**Cognitive Reflection Predicts Decision Quality in Individual and Strategic Decisions**

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**Abstract**

Cognitive reflection has been shown to be an important trait which is correlated with the propensity to: take risks, delay gratification, and form accurate beliefs about others' behavior. However, previous research has not cleanly identified whether reflective thinkers make 'better' decisions than intuitive thinkers, since inferences of decision quality are confounded by inferences regarding risk preferences, time preferences, and beliefs. We directly test for differences in decision quality between reflective thinkers and intuitive thinkers in both individual and strategic decisions using a design which makes it possible to objectively rank risky and strategic choices, independent of one's attitudes toward risk or one's beliefs about the strategic sophistication or altruism of other decision makers. Employing a lottery choice task involving a dominant and a dominated alternative, and implementing multiple rounds of a second price auction, we find that the tendency to cognitively reflect has strong predictive power across domains (reasoning tasks, choices between lotteries, bidding behavior in auctions), and across time (as the tasks were administered on separate dates). In particular, the *same* subjects who engaged in reflective thinking on simple reasoning problems were also more likely to choose optimally in the lottery choice task and to bid closer to the dominant strategy equilibrium in second price auctions. We also find that experience helps to narrow the gap in performance between reflective and intuitive thinkers.

**Keywords: Cognitive Reflection; Stochastic Dominance; Second Price Auction**

## Introduction

In economics, searches for variation in choice behavior often focus on differences in risk preferences and time preferences – how people differ in their degree of risk taking and their degree of patience. Yet studies have shown that risk preference characteristics are not stable across contexts (1). Given the focus in economics of making general predictions regarding human behavior, it is important to identify individual characteristics that are not highly context-specific, but rather influence decisions across different domains.

One individual characteristic which has received much attention in recent years is a person's natural tendency to engage in reflective versus intuitive thinking. Spurred by Frederick's (2) cognitive reflection test (CRT), subsequent research has employed the CRT and related measures of cognitive skills to identify their relationship with risk preferences and time preferences (2 – 4), the propensity to engage in backward induction (5 – 6), and the ability of a market of traders who have all high levels or have all low levels of cognitive ability to aggregate information (7).

While recent work (2 – 4) has identified differences in subjective characteristics between people with high and low cognitive ability (e.g., differences in risk preferences, time preferences, and beliefs), previous work has not cleanly identified whether objective characteristics (e.g., differences in decision quality) are related to cognitive ability or cognitive reflection. A basic problem with addressing this question is the absence of a normative benchmark in many economic decisions. Economic theory generally imposes only consistency requirements on preferences while deliberately avoiding claims about the 'content' of preferences. Under standard economic theory, we cannot draw normative conclusions about differences in risk and time preferences between intuitive and reflective thinkers. Even claims that people should engage in backward induction or play a Nash equilibrium strategy in games are not compelling because there is little basis in such experiments for subjects to assume common knowledge of other subjects' rationality. Rather, in guessing games, for instance, the winning guesses depend on other people's guesses, and those who follow the Nash equilibrium strategy generally do not win (5 – 6), making it hard to claim that people should follow that strategy.

The determinants of decision quality – the factors that lead people to make better decisions are important to understand both for theoretical reasons and for evaluating and designing economic policies and in forecasting their effectiveness. In this report we employ an experimental design which enables us to directly measure differences in decision quality between high and low CRT subjects in both individual and strategic decisions. Our approach is to focus on decisions in which there is a dominating option which can be objectively ranked above other choices. In individual choices between lotteries, this approach enables us to objectively evaluate subject responses regardless of their attitudes toward risk since economic theory assumes that any rational decision maker will choose a lottery A over a lottery B if A stochastically dominates B (that is, if A offers at least as a good a prize at every probability level as B and offers a strictly better prize at some probability levels), independent of her degree of risk taking or other special properties of her preferences. In strategic decisions, this approach enables us to objectively evaluate subjects' behavior, independent of their beliefs about other players' actions. To do so, we conducted experimental second price sealed bid auctions based on the design of (8), separately for groups of high CRT subjects and low CRT subjects. In such auctions, there is a dominant strategy for how a person

should bid, although previous experiments have found that many subjects do not 'discover' this strategy (8 – 10).

We find that the CRT is a powerful predictor of decision quality in both individual and strategic decisions, and also that decision quality in individual decisions correlates significantly with decision quality in strategic decisions. For the experimental subjects who participated in both the individual and strategic task, our approach also implicitly tests for the stability of cognitive reflection over time as the three tasks (the CRT, the individual decision task, and the strategic decision tasks) were administered on different dates[1]. In particular, we found the CRT to accurately predict violations of stochastic dominance and the magnitude of deviations from the dominant bidding strategy in second price auctions for the same individual subjects who participated in all three tasks.

A related paper (3) considers risk preferences, time preferences, and choices in a sequential prisoner's dilemma game, and finds a relationship between cognitive skills and choices in these three domains. However, it is difficult to determine whether agents with higher cognitive skills perform closer to game theory benchmarks than agents with lower cognitive skills in that study. They report only that those with higher cognitive skills better predicted the actions of the other player, but note that agents with higher cognitive skills often reciprocated in sending money back, in contrast to the game theory prediction. To better identify differences in strategic behavior between people with high and low tendencies to cognitively reflect, it would be preferable to design a game where considerations of risk and considerations of reciprocity are removed. Implementing a second price sealed bid auction accomplishes this objective in principle since in such auctions, there is no room for social preferences, risk preferences, or beliefs about others' actions to affect rational strategic behavior. Social welfare is maximized if everyone plays the dominant strategy of bidding their valuations, and this strategy is optimal regardless of bidders' risk preferences or beliefs about how others will bid. Employing the second price auction also stretches the limits of the CRT which is typically used in simple decision tasks to test if it can reliably sort out differences in bidding strategies in a more complex environment.

Aside from (3) there is relatively little work comparing individual differences in behavior across risky and strategic decisions. Indeed, making choices between lotteries, and bidding in second price auctions are very different tasks. However, economics offers a unified perspective on these decisions as examples of 'dominance'. But economics also offers a unified perspective on risk preferences that should apply across domains which has found little empirical support (1). Controlling for subjective characteristics (i.e., preferences and beliefs) we test if there are relationships between normative choices in individual and strategic settings, and whether a popular metric for identifying reflective thinking is predictive of rational behavior.

[1] Of the eight separate experimental auction sessions, and the sixteen separate individual decision (risky choice) sessions that we conducted, there was one case where an individual decision session (with 24 subjects) and an auction session (with 14 subjects) were administered on the same day (one in the morning, the other in the afternoon). Only one subject participated in both of these sessions.

**Experimental Design**

Two experiments were conducted in separate laboratory sessions – one involving choices between lotteries and the other involving participation in multiple rounds of a second price auction. All of the subjects who participated in each experimental session had previously taken the seven question version[2] of the CRT (11) at an earlier date when they signed up to participate in economic experiments. The three tasks – the CRT, the lottery task and the auction task were administered in three separate experimental sessions.

**Individual Decision Task:** A total of 328 undergraduate students at a private western university participated in an experiment in which they each made 100 choices between pairs of lotteries. Subjects who had previously taken the CRT were randomly recruited through an e-mail announcement. In the experiment, each participant was seated at a computer terminal in the laboratory in a cubicle and could not see other subjects' choices or computers. Each lottery specified a potential monetary amount that would be earned depending on the draw of a red or blue colored ticket. A sample choice is shown in Figure 1. Lottery pairs were presented in random order and the option that appeared on the top or bottom row of a choice pair was also randomized. In Figure 1, if a subject chose the 'red' option and this choice was randomly selected for payment, that subject would draw a ticket from an opaque bag containing 100 red raffle tickets. If the number on the ticket was between 1 and 90, that subject received $30. If the number was between 91 and 97, that subject received $25. If the number was between 98 and 100, the subject received $0. At the end of the experiment, two ten-sided dice were rolled by each subject to randomly select one of the 100 choices made during the experiment to count for payment. That particular choice was then brought to their screen and they drew a ticket from either a bag containing only red tickets or only blue tickets, depending on whether that subject chose the 'red' or 'blue' option in that lottery pair. All of this information was explained in both general terms and with specific examples in the instructions. These instructions are included in the supplementary information. After determining all subjects' payoffs, subjects were paid their earnings in cash in addition to a $7 participation fee.

Of the 100 lottery pairs, only three involved a choice between a dominant and a dominated lottery. One of these three choices is the pair shown in Figure 1. The other two pairs were similarly designed and are shown in the supplementary information. These pairs are similar to a lottery pair used by Tversky and Kahneman (12), although to our knowledge, they have not been used in conjunction with the CRT.

| Select One | $ | Tickets | $ | Tickets | $ | Tickets | $ | Tickets |
|---|---|---|---|---|---|---|---|---|
| ○ Red | $30 | 90 | $25 | 7 | $0 | 1 | $0 | 2 |
| ○ Blue | $30 | 90 | $25 | 6 | $20 | 1 | $0 | 3 |

**Fig. 1.** Choice between a dominant and a dominated lottery. The salient comparison ($20 vs. $0) favors the dominated lottery.

[2] The seven question CRT includes the original three items from (2) plus four additional items which have been shown to have similar validity.

**Strategic Decision Task:** Knowing the subjects' CRT scores before they come to participate in an experiment makes it possible to recruit subjects who only obtained particular scores (e.g., high scores or low scores). We hypothesized that sampling from the tails of the distribution would reveal the starkest difference in performance based on CRT scores and reduce the noise in the measurement of a subjects' tendency to cognitively reflect. We thus recruited "Low CRT" auction sessions in which all subjects had previously scored 0 or 1 on the CRT, as well as "High CRT" auction sessions in which all subjects had previously scored in the top 20% of the distribution of CRT scores (subjects who scored a 5, 6, or 7 on the CRT).

The auction experiments were based on the design of Kagel and Levin (8). In each auction period, subjects participated in both a large market (where subjects competed in a group of 10 bidders) and a small market (where subjects competed in a group of 5 bidders)[3], by submitting a bid in each market via their bidding dashboard. Each subject received the same private valuation in the large market and the small market, but private valuations differed across subjects and across auction periods. For each auction period, private valuations were randomly drawn from a discrete uniform distribution with step size of $0.01, over the interval [$0.00, $28.30] which was the same distribution employed in (8). Subjects knew their private valuation, the distribution from which all values were drawn, and the total number of bidders in each market. Subjects did not need to recall this information as it was always displayed to them on their bidding dashboard, as shown in Figure 2. After each period, the dashboard also displayed the winning bid, the profit made by the winning bidder and the subject's own bid. In each period, either the large market or the small market was randomly selected for payment. As in (8), subjects were each given a starting cash balance of $10 to cover the possibility of losses.

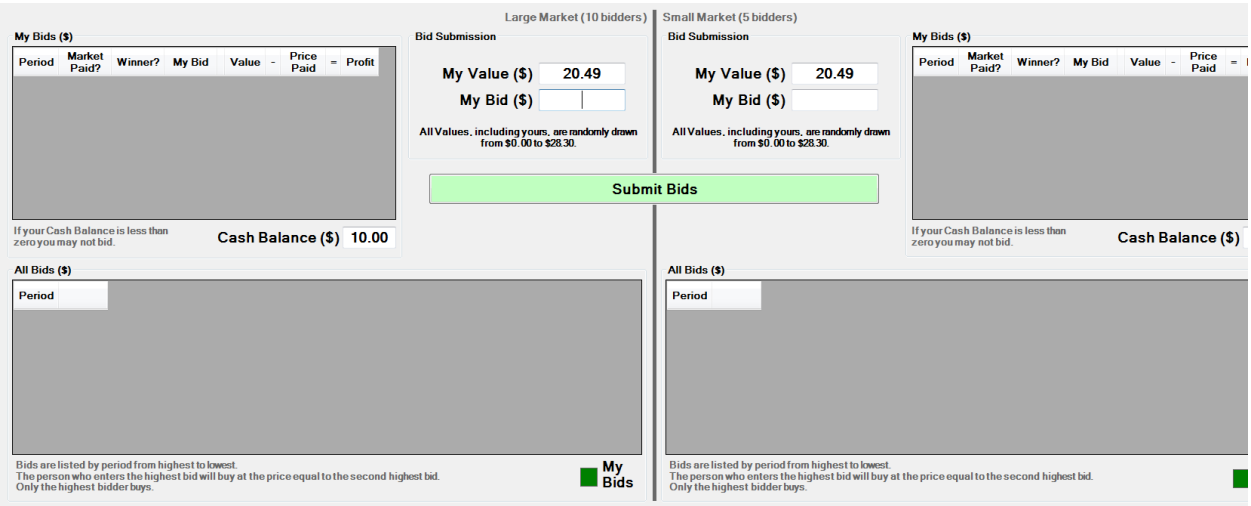


**Fig. 2. Bidding Dashboard used in Second Price Auction.** Each subject submits a bid in a large market (10 bidders) and a small market (5 bidders) in each period, with the same valuation in both markets.

[3]In auction periods where more than the number of 'reserve' bidders had gone bankrupt (i.e., their cash balance had gone negative), the large (small) market contained less than 10 (5) bidders.

We conducted eight experimental second price auction sessions, four each for high CRT subjects and low CRT subjects. A total of 127 subjects (63 high CRT subjects and 64 low CRT subjects) participated in one of the auction sessions. In each session, each subject was seated at a separate computer terminal in a cubicle such that no subject could observe the actions or computers of other subjects. The first two auction sessions involved 20 auction periods. The last six auction sessions (three each for high CRT and low CRT subjects) involved two iterations of 20 rounds each. That is, subjects participated in 20 rounds of the second price auction, their earnings were calculated. Gains or losses in each period were added to each subject's balance. If a subjects' balance went negative, they were no longer permitted to bid in that auction iteration. At the beginning of the experiment, subjects were informed that they would participate in two iterations of the experiment, that they would be paid the sum of their earnings across both iterations, and that their balance would be reset to $10 before the second iteration (so any losses did not carry over). Conducting two iterations in a session enabled us to investigate potential learning effects. Since many low CRT subjects went bankrupt in the first iteration (i.e., their cash balance went negative), conducting a second iteration also enabled us to observe the outcome of a full session of active bidders, as very few low CRT subjects went bankrupt in the second iteration.

At the start of each auction session, the large market contained ten bidders and the small market contained five bidders. It was intended for the large market and the small market to retain their respective sizes across all auction periods but this was not always possible in later auction periods due to bankruptcies. To anticipate this possibility, following (8), we recruited more than ten subjects and each subject were randomly assigned to 'play' or 'observe' in each period. Doing so allows for 'reserve bidders' to maintain the size of the large and small markets in case of bankruptcies. There were typically four extra bidders in each auction session, but even this was not always sufficient to keep the number of bidders constant in the large and small markets. The software was programmed with a schedule of how to adjust the market sizes in the case of bankruptcies. When the total number of bidders dropped below ten, the large market always contained all remaining bidders. The small markets were balanced to be as close in size as possible.

Subjects were given detailed instructions, which are provided in the supplementary information. They were informed of the second price rule for selecting the winning bidder and how payments were determined. Subjects were also informed that they could not bid more than $50 for the item being auctioned. We did not include statements which could be seen as censoring the bidding process or nudging bidders in a certain direction such as "It is possible to lose money if you bid above your value, but not if you bid below your value." Rather, after explaining the rules, we wanted to provide as little nudging as possible to give bidders the opportunity to discover the dominant bidding strategy without providing any 'hints'.

Viewing interactive learning to also be effective in helping participants understand the rules of the auction, each participant saw three interactive examples, one each in which they were assigned a low value, an intermediate value, and a high value. In each example participants submitted bids in their bidding dashboard and computerized agents were programmed with a fixed set of bids to complete the auction. From this part of the instructions, subjects could experience the bidding process and observe their profits or losses at no cost to themselves. Subjects were also quizzed by the software on the auction instructions and were paid $0.50 for each correct answer they provided to the five-question quiz. After all subjects completed the instructions, the experiment began. After all auction periods had ended, subjects

were paid their earnings from the quiz and from the auction periods in cash in addition to a $7 participation fee.

**Experimental Results**

**Individual Decision Task:** Returning to the pair of lotteries in Figure 1a majority of subjects in our experiment chose the 'blue' option. Two related reasons for this choice are that (i) one's attention is naturally drawn to the most salient difference between lotteries which is the difference between $0 and $20 that favors Blue, and (ii) Blue has more outcomes displayed which pay more than $0. However, upon inspection it is clear that the red option has the dominating probability distribution as it offers at least as good a prize as Blue at every probability level and offers a strictly better prize at some probabilities. The choice of blue is thus a dominated choice. The percentage of dominated choices across all eight CRT scores are shown in Table 1, along with the number of subjects who received the corresponding CRT score. Recall that each subject responded to three choice pairs involving dominated options so we could obtain repeated measures for each subject. Thus, the overall percentage of 66.5% dominated choices includes 984 individual choices in total.

**Table 1. Percentage of dominated choices across CRT scores**

| CRT Score | n | % Dominated Choices |
|---|---|---|
| 0 | 43 | 0.783 |
| 1 | 46 | 0.855 |
| 2 | 62 | 0.742 |
| 3 | 57 | 0.684 |
| 4 | 57 | 0.550 |
| 5 | 27 | 0.481 |
| 6 | 22 | 0.515 |
| 7 | 14 | 0.310 |
| Overall | 328 | 0.665 |

From Table 1, we see that the CRT is a good predictor of one's performance in the lottery choice task: Those with low CRT scores chose the dominated option roughly 80% of the time, those with moderate CRT scores reduced violation rates to a little over 50%, and those with the highest CRT score chose the dominated option only about 30% of the time. The correlation between CRT scores and the percentage of dominated choices is -0.372 ($p < 0.001$, two-tailed Pearson correlation test). We also found support for the hypothesis that analyzing performance on the CRT from the tails of the distributions reduces the noise in measuring differences in cognitive reflection: If the correlation is computed by comparing the percentage of dominated choices between low CRT subjects (scoring a 0 or 1) and high CRT subjects (scoring a 5,6, or 7), the correlation changes to -0.495. In both cases, the result is highly significant.

**Strategic Decision Task:** Since the classic work of Vickrey (13), the second price auction (SPA) has attracted much attention in economics research due to its appealing properties. For instance, in such an auction with private valuations, it is a dominant strategy to bid exactly one's valuation. That is,

regardless of what other bidders do, it is optimal to bid your value. This dominant strategy equilibrium is a stronger property than a Nash equilibrium where one typically needs to invoke common knowledge assumptions about other bidders' payoffs and their rationality and condition one's bidding strategy on how he expects others to bid. Yet despite the simplicity of the dominant strategy equilibrium, it is often not discovered by subjects in experimental auctions. For instance, in (8) only 30% of all bids were approximately equal to valuations. They also observed frequent overbidding which they explain by noting that "the dominant bidding strategy is not transparent." Similar results to those in (8) were also observed in (9). Kagel and Levin (8) further note, "Earlier reports of convergence to the dominant bidding strategy in SPA (14) employed procedures which prohibited bidding above valuations." Kagel (10) provides a review of other early studies of the SPA.

To get a sense of our data without learning effects, we first compared the distribution of initial bids for high and low CRT subjects. In particular, we looked at the first bid made by each bidder across all experimental sessions, and computed (i) the average difference (in dollars) between that bidder's bid and value, and (ii) the proportion of bidders who bid within $1 of their value on their initial bid. We performed these calculations for both the large and small markets. The average deviation of bids from values for low CRT scorers in the large (small) market was $7.59 ($6.97). The average deviation for high CRT scorers in the large (small) market was $2.84 ($2.74). The proportion of low CRT scorers who bid within $1 of their value on their first bid in the large (small) market was 0.297 (0.266). The proportion for high CRT scorers in the large (small) market was 0.524 (0.571). Thus, high CRT subjects were much more likely to bid within $1 of their value than low CRT subjects. The difference between the proportion of first bids within $1 of the value for high and low CRT subjects is significant at the 0.01 level for both the large and small markets (2-tailed Pearson correlation test, $p = 0.009$ for large market and $p = 0.0004$ for small market).

Table 2 provides summary statistics for the sessions in which subjects participated in two iterations of the auction, with 20 periods per iteration. The table displays (i) the proportion of subjects in these "Double-iteration" sessions who went bankrupt, (ii) the proportion of subjects who lost money relative to their $10 endowment, (iii) the average earnings of subjects relative to what they would have earned if everyone ended with exactly their $10 endowment (where bankruptcies are calculated as earnings of $0), (iv) the proportion of efficient allocations across all 20 periods for each iteration (where an allocation is viewed as efficient if the bidder with the highest valuation won the item and did not lose money) and (v) the proportion of subjects whose average bias in a given iteration is within $1 of valuations in the large market.[4]

**Table 2. Summary Information for Double-Iteration Sessions**

| Double-Iteration Sessions | Bankrupt | Lost Money | Average Earnings | Efficiency | Average Bias < $1 |
|---|---|---|---|---|---|
| Low CRT - First Iteration | 0.667 | 0.690 | -$2.52 | 0.364 | 0.095 |
| Low CRT - Second Iteration | 0.119 | 0.238 | $4.03 | 0.639 | 0.381 |
| High CRT - First Iteration | 0.077 | 0.231 | $3.47 | 0.661 | 0.462 |
| High CRT - Second Iteration | 0.000 | 0.179 | $9.43 | 0.828 | 0.769 |

[4]The average bias for a given subject is calculated as the average absolute deviation of a subject's bid from that subject's value across all periods in which that subject was an active bidder.

In Table 2, we observe large differences when comparing low and high CRT subjects for a given iteration. In the first iteration, for instance, roughly two-third of low CRT subjects went bankrupt, whereas less than 8% of high CRT subjects did so. In addition, average earnings for low CRT subjects were negative, indicating they would have been better off by not bidding at all (and walking away with their full $10 endowment). In contrast, average earnings for high CRT subjects were positive in both iterations.

When comparing performance across iterations, note that low CRT subjects in the second iteration perform close to high CRT subjects in their first iteration. For instance, the proportion of subjects who went bankrupt or lost money, and the average earnings and efficient allocations are very similar for 'experienced' low CRT subjects and 'inexperienced' high CRT subjects. This suggests that experience can help to narrow the gap in decision quality between high and low CRT subjects, thereby helping to compensate for initial differences in cognitive reflection. Finally, note that high CRT subjects in the second iteration did quite well, with over 75% of high CRT subjects producing average bids within $1 of valuations.

The High CRT subjects also produced a welfare outcome that is socially optimal more frequently than low CRT subjects (for instance producing over 80% efficient allocations in the second iteration, compared to 36.4% efficient allocations for low CRT subjects in their first iteration). Note that overbidding in second price auctions has detrimental effects on efficiency – not only because the winning bidder may lose money, but also because that bidder displaces other participants who would have otherwise gained positive surplus. Thus overbidding in these auctions can generate a negative externality, which should not arise as there are no incentive conflicts between agents. Under classical economic theory, all bidders have the incentive to bid exactly their valuation for the item being auctioned in second price auctions, and thus there should be no conflict in such cases between individual self-interest and social welfare.

To better visualize the difference in auctions involving high CRT subjects and low CRT subjects, Figure 3 displays the distribution of bids in periods 1 through 10 of each double iteration session. The box plots with a label ending "I1" display the average of periods 1 through 10 in the first iteration in that session; the box plots with a label ending "I2" display the average of periods 1 through 10 in the second iteration. Since many low CRT subjects when bankrupt in the first iteration before period 10, periods 11 through 20 would be biased, displaying the bids of only a few bidders who 'survived' the market. From Figure 3 we can see that the high CRT subjects bid very close to their value, even in the first iteration, with relatively small deviations from truthful bidding. In contrast, low CRT subjects had a much wider and more volatile distribution of bids, deviating considerably from the dominant strategy equilibrium in which bids equal values. We can also see that low CRT subjects bid much closer to their values in the second iteration, relative to their first iteration.

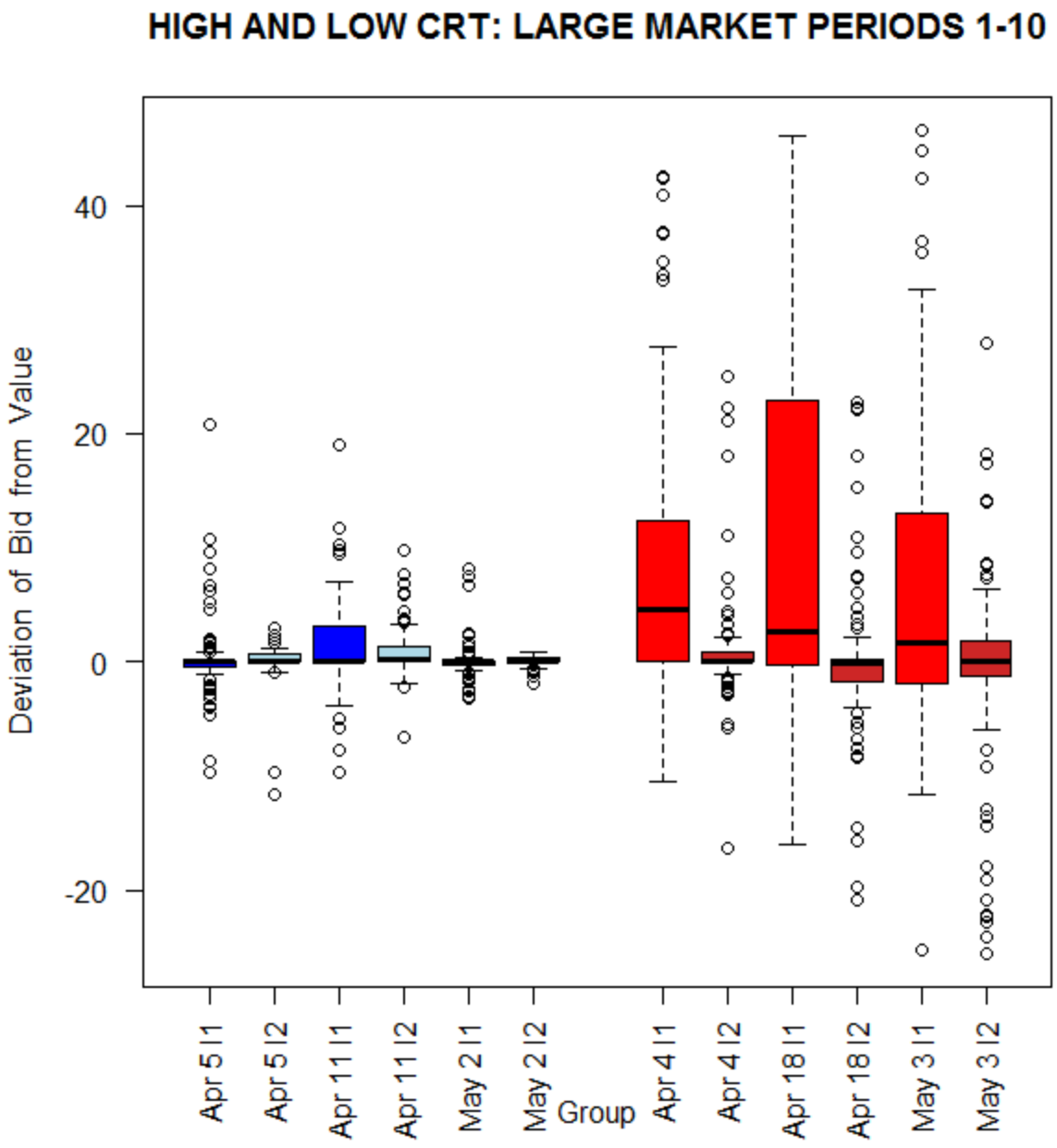


**Fig. 3. Deviation of bids from values in the first and second iteration of the second price auction (large market, periods 1 through 10) for high CRT subjects (left) and low CRT subjects (right).** The line in the interior of each boxplot is the median deviation from bidding one's value in periods 1 through 10. The ends of each box display the first and third quartiles of the distribution. The ends of the whiskers extending from each box correspond to 1.5 times the interquartile range. The boxes ending with the label "I1" ("I2") correspond to the first (second) iteration in that session.

**Within Subject Results:** We can further analyze within subject results across tasks since 34 of the low CRT subjects and 37 of the high CRT subjects participated in both the individual decision task and the strategic decision task that were administered in separate experimental sessions. For these 71 subjects, we can investigate whether the CRT is predictive of their behavior in both the individual and strategic decision tasks, and also whether behavior in the individual decision task is itself related to behavior in the strategic decision task. Our results are summarized in Table 3. In the table, violations of stochastic dominance were computed as the average number of dominated choices made by a subject out of the three stochastic dominance decisions he encountered. The average bias in the second price auction task was computed as the average absolute difference between a subject's bid and his value across all auction periods in which he was an active bidder.

**Correlations between the CRT, Lottery Choices, and Bidding Behavior**

| Task | 1 | 2 | 3 |
|---|---|---|---|
| 1. Seven Question CRT | 1 | | |
| 2. Violations of Dominance | -0.499 ** | 1 | |
| 3. Average Bias in Auction | -0.504 ** | 0.283 * | 1 |

* $p < 0.02$; ** $p < 0.001$, two-tailed correlation test

From Table 3, we see that the CRT is highly predictive of behavior in both tasks even for the *same* subjects who participated in all three tasks (CRT, lottery choice, auction) on three *different* dates. The effect size is large (correlations of approximately 0.50 between the CRT and each task) and highly significant ($p < 0.001$ for both two-tailed Pearson and Spearman correlation tests). We also see that behavior in the individual and strategic decision tasks is significantly correlated when these tasks are compared directly: The same subject who did not violate dominance in the individual decision task also bid closer to his valuation in the second price auction.

The observed stability in performance across reasoning tasks (the CRT), decisions under risk (the lottery choice task), and strategic decisions (the second price auction) is remarkable, particularly given the instability of other important characteristics within a domain (such as risk preferences) across contexts even within the same experiment (1). This report, in conjunction with other research on the CRT suggests that it may provide a unified metric for predicting performance across the domains of reasoning, individual choice, and strategic interactions.

**Discussion**

One occasionally hears the recommendation to "think carefully before you choose," expressing the sentiment that more reflection on one's choices will lead to better decisions. On the other hand, well-cited experimental studies have argued that "choices in complex matters…should be left to unconscious thought" (15). In this report, we test whether differences in reflecting on one's thought processes systematically reveal differences in decision quality.

Using an objective method for ranking the quality of decisions, we compared the performance of reflective thinkers and intuitive thinkers and assessed the ability of the cognitive reflection test to predict behavior in both individual and strategic decisions. Subjects with higher CRT scores make fewer dominated lottery choices and bid closer to the dominant strategy equilibrium in second price auctions.

Moreover, this result holds for the *same* subjects who participated in each task on *different* dates, suggesting that cognitive reflection is a relatively stable characteristic and that the CRT provides a unified measure of cognitive reflection which has predictive power across reasoning tasks, choices under risk, and strategic interactions even for the same individuals. To the extent that objectively better decisions correspond to higher degrees of rationality, this may suggest that a person's degree of rationality is also a relatively stable characteristic both over time and across individual and strategic decisions.

We found that experience significantly reduces the gap between high and low CRT subjects, in that low CRT subjects with experience, perform approximately as well in the second price auction as high CRT subjects without experience. This suggests that 'learning by mistakes' can compensate low CRT subjects for their comparative disadvantage in cognitive reflection.

From a practical perspective, the CRT is important because the types of errors it measures may actually arise in many real world situations. For instance, in the lottery choice task, the intuitive response seems to involve focusing on the most salient payoff difference and choosing the alternative with the larger salient payoff. Some reflection is needed to detect the dominance relation. In the second price auction, a low CRT agent may think that since his payment does not depend directly on his bid, he can place a very high bid to win the auction. It requires further reflection (*or* experience) to recognize that bidding too high can result in losses. That is, experiencing the outcomes of a poor decision may make one "sadder but wiser."

A strong implication for a decision analyst or policy maker is to help decision makers acquire experience with a particular task or perhaps extensively simulate decisions with feedback before making choices with large consequences. This may help decision makers converge toward rational benchmarks without them having to learn the "hard way".

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