Risk preference instability across institutions: A dilemma

Joyce Berg*, John Dickhaut†‡, and Kevin McCabe§

*Department of Accounting, University of Iowa, 5284 Pappajohn Building, Iowa City, IA 52242; †Department of Accounting, Carlson School of Management, University of Minnesota, 321 19th Avenue South, Minneapolis, MN 55455; and §Department of Economics, George Mason University, 4400 University Drive, Fairfax, VA 22030

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In this article we use laboratory experiments to ask a fundamental question: 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: a value elicitation procedure for the sale of a risky asset, an English clock auction for the sale of a risky asset, and a first-price auction for the purchase of a riskless asset. We first do a simple categorical comparison of each subject's risk preferences across tasks by comparing the individual's decisions with an expected value maximizer. All subjects acted as if they were risk-loving in the English clock auctions and risk-averse in the first-price auctions. In the Becker, Degroot, and Marschack procedure, behavior was split between risk-loving and risk-averse bidding. For each institution we also estimate an individual's risk coefficient. We test the hypotheses that for the same individuals the estimated risk coefficient across institutions is the same. We find that these estimates are statistically different.

Every domain concerned with finding solutions and understanding social problems requires either an assumption about individuals' risk preferences or some attempt to gather information about such preferences. These preferences are believed to be independent of the policy or phenomena under consideration. For example, in theories about optimal designs of contracts it is not uncommon to assume agents are risk-averse (1). A similar assumption is often made in designing public information systems (2) or understanding portfolio choice (3). In all such theoretical endeavors assigning such preferences plays a major role in attempting to deduce how such institutions function. This study highlights a potential dilemma. Suppose risk preferences cannot be disentangled from the institution under study. We ask whether the risk preferences exhibited by individuals in institutions change when we move across three institutions in which preferences can be inferred. Those institutions are the Becker, Degroot, and Marschack (BDM) pricing procedure (4), an English clock auction, and a first-price auction. We find dramatic differences in preferences.

The potential problem extends beyond the theoretical domain. Today it is not unusual to elicit a patient's risk preferences in designing health plans (5) as well as choosing perinatal care (6). Elicited risk preferences are used to design means for protecting the environment from pollution (7), and the elicitation of preferences has been undertaken to address the issue of educational alternatives for the disadvantaged (8). These approaches make the assumption that the risk preferences elicited are not related to the institution to be implemented.

Economists have returned to using experiments to improve on the preference elicitation process. Holt and Laury (9) have asked how the size of monetary incentives leads to different preferences. Harrison, Lau, Rutström, and Sullivan (10) have attempted to see whether field experiments could be modified to elicit preferences similar to those elicited in the laboratory.

We began our study of this problem with a working paper in 1992 detailing many of the results provided here. In a related study, Isaac and James (11) compared behavior of the same individuals in the first-price auction and BDM. They found, under the assumption that their subjects were constantly relative risk-averse, that subjects' estimated risk coefficients were risk-averse in the first-price auction; the same subjects were often risk-neutral in BDM. Isaac and James also found that the set of inferred risk coefficients under one mechanism was not simply a monotonic transformation of the other risk coefficients.

One problem with finding different risk coefficient estimates for different institutions is the degree that a policy can be inappropriately used. If policy makers assume risk aversion instead of risk neutrality then too much or too little of the policy may be used. So it is important to further understand this result.

The Isaac and James study assumes a specific form of the utility function to reach its conclusion; furthermore it uses the BDM procedure in a restricted manner. The current study is able to show a result that is independent of the specification of a specific utility function. This approach yields the strong result that the findings cannot be reversed by specification of a functional form. Isaac and James used only one gamble in their administration of the BDM procedure and based their evaluation of BDM on only two judgments of that gamble. The gamble was one with a 0.5 chance of \$4.00 and a 0.5 chance of \$0.00. In our own published work we have reported large variability in the pricing choice under BDM (12). Furthermore in the Isaac and James study, there could possibly be a tendency for subjects to automatically report the expected value of \$2.00 because that number was so easy to compute. (Issac and James' 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, the present study not only extends the set of possible gambles used in BDM but it also adds 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 out this conjecture at both a qualitative level as well as through hypothesis testing. Moreover we are able to add the strong finding that under English clock auctions subjects are risk-preferring, whereas under the first-price auction they are risk-averse. This finding suggests the possibility that depending on the mechanism used to assess preferences a person could possibly be assessed to be risk-averse when in fact the person was risk-preferring. Such a result would mean that a policy was applied in a diametrically unfavorable way.

We use laboratory experiments to ask our fundamental question. Do individuals behave as if their risk preferences are stable across institutions? We study the decisions of cash-motivated subjects in the repeated play of three different institutions, the

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Abbreviation: BDM, Becker, Degroot, and Marschack.

‡To whom correspondence should be addressed. E-mail: jdickhaut@csom.umn.edu.

BDM (1) pricing procedure for the sale of a risky asset; an English clock auction for the sale of a risky asset; and a first-price auction for the purchase of a riskless asset.

We first do a simple categorical comparison of each subject's risk preferences across tasks by comparing the individual's decisions with an expected value maximizer. Subjects generally 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. For each institution we also estimate an individual's risk coefficient. We test the hypotheses that for the same individuals the estimated risk coefficient across institutions is the same. We find that these estimates are statistically different.

Experimental Design

Let $U(x)$ be an individual's utility function over monetary wealth x, and, $g = [(x_1, p_1), \dots, (x_n, p_n)]$ be a gamble that returns monetary wealth x_i with probability p_i, then expected utility is defined to be $EU(g) = p_1 U(x_1) + \cdots + p_n U(x_n)$. 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 subject, the certainty equivalent of a gamble g is an amount of wealth x_g such that $U(x_g) = EU(g)$. If $x_g < p_1 x_1 + \cdots + p_n x_n$, then the individual is risk-averse.

Because U is unobservable, 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 inferred from theory.

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. 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. Also the subject was given a cutoff value, p, between 1 and 30. If the roll of a 30-sided die was less than p (the zero range) the subject earned 0 points. If the number was more than p (the prize range) the subject earned the point prize.

In constructing 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. For each gamble, once everyone had chosen a selling price a ball was drawn from a bingo cage that contained balls labeled 1–225. 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 by using the conversion rate of two points percent.

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 prespecified rate.

Table 1. Gambles for subjects

Point prize	Prize 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

Point prize denotes the number of points that will be won if a 30-sided die (numbered 1–30) lands at prize range or above. Thus the first gamble pays off 56 points if the die lands at 8 or above.

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, whereas 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 2 s. 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 by using the conversion rate of two points percent.

McCabe, Rassenti, and Smith (13) have studied the English clock with riskless assets. They found that subjects behave in a manner that closely parallels the dominant strategy prediction. They also found that the English clock outperforms 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 to compare the behavior of English clock auctions with BDM. It is useful to note that in any single English auction with n participants we know the values of only $n - 1$ participants because the winner of the auction sells at the exit price of the last person to exit.

First-Price Auctions. In a first-price auction N buyers are each given a value drawn uniformly between V_{min} and V_{max}. Buyers 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 $U_i[v_i - b_i(v_i)]$.

Vickrey (14) 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:

$$b_i(v_i) = [(N-1)/N]v_i. \quad \textbf{[1]}$$

In laboratory experiments Cox, Smith, and Walker (15) found that most subjects followed a linear bidding rule but they tended to bid higher than the bids predicted in Eq. **1**. Because higher bidding could be explained by subjects' risk aversion over losing the auction to another bidder, Cox *et al*. looked at the class of constant relative risk-averse utility functions, i.e., $U_i(x_i) = x_i^{r_i}$. They 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:

$$b_i(v_i, r_i) = [(N-1)/(N-1+r_i)]v_i. \quad \textbf{[2]}$$

In estimating r_i from individuals' bid functions Cox *et al*. find values of r_i are significantly less than one for most subjects.

Our first-price auctions were run 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 its 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.

Within-Subject Design. To minimize the complexity of the experiment to subjects we sequenced the two selling tasks before the first-price task, a buying task. We also moved from a choice task in an individual setting to tasks in multiperiod environment. A typical experimental session consisting of all three tasks lasted ≈2½ h. While subjects played for points they were told from the beginning that these points would be converted to dollars by using fixed exchange rates (2 points = 1 cent in BDM and English clock auction and 1 point = 4 cents for first-price auction). Exchange rates were chosen to make the expected payoff from each task roughly the same.

Experimental Methods

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

Experimental Procedures. Most sessions were conducted in concurrent pairs. Session pairs 1–2, 3–4, 6–7, 9–10, and 11–12, as well as single session 8 used inexperienced participants. Session 5 used "experienced" subjects who had participated in sessions 3 or 4. Each session consisted of four subjects. Subjects in the same session participated in the same first-price and English clock auctions. 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 3-h experiment. Subjects received \$5 for showing up and an additional \$3 if they were bumped because of overbooking. When they showed up subjects chose a numbered

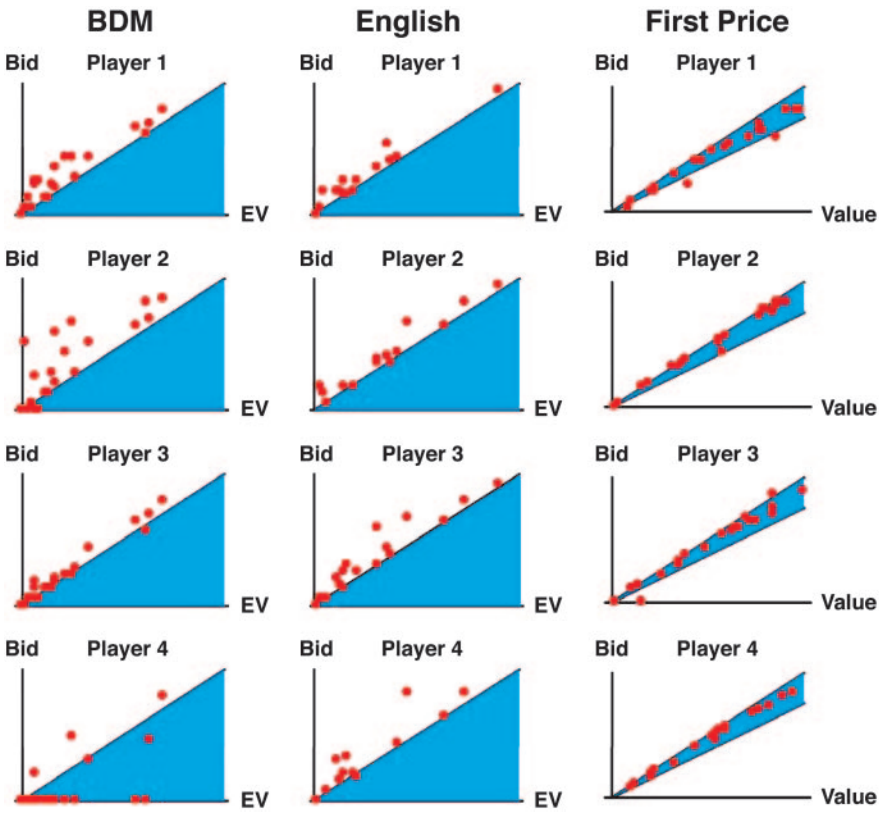

Fig. 1. Bidding behavior in the BDM, English clock, and first-price auctions. Each row shows bidding behavior. Points (in red) show specific bids. For the BDM procedure and English clock auction bids are graphed against expected value (EV). In the first-price auction the bid of the winning bidder is graphed against value. Shaded areas denote risk aversion.

chip without replacement from a cup, which indicated which computer terminal they should take. The terminals that were used were surrounded by a partition that 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. Efforts were made to allow subjects to examine the randomizing devices before the experiment was run. To create the 1–225 draw a bingo cage was filled with 225 numbered balls. The balls were contained in 22 cups with 10 balls each, and 1 cup had 5 balls. 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 that time we also explained the role of a monitor in implementing the randomizing devices during the experiment.

Data Analysis Procedures. ***Categorical approach to assessing risk preferences.*** In the first-price auction we compare subject's bids against the values 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 to improve his chances of winning. However, he will not bid above the 45% line because this means bidding above value, which results in a loss. A risk-loving subject will bid below the risk-neutral bid because he is willing to reduce his chances of winning to get a larger payoff. Thus, for risk-averse subjects, we will see bids between these two lines, and for risk-loving subjects we will see points below the risk-neutral prediction. We classify each of the subjects according to this criterion.

In the BDM and English clock procedures we plot subjects' minimum selling prices (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 because a subject must be paid more to give up his gamble. Points below the 45% line reflect risk-averse behavior because subjects are willing to take less to sell their gamble. In both the BDM and English we classify each subject according to this criterion.

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 $\{(v_1, z_1), \ldots, (v_{20}, z_{20})\}$ the Cox *et al.* procedure (15) estimates the regression equation,

$$z_t = a + bv_t + e_t. \qquad [3]$$

If the subject has a constant relative risk-averse utility function, then from Eq. **2** we know that $a = 0$, $b = [(N - 1)/(N - 1 + r_i)]$ and our estimate of r_i is $[(1 - b)/b](N - 1)$. 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

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

Given Eqs. **2** and **4**, we can then estimate Eq. **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 Eq. **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 an 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.,

$$ce_t^{ri} = (1 - p_t)0^{ri} + p_t H_t^{ri}. \qquad [5]$$

We can estimate this expression by using ordinary least squares on Eq. **6**

$$\ln ce_t = a + b \ln p_t + c \ln H_t + e_t, \qquad [6]$$

where a is 0, $b = 1/r$, and $c = 1$.

Experimental Results

Fig. 1 graphs subjects' bids in session 1. In that session the first three subjects are consistent with risk-loving behavior in the BDM procedure and the English auction whereas they are risk-averse in the first-price auction. Subject 4 meets the criterion for risk-averse in BDM and first-price whereas he is risk-loving in the English auction. Letting D represent the fact that a subject exhibited different behavior and S represent the same behavior in two auctions we describe the results of all auctions in Table 2. Subjects tended to behave the same in BDM and English auctions. In particular, a total of 33 of our 48 subjects bid consistently above the risk-neutral bid line. Subjects behaved somewhat differently in the BDM and first-price auctions (28 of 48 bid differently.) The major difference occurred between the English and first-price auctions (39 of 48 behaved differently). Furthermore if we analyze the data only at the auction level we find that in the English and first-price the majority is different in all but two auctions and in these auctions there are ties. Under a null hypothesis that the majority is just as likely to be the same as different we can reject the null hypothesis that English and first-price data are the same at the 0.005 level.

We now turn to the task of quantitatively assessing risk preferences. Fig. 2 summarizes our regression estimates of a

Table 2. Between-auction comparisons

Session	BDM, English	BDM, first-price	English, first-price
1	D, 3 S	3 D, S	4 D
2	2 D, 2 S	D, 3 S	3 D, S
3	2 D, 2 S	3 D, S	3 D, S
4	D, 3 S	2 D, 2 S	3 D, S
5	2 D, 2 S	2 D, 2 S	4 D
6	2 D, 2 S	D, 3 S	3 D, S
7	D, 3 S	3 D, S	4 D
8	D, 3 S	3 D, S	2 D, 2 S
9	D, 3 S	3 D, S	4 D
10	D, 3 S	D, 3 S	2 D, 2 S
11	4 S	4 D	4 D
12	D, 3 S	2 D, 2 S	3 D, S

Compared are results between the BDM procedure and English auction, the BDM procedure and first-price auction, and the English auction and first-price auction. D denotes that for a given subject there was a difference in whether the subject was evaluated to be risk-averse or risk-preferring in the two institutions. For example, in auction one, one of the subjects was classified as different under BDM and English, while three subjects were classified the same. In all of session 1, three subjects were classified as different under BDM and first-price, while one subject was classified the same (S). In classifying between English, all subjects were classified differently. The differences in classification do not depend on a particular utility function, so the result generalizes across possible utility functions. Under the assumption that the majority of individuals are just as likely to be the same or different the likelihoods of observing the results the three different classifications are 0.5, 0.11, and 0.005, respectively. These numerical calculations excluded session 8, which used experienced subjects although the results are robust to their inclusion.

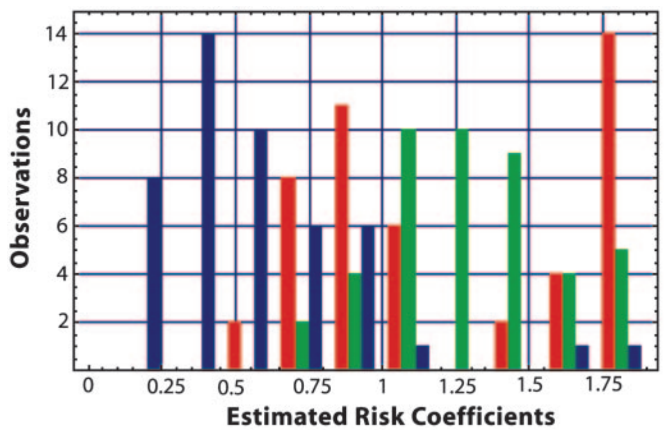

Fig. 2. Estimated risk coefficients. Blue bars, risk coefficients in the first-price auctions; red bars, coefficients in the BDM pricing procedure; green bars, estimates in the English clock auction.

subject's risk coefficients. Consistent with previous studies of first-price auctions we find >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 0.01% level) between all pairwise comparisons of these three distributions.

Fig. 3*c* summarizes the R^2 statistics for our estimated equations. To test our hypothesis that an individual has stable risk preferences within a task we require an $R^2 > 0.9$. We find that 78% of our subjects have $R^2 > 0.9$ in first-price auctions, 30% of our subjects have $R^2 > 0.9$ in the BDM auctions, and 82% of our subjects have $R^2 > 0.9$ in the English clock auctions.

Most of the regression coefficients associated with the calculation of a subject's risk coefficient were significant at the 0.05 level. Fig. 3*a* summarizes our consistency checks on these estimates by looking at the distribution of t tests on the other ordinary least squares coefficients not directly used in estimating risk coefficients. In the first-price regressions this coefficient is the intercept, a, in Eq. **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 Eq. **6** to be 0.

Regarding the hypothesis that the rank order of the coefficients is preserved, regressions of coefficients from the BDM procedure, English clock auction, and first-price auction on one another yielded no significant results at the 0.25 level or lower. Even if the rank order were preserved such preservation would not avoid the problem that a risk-averse recommendation could be systematically made to a risk preferrer.

Discussion

We conclude that our assessment of risk preferences varies across institutions. Subjects act as risk-loving in the English clock auctions and then act as 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 persons', risk preferences from one institution to another. Without appropriate benchmarks on the preferences of individuals, researchers can mistake changes in behavior caused by risk preferences for change in behavior caused by other stimuli such as information or rule changes.

A rallying cry of much of experimental economics is that "institutions matter" (16). 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 article demonstrates that the preferences revealed are not independent of the procedure (institution) through 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") (17) 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 (18) 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.

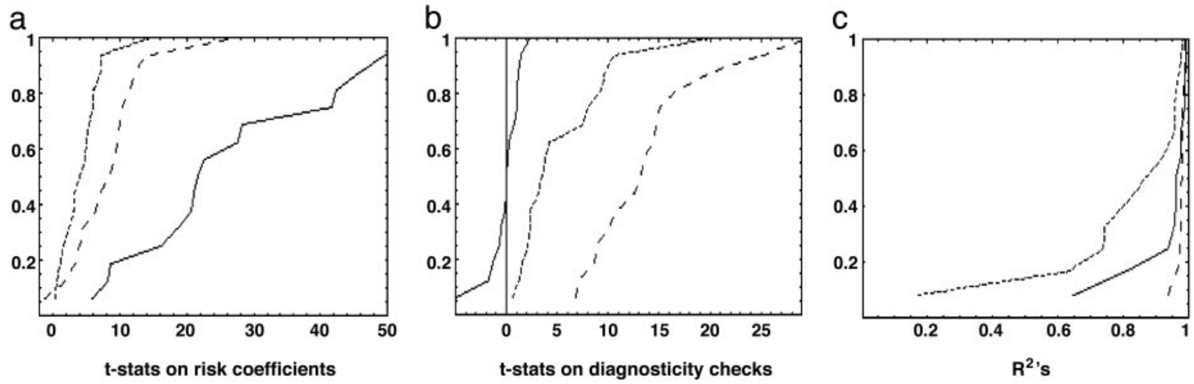

Fig. 3. Cumulative distribution functions of t statistics on risk coefficient estimates, t statistics on diagnosticity checks, and R^2. Dotted lines, BDM procedure; dashed lines, English clock auction; solid lines, first-price auction. (*a*) A cumulative distribution function of the estimates of t statistics for the BDM procedure, English auction, and first-price auction. The graph demonstrates that the two most distinguishable sets of risk assessments were the English and the first-price. The first-price estimates are the estimates of b in Eq. **4** divided by the standard deviation of that estimate. The English and BDM procedure use estimation Eq. **6**. (*b*) 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 be 1, and hence the t statistics should be significantly >0. The estimate for the constant a in the first-price auction should be 0, and we find the median estimate is virtually 0. (*c*) A cumulative distribution of R^2 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.

ECONOMIC SCIENCES

Recently, researchers have begun to take a more fundamental approach to try to isolate idiosyncratic differences that occur because of subtle changes in the environment. Attempts are being undertaken to try to specify the proposition that decision processes in the brain are susceptible to very subtle changes in the context in which choice is made (19, 20). Related work with auctions isolates psycho-physiological processes that can give a more complete picture of how these auctions function (21, 22). A more robust approach could arise from hypothesizing models that can represent a subject switching between models as a consequence of slight environmental changes. In 1964, Paul Slovic (23) called for the need to find appropriate methods for assessing risk preferences and some of the numerous obstacles involved. Since then it has become possible to achieve a successful level of predictability of our techniques such as those represented by the English clock and first-price auctions. Now we must examine the dilemma that such estimates can depend on the institution to which they are applied.

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1. Salanie, B. (1997) *The Economics of Contracts: A Primer* (MIT Press, Cambridge, MA).
2. Christensen, J. & Demski, J. (2002) *Accounting Theory: An Information Content Perspective* (McGraw–Hill, New York).
3. Fabozzi, F., Kostovetsky, L. & Markowitz, H. (2004) *The Theory and Practice of Investment Management Workbook: Step Exercises and Tests to Help You Master The Theory and Practice of Investment Management* (Wiley, New York).
4. Becker, G. M., Degroot, M. H. & Marschak, J. (1964) *Behav. Sci.* **9,** 226–232.
5. Booske, B. C., Sainfort, F. & Hundt, A. S. (1999) *Health Service Res.* **34,** 839–854.
6. Saigal, S., Stoskopf, B. L., Burrows, E., Streiner, D. L. & Rosenbaum, P. L. (2003) *Arch. Pediatr. Adolesc. Med.* **157,** 261–269.
7. Peterson, J. M. & Boisvert, R. N. (2004) *Am. J. Agric. Econ.* **86,** 91–306.
8. Eckel, C., Johnson, K. & Montmarquette, C. (2005) in *Field Experiments in Economics*, eds. Carpenter, J., List, J. & Harrison, G. (JAI Press, Greenwich, CT), pp. 219–260.
9. Holt, C. & Laury, S. (2002) *Am. Econ. Rev.* **92,** 1644–1655.
10. Harrison, G. W., Lau, M. I., Rutstrom, E. E. & Sullivan, M. B. (2005) in *Field Experiments in Economics*, eds. Carpenter, J., List, J. & Harrison, G. (JAI Press, Greenwich, CT), pp. 125–218.
11. Isaac, R. M. & James, D. (2000) *J. Risk Uncertainty* **20,** 177–187.
12. Berg, J. E., Daley, L. A., Dickhaut, J. W. & O'Brien, J. (1986) *Q. J. Econ.* **101,** 281–306.
13. McCabe, K. A., Rassenti, S. J. & Smith, V. L. (1990) *Am. Econ. Rev.* **80,** 1276–1283.
14. Vickrey, W. (1961) *J. Finance* **16,** 8–37.
15. Cox, J. C., Smith, V. L. & Walker, J. M. (1988) *J. Risk Uncertainty* **1,** 61–99.
16. Smith, V. L. (1982) *Am. Econ. Rev.* **72,** 923–955.
17. Tversky, A. & Thaler, R. H. (1990) *J. Econ. Perspect.* **4,** 201–211.
18. Berg, J., Dickhaut, J. & Rietz, T. (2003) *J. Risk Uncertainty* **27,** 139–170.
19. Dickhaut, J., McCabe, K. A., Nagode, J., Rustichini, A., Smith, K. & Pardo, J. (2003) *Proc. Natl. Acad. Sci. USA* **100,** 3536–3541.
20. Smith, K., Dickhaut, J., McCabe, K. & Pardo, J. (2002) *Management Sci.* **48,** 711–718.
21. Dickhaut, J., McCabe, K. A., Peck, N., Smith, K. & Rajan, V. J. (2001) in *First Asian Conference on Experimental Business Research*, ed. Zweik, R. (University of Science and Technology Press, Hong Kong), pp. 230–237.
22. Smith, K. & Dickhaut, J. (2005) *Games Econ. Behav.*, in press.
23. Slovic, P. (1964) *Psychol. Bull.* **61,** 220–233.