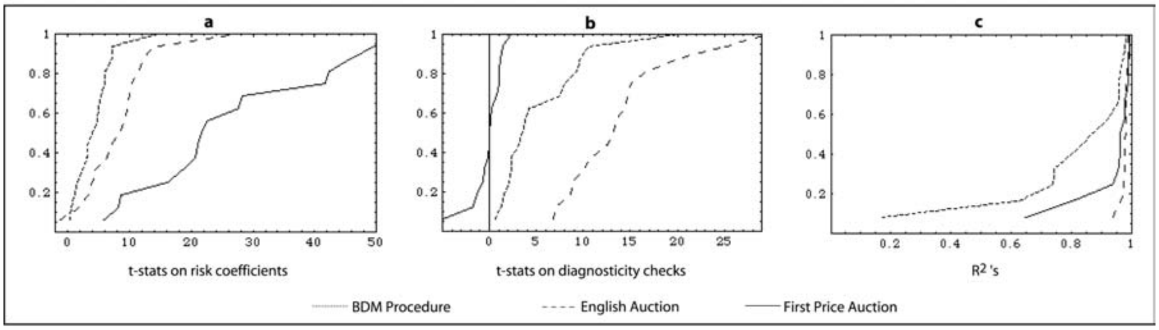


Figure 3.a is a cumulative distribution function of the estimates of t-statistics for the BDM Procedure, English Auction and First Price Auction. The picture demonstrates that the two most distinguishable sets of risk assessments were the English and First Price. The first price estimates are the estimates of "b" in expression (4) divided by the standard deviation of that estimate. The English and BDM procedure employ estimation equation (6).

Figure 3.b is a cumulative distribution function of the estimates of diagnostic t-statistics for the BDM Procedure, English Auction and First Price Auction. The BDM and English Estimates are predicted to 1 and hence the t statistics should be significantly greater than 0. The estimate for the constant "a" in the first price auction should be 0 and we find the median estimate is virtually 0.

Figure 3.c is a cumulative distribution of R^2 's for the BDM Procedure, English Auction and First Price Auction. The graph indicates that the explanatory power of the regression is shifted to the right in moving from BDM to first price to English.

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