

Online Appendix for:

Selection Bias, Demographic Effects and Ability Effects in Common Value Auction Experiments by Marco Casari, John C. Ham, and John H. Kagel

This appendix is designed to cover a number of issues:

1. Details of the experimental procedures. Here we apologize for considerable repetition with the text as many of these details only make sense within the context of the description of procedures reported in the text. We include a copy of the instructions at the end of the appendix as well.
2. A second table relating demographic and ability characteristics of our sample to the university population categorized by major.
3. Technical issues relating to the statistical estimates reported in the text including details relating to our attempts to identify selection bias for both inexperienced and experienced bidders using standard econometric techniques.
4. Tables repeating the statistical estimates reported in the text where we replace our composite SAT/ACT ability measure with separate measures of math ability and verbal ability based on SAT/ACT test scores.

1. Experimental Procedures: An admissible bid was any real number between zero and $x + \$17$. The latter is \$2 greater than any possible value of x_0 , with the restriction intended to prevent bankruptcies resulting from typing errors. A reservation price equal to $x_0 - \$30$ was in effect at all times, with the reservation price rule (but not its realizations) announced. Winning bids always exceeded the reservation price.

To hold the number of bidders, n , constant in the face of potential bankruptcies, extra bidders were recruited for each session. Bidders were randomly rotated in and out of active bidding between auctions.¹ In sessions where the total number of bidders fell below 12, the number of bidders in each market was reduced proportionately; e.g., with 11 bidders there would be 5 in one market and 6 in the other, with 10 bidders there would

¹ Inactive bidders got to see the outcomes for one of the two markets. In the first seven auction sessions (all with inexperienced subjects) extra bidders only became active following a bankruptcy. Prior to this they were seated next to an active bidder, observing auction outcomes but with discussions between active and inactive bidders prohibited.

be 5 bidders in both markets, and so on.² The number of active bidders in each market was always posted at the top of bidders' computer screens, with a bidder's status (active or inactive) clearly indicated as well.

In recruiting, all subjects were informed that they were needed for two sessions to be conducted at the same time in two consecutive weeks, and to only register if they could meet that commitment. Only after registering were subjects in the bonus treatment informed that they would receive a \$20 show-up fee conditional on attending both sessions and that they would lose half their earnings if they did not participate in a second session. They were then permitted to withdraw from participating, which no one did. There were also no noticeable differences in week 1 show-up rates between the bonus and the other two treatments.

Each inexperienced session (week 1) began with two dry runs, followed by thirty auctions played for cash. Earnings from the auctions were added to or subtracted from starting cash balances. Lottery earnings were added to cash balances as well. Once a bidder's cash balance was non-positive they were declared bankrupt and no longer permitted to bid. Experienced subject sessions employed an abbreviated set of instructions, a single dry run, and thirty-six auctions played for cash (as the shorter instructions permitted more auctions).

Subjects were recruited by e-mail from the general student population at Ohio State University. Just under 93% were undergraduate students, with the remainder either graduate students or of unknown status. The consent form gave us permission to collect demographic information. Week 1 sessions lasted approximately 2 hours, with week 2 sessions being shorter as only a summary of the instructions were read and subjects were familiar with the procedures.

Because of large numbers of subjects choosing not to return in week 2 for the control and random treatments, in conjunction with the need to recruit enough subjects in week 2 to be assured of being able to conduct two auction markets simultaneously with $n = 6$, we had to cancel a total of three week 2 sessions scheduled (on the same day and

² In the first seven auction sessions one market always had 6 bidders, with any required reduction in the number of bidders confined to the second market. Assignments to markets continued to vary randomly between auctions.

time as in week 1) for these two treatments. Instead, these subjects were invited back on different days or at different times in week 2.³

A number of observations were dropped from the dataset. There were three possible reasons for this. First, the signal was not in region 2, [65, 935] (3.0% of total observations). Second, problems with the software, such as crashes, that made some data points unreliable or unavailable (1.9% of total observations). Third, the bid was an outlier, defined as a bid of more than \$60 below the signal or more than \$17 above it (1.0%).

2. Demographic and ability measures of our sample versus the university

population by major: Table A1 compares the experimental sample with the university population conditional on students' academic major. In this table and the corresponding table reported in the text we drop the handful of graduate students (10 of them) who participated in the experiment in order to compare our sample of undergraduates with the undergraduate university population from which they were drawn.⁴

³ The experiment actually took place over a four-week period with all inexperienced subjects invited back for the week following their initial experimental session.

⁴ The sample employed here differs slightly from the sample employed in the regressions reported in the text as the latter (i) include graduate students and (ii) exclude subjects who were bystanders in some of the initial experimental sessions and never got to bid. The latter are relevant for comparing our sample to the university population. Note, we do not have information on the handful of "extra" subjects who were sent home and did not participate in a session. Extras were determined randomly at the start of a session after first determining which subjects could return for a later session (with the guarantee that they would get participate upon returning).

Table A1
Sample versus Population Differences by Academic Major
(Percentages)

	Economics and Business		Science and Engineering		Other	
Gender	Sample	Population	Sample	Population	Sample	Population
Male	69.3	60.1	82.8	67.8	41.7	43.5
Female	30.7	39.9	17.2	32.2	58.3	56.5
SAT/ACT Verbal						
Top 5%	21.3	5.9	20.7	10.6	13.9	5.7
Above median but not top 5%	57.3	47.1	62.1	49.1	41.7	41.0
Below median	17.3	26.9	15.5	23.0	19.1	30.4
No score	4.0	20.1	1.7	17.4	25.2	22.8
SAT/ACT Math						
Top 5%	33.3	7.7	48.3	17.5	7.8	3.8
Above median but not top 5%	56.0	58.1	46.6	55.2	52.2	45.8
Below median	6.7	14.2	3.5	9.9	14.8	27.5
No score	4.0	20.1	1.7	17.4	25.2	22.8
SAT/ACT Composite						
Top 5%	20.0	4.2	37.9	9.8	11.3	3.0
Above median but not top 5%	66.7	59.5	58.6	60.5	51.3	48.8
Below median	9.3	16.2	1.7	12.3	12.2	25.4
No score	4.0	20.1	1.7	17.4	25.2	22.8
Grade Point Average						
A	10.7	6.7	6.9	5.7	3.5	3.9
B+ / B	28.0	32.8	34.5	19.6	20.0	16.9
B- or below	6.7	24.0	17.2	25.8	13.9	29.1
Freshman, Sophomore or no GPA	54.7	36.5	41.4	48.9	62.6	50.2

3. Estimation details and results for standard econometric tests for selection bias:

3.1 Estimating Duration Dependence and Unobserved Heterogeneity in a Duration Model: One faces a tradeoff in choosing the degree of the polynomial in $\ln(t)$ in (2) in the text. On the one hand, it is helpful to have a relatively high order polynomial since the parameters on the control variables can be severely biased if one uses too low an order polynomial (Ridder and Verbakel 1984). On the other hand, there can be substantial small sample bias if one chooses too high an order polynomial (Baker and Melino 2000). In response to this we choose the duration dependence assuming no

unobserved heterogeneity in the model, since this gives the duration dependence the best opportunity to affect the hazard rate.⁵ We then use the Schwartz criterion to choose the order of the polynomial since this will lead to a less parameterized model than the likelihood ratio test and help us to avoid small sample bias (Ham, Svejnar and Terrell 1998, Baker and Melino 2000). In all specifications this procedure yielded a first order polynomial in $\ln(t)$ for the duration dependence.

In terms of the unobserved heterogeneity, a more general treatment would let the term θ_i be a random variable with distribution function $\Phi(\theta_i)$. We would use the (now standard) Heckman-Singer (1984) approximation for $\Phi(\theta_i)$. That is to say, we assume that θ takes on J distinct values $(\theta_1, \dots, \theta_J)$ with $P(\theta = \theta_j) = P_j$ and $P_j = 1 - \sum_{j=1}^{J-1} P_j$. The terms θ_j and P_j are parameters to be estimated. As in the text we would first consider the case of $J=2$; i.e. two points of support for the unobserved heterogeneity distribution. If we find evidence of unobserved heterogeneity in this case, we would then consider higher values of J . However, we found no evidence of unobserved heterogeneity in the case of $J=2$ and do not proceed further.

3.2 Probit Equation for Ever Going Bankrupt: Table A2 uses a probit equation to determine factors underlying bankruptcy in week 1 since this type of equation may be more familiar to some readers than the duration model. The coefficient on the female dummy is positive and statistically significant in this probit.

⁵ In empirical work, adding unobserved heterogeneity tends to lower the order of the polynomial, see, e.g., Ham and Rea (1987).

Table A2
 Probit Estimates for Going Bankrupt in Week 1
 (Composite Scores Used)

Initial Cash Balance	-.0773 (.0274)***
Lottery Participation	-.0444 (.1148)
Female	.2071 (.1045)**
Engineering/Science Major	-.1194 (.1346)
Economics/Business Major	.0370 (.1217)
No SAT/ACT Scores	.0404 (.1582)
Above 95 th Percentile SAT/ACT	-.2771 (.1468)*
Below Median SAT/ACT	.4914 (.1686)***
 <i>P-value (H0: Initial Cash Balance = Lottery Part. = 0)</i>	 <i>.0016</i>

Note: * Significant at the 10% level; ** Significant at the 5% level; ***Significant at the 1% level.

3.3 Testing for selection bias for inexperienced (week 1) bidders using standard econometric techniques: There are several ways of proceeding. One is to consider a panel data maximum likelihood model. Another is to estimate a two-step Heckman (1979) type model. Both alternatives tend to be computationally and data intensive; e.g., Ridder (1990), and do not seem like sensible procedures given that we have only 251 individuals.⁶

An alternative due to Ryu (2001) is based on the duration model of attrition estimated in the text. Ryu provides a feasible and natural means of dealing with selection bias based on the estimates of the parameters of the duration model. Unfortunately, his approach relies on obtaining relatively precise estimates of the parameters of the density for θ_i in the duration model (equations 5a and 5b). As already noted, this is a very hard

⁶ We also considered a simpler Heckman type model where we looked only at those who never went bankrupt and estimated a simple probit equation for whether a subject went bankrupt at all during week 1. We could find no evidence of selection bias using this approach. (See section 3.3 below for a description of the Heckman approach.)

estimation problem given our sample size, and we did not find any evidence of unobserved heterogeneity in the duration model reported in the text.

Here we present Ryu's (2001) correction for selection bias based on first estimating a duration model for attrition. We work in discrete time (while he worked in continuous time) as we use a discrete time hazard. Write the bid function as

$$x_{it} - bid_{it} = W_{it}\alpha + c\theta_i + \varepsilon_{it}, \quad (\text{A-1})$$

where W_{it} is a M dimensional vector of explanatory variables, α is a M dimensional vector of parameters (including the constant) and the error term consists of $c\theta_i + \varepsilon_{it}$.

Recall that we wrote the hazard function as

$$\lambda_i(t|\theta_i, Z_{it}; \delta, \gamma) = \left(1 + \exp - \left\{ Z_{it}\delta + \sum_{k=1}^K \gamma_k \ln(t)^k + \theta_i \right\} \right)^{-1}. \quad (\text{A-2})$$

Selection bias arises because θ_i enters both (A-1) and (A-2). In fact, Ryu shows that the regression function for someone who goes bankrupt in period \tilde{t}_i is given by

$$x_{it} - bid_{it} = W_{it}\alpha + c\mu_i^*(\tilde{t}_i) + \varepsilon_{it}^* \quad \text{where } t = 1, \dots, \tilde{t}_i, \quad (\text{A-3a})$$

$$\mu_i^*(\tilde{t}_i) = \left[\sum_{j=1}^J P_j \theta_j f_i(t = \tilde{t}_i | \theta_j) \right] / \left[\sum_{l=1}^J P_l f_i(t = \tilde{t}_i | \theta_l) \right] \quad \text{and} \quad (\text{A-3b})$$

$$f(t = \tilde{t} | \theta_j) = \lambda(\tilde{t} | \theta_j) \prod_{r=1}^{\tilde{t}-1} (1 - \lambda(r | \theta_j)). \quad (\text{A-3c})$$

Ryu also shows that the appropriate regression equation for someone who does not go bankrupt in the T periods of week 1 is given by

$$x_{it} - bid_{it} = W_{it}\alpha + c\gamma_i^*(T) + \varepsilon_{it}^* \quad \text{where } t = 1, \dots, T, \quad (\text{A-4a})$$

$$\gamma_i^*(\tilde{t}_i) = \left[\sum_{j=1}^J P_j \theta_j S_i(t = \tilde{t}_i | \theta_j) \right] / \left[\sum_{l=1}^J P_l S_i(t = \tilde{t}_i | \theta_l) \right] \quad \text{and} \quad (\text{A-4b})$$

$$S(t | \theta_j) = \prod_{r=1}^T (1 - \lambda(r | \theta_j)). \quad (\text{A-4c})$$

Thus Ryu provides a feasible and natural means of dealing with selection bias. One estimates the parameters of the duration model, calculates the correction terms in (A-3b) and (A-4b) using the estimated parameters, and includes the estimated correction terms in

the regression functions (A-3a) and (A-4b). Because we do not find evidence of unobserved heterogeneity we cannot implement Ryu's approach.

3.3 Testing for selection bias for experienced (week 2) bidders using standard econometric techniques: The potential problem associated with the experienced subject bid function is as follows. Assume that an individual returns in week 2 if

$$y_i^* = Z_i\gamma + v_i > 0, \quad (\text{A-5})$$

where the Z_i are a set of explanatory variables, including demographic and ability measures. Write the bidding equation for experienced bidders, analogous to (6a), in compact notation as

$$x_{it} - bid_{it} = W_{it}\alpha^* + e_{it}, \quad (\text{A-6})$$

For now we assume that $(v_i, e_{it}) \sim iid N(0, V)$. The expected value of the experienced subject bid equation is

$$\begin{aligned} E[x_{it} - bid_{it} \mid Z_i\gamma + v_i > 0] &= W_{it}\alpha^* + E[e_{it} \mid Z_i\gamma + v_i > 0] \\ &= W_{it}\alpha^* + \sigma_{ev}\mu(-Z_i\gamma) \end{aligned} \quad (\text{A-7})$$

where $\mu(-Z_i\gamma) = g(-Z_i\gamma)/(1-G(-Z_i\gamma))$ and $g(\cdot)$ and $G(\cdot)$ are the standard normal density and cumulative distribution function respectively. Note that if we exclude the term $\mu(-Z_i\gamma)$ from the regression (A-7) and instead run (A-6) for the subjects that return in week 2, the bid function coefficients will be biased and have expected value

$$E[\hat{\alpha}_k] = \alpha_k + \sigma_{ev}\partial\mu(-Z_i\gamma)/\partial W_m, \quad m = 1, \dots, M. \quad (\text{A-8})$$

Equation (A-8) says that if we ignore the selection bias, the variables included in the experienced subject bid function are likely to have biased coefficients, conditional on $E(v_i e_{it}) = \sigma_{ev} \neq 0$. Equation (A-8) includes, of course, the constant, whose value is the main element of any estimated bid factor.⁷

Heckman (1979) provides one possible solution to the issue of selection bias: Estimate γ in (A-5) by probit analysis to obtain $\hat{\gamma}$, and then use this to obtain an

⁷ One can show that if W_m increases the probability of participation, then $\partial\mu(-Z_i\gamma)/\partial W_m < 0$, so that one can sign the bias given the sign of σ_{uv} .

estimated value $\mu(Z_i\hat{\gamma})$ of the bias term in (A-7). One then uses this estimated value in the regression (A-7) to obtain unbiased estimates of α .

A concern is that the normality assumption may not hold. In this case Lee (1982) suggests modifying the estimated regression to obtain

$$x_{it} - bid_{it} = W_{it}\alpha + \sum_{l=1}^L \pi_l \mu^l(-Z_i\hat{\gamma}) + \tilde{\varepsilon}_{it}. \quad (A-9)$$

In other words, one uses a polynomial in $\mu(-Z_i\hat{\gamma})$ rather than simply using the term itself.

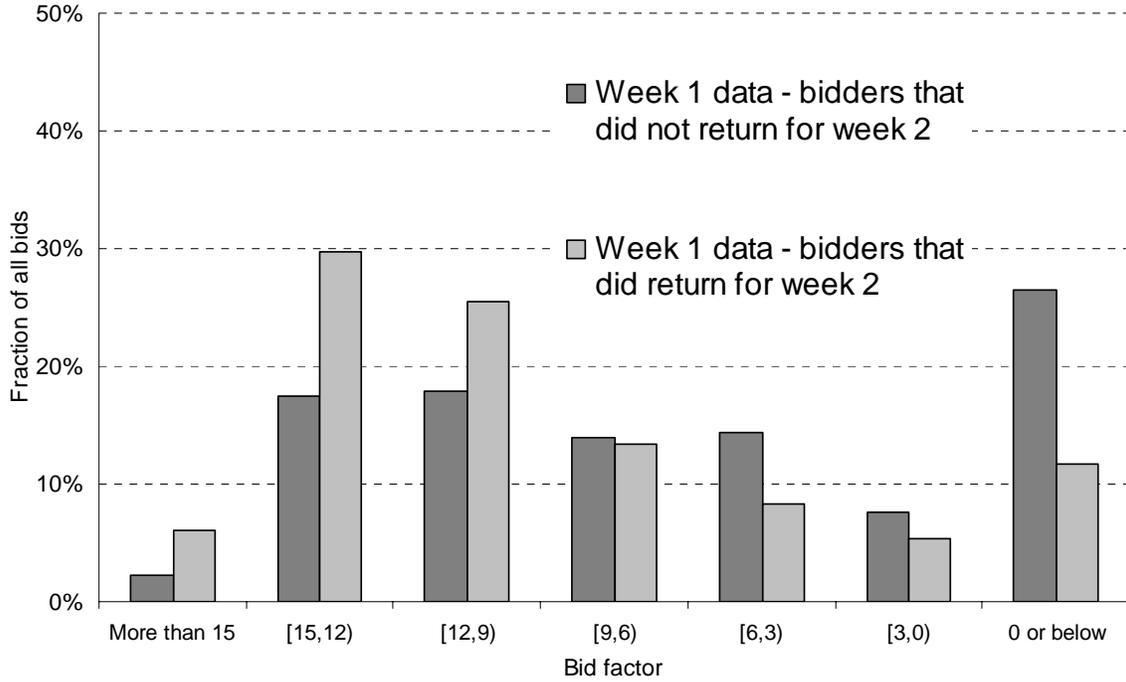
Table A3 reports the probit estimates for the probability of returning in week 2 that constitute the first step in the Heckman-Lee bias correction procedure. The probit estimates for the case where we do not use demographics are in column 1 of Table A3, while the probit estimates for the case where we include demographics are in column 2 of this table. Note that the bonus, high-return fee and same-day dummy variables are all positive and statistically significant in both columns. Hence, the selection model is well identified in the sense of having variables in the probit equation but not in the bidding equation.⁸ In terms of the demographic and aptitude variables included in the probit equation in Table A3, being an engineering or science major, and having a composite SAT/ACT score in the 95th percentile or higher, leads to a higher probability of returning. There are no differences between these results and those using math or verbal scores alone.

Figure A1 provides a histogram of the bid factors from the first five auctions in week 1 for those bidders who returned in week 1 versus those who did not return. If there is no selection bias resulting from the attrition between week 1 and week 2, we would expect the distributions to be the same. However, this figure shows clear cut evidence of selection bias since those who return in week 2 clearly have much larger week 1 bid factors than those who do not return.⁹

⁸ The positive coefficient for the low fee return group reflects the fact that they are more likely to return than the control group as earnings for these subjects were higher, on average, in week 1 than the controls due to higher starting cash balances and/or the lottery payments.

⁹ For those readers familiar with the estimates of treatment effects in the training literature, this comparison of the initial week 1 bid factors in Figure 3 is analogous to comparing pre-training earnings of training participants to those of non-participants to see if there is non-random selection in those who undertake

Figure A1: Distribution of the bid factor of inexperienced bidders
(Signal minus bid)



Notes: First five bidding periods only (periods 3-7). Data from all treatments are included (week 1, region 2, markets with 6 bidders only). A bid factor of zero means a bid equal to the signal. The risk neutral Nash equilibrium bid (RNNE) is at about 15; The cut-off point for the definition of the winner's curse (expected zero profits) is at 10.71.

training. Note the bonus group is included in week 2 with its extraordinarily high return rate, so that selection bias is likely to be even higher in the standard experimental design.

Table A3
 Probit Estimates of Probability of Returning to Week 2 Session
 (Composite Scores Used)

	<i>No Demographics</i>	<i>With Demographics</i>
Bonus	1.4362 (0.2763)***	1.6153 (0.3048)***
High Return Fee	0.6794 (0.2741)**	0.8564 (0.2930)***
Low Return Fee	0.3837 (0.2494)	0.5472 (0.2638)**
Female	-	-0.1096 (0.2071)
Engineering/Science Major	-	0.7123 (0.2939)**
Economics/Business Major	-	0.2147 (0.2312)
Above 95 th Percentile SAT/ACT	-	0.5432 (0.2992)*
Below Median SAT/ACT	-	-0.2239 (0.3194)
No SAT/ACT Scores	-	-0.2528 (0.2781)
Same Day	0.4174 (0.2130)*	0.4874 (0.2253)**
Constant	-0.1186 (0.2224)	-0.4301 (0.2916)
P-value (H0: Bonus= High Return Fee=Low Return Fee = Same Day=0)	0.0000	0.0000

Note: * Significant at the 10% level; ** Significant at the 5% level; ***Significant at the 1% level.

Tables A4 reports the results of the Heckman-Lee tests for selection bias under various specifications and for the composite ability measure (SAT/ACT) scores. Note that under all specifications we fail to reject a null hypothesis of no selection effect at conventional significance levels.¹⁰

¹⁰ The qualitative results in Tables A2-A4 do not change if we use the math or verbal aptitude scores instead of the composite scores.

Table A4
Testing For Selection Bias Using Heckman's Approach-Experienced (Week 2) Subjects
(Composite Scores Used)

	No Demographics			With Demographics		
	(1)	(2)	(3)	(4)	(5)	(6)
Cash Balances	0.0411 (0.0105)***	0.0406 (0.0099)***	0.0405 (0.0105)***	0.0409 (0.0105)***	0.0408 (0.0104)***	0.0412 (0.0105)***
h(x)	-0.2804 (0.1387)***	-0.2789 (0.1384)**	-0.2785 (0.1382)**	-0.2717 (0.1384)**	-0.2716 (0.1384)**	-0.2717 (0.1384)**
1/ln(t+1)	-0.1136 (0.1783)	-0.1094 (0.1782)	-0.1033 (0.1781)	-0.1036 (0.1780)	-0.1044 (0.1780)	-0.1010 (0.1781)
Female	-	-	-	0.1476 (0.3414)	0.1414 (0.3415)	0.0750 (0.3416)
Engineering/Science Major	-	-	-	1.0397 (0.4253)**	1.0266 (0.4258)**	1.0593 (0.4238)**
Economics/Business Major	-	-	-	-0.3658 (0.3937)	-0.3471 (0.3953)	-0.3064 (0.3937)
Above 95 th Percentile SAT/ACT	-	-	-	-0.2506 (0.3835)	-0.2682 (0.3847)	-0.3089 (0.3831)
Below Median SAT/ACT	-	-	-	-2.7469 (0.6031)***	-2.7754 (0.6051)***	-2.9375 (0.6093)***
No SAT/ACT Scores	-	-	-	-0.8887 (0.4983)*	-0.8775 (0.4988)*	-0.9037 (0.4961)*
Lambda	0.0872 (0.6277)	4.1329 (2.6216)	5.0201 (8.1292)	0.0729 (0.5895)	-0.7675 (1.6506)	4.6396 (3.5116)
(Lambda)**2	-	-5.0396 (3.1771)	-7.3349 (20.1999)	-	0.8746 (1.6091)	-11.8470 (7.4761)
(Lambda)**3	-	-	1.6391 (14.2061)	-	-	7.5724 (4.3474)*
Constant	11.2627 (0.3829)***	10.7557 (0.4881)***	10.6734 (0.7918)***	11.3862 (0.5289)***	11.5051 (0.5661)***	11.1195 (0.6066)***
Observations	5172	5172	5172	5172	5172	5172
Number of Subjects	189	189	189	189	189	189
P-value(Selection terms Jointly significant)	-	0.28	0.49	-	0.86	0.34

Note: Standard errors in parentheses. *significant at the 10% level; **significant at the 5% level; *** significant at the 1% level.

4. *Analysis Using Math SAT/ACT Scores and Verbal SAT/ACT scores in Place of Composite SAT/ACT Scores:* Table A5 provides estimates of the duration model when we use the verbal and math scores. Tables A6a and A6b contain the inexperienced subject bid functions when we use the verbal and math scores respectively. Tables A7a and A7b contain the experienced subject bid functions when we use the verbal and math scores respectively.

Table A5
Estimates of the Conditional Probability Of Going Bankrupt In Week 1

	Verbal Scores Used		Math Scores Used	
Initial Balances Plus Lottery Winnings	-0.156 (0.039)***	-0.174 (0.042)***	-0.165 (0.040)***	-0.175 (0.043)***
Received Highest Signal This Period	2.647 (0.316)***	2.691 (0.322)***	2.635 (0.317)***	2.677 (0.325)***
Received 2 nd Highest Signal This Period	2.232 (0.330)***	2.233 (0.335)***	2.261 (0.332)***	2.273 (0.336)***
Female	0.651 (0.244)***	0.693 (0.265)***	0.539 (0.246)**	0.571 (0.261)**
Above 95 th Percentile SAT/ACT	-0.394 (0.352)	-0.482 (0.382)	-0.309 (0.331)	-0.275 (0.345)
Below Median SAT/ACT	0.846 (0.277)***	0.952 (0.316)***	1.169 (0.331)***	1.207 (0.349)***
No SAT/ACT Scores	0.148 (0.348)	0.593 (3.886)	0.141 (0.341)	1.157 (3.617)
Fraction Prev. Periods Received High Signal	-2.973 (0.984)***	-2.910 (1.007)***	-3.320 (0.980)***	-3.233 (1.000)***
Fraction Prev. Periods Received 2 nd High Signal	-0.812 (0.695)	-0.854 (0.730)	-0.857 (0.705)	-0.872 (0.723)
Engineering/Science Major	-0.469 (0.334)	-0.487 (0.358)	-0.325 (0.337)	-0.374 (0.357)
Economics/Business Major	0.125 (0.273)	0.082 (0.298)	0.196 (0.275)	0.168 (0.290)
Log Duration	-0.278 (0.129)**	-0.209 (0.141)	-0.254 (0.130)*	-0.216 (0.142)
Constant	-2.828 (0.584)***	-	-2.687 (0.581)***	-
Theta1	-	-3.101 (0.651)***	-	-2.791 (0.608)***
Theta2	-	-1.857 (0.791)**	-	-1.402 (0.963)
P-value (Theta1=Theta2)	-	0.606 (0.275)**	-	0.848 (0.201)***
Unobserved heterogeneity?	No	Yes	No	Yes
Log likelihood	-352.0	-350.6	-352.0	-351.6

Note: Standard errors in parentheses.* significant at the 10% level;** significant at the 5% level;*** significant at the 1% level.

Table A6a
 Bidding Equation For Inexperienced (Week 1) Subjects
 (Verbal Scores Used)

	No Demographics		Learning without Gender Interaction		Learning with Gender Interaction	
	Low Bankruptcy Group	High Bankruptcy Group	Low Bankruptcy Group	High Bankruptcy Group	Low Bankruptcy Group	High Bankruptcy Group
Cash Balances	0.1285 (0.0566)**	0.0962 (0.0240)***	0.1232 (0.0562)**	0.0959 (0.0239)***	0.1088 (0.0551)**	0.0945 (0.0238)***
h(x)	0.2386 (0.3196)	0.0783 (0.2401)	0.2337 (0.3181)	0.0749 (0.2392)	0.2173 (0.3131)	0.0879 (0.2390)
1/ln(t+1)	-3.0306 (0.4269)***	-0.8690 (0.2749)***	-2.9778 (0.4249)***	-0.7948 (0.2739)***	-	-
Male*(1/ln(t+1))	-	-	-	-	-1.3363 (0.5564)**	-0.1771 (0.3409)
Female*(1/ln(t+1))	-	-	-	-	-5.6515 (0.6363)***	-1.8253 (0.4212)***
Female	-	-	-3.1188 (0.9760)***	-2.4825 (0.7687)***	-0.9471 (1.1082)	-1.4696 (0.8318)*
Above 95 th Percentile SAT/ACT	-	-	-1.1057 (1.0466)	2.4268 (0.9878)**	-1.0982 (1.0652)	2.3861 (0.9858)**
Below Median SAT/ACT	-	-	-0.9254 (1.1466)	-3.1107 (0.9887)***	-1.2447 (1.1658)	-3.0929 (0.9867)***
No SAT/ACT Scores	-	-	-5.3849 (1.5464)***	-0.5547 (1.0724)	-5.2597 (1.5693)***	-0.5369 (0.0703)
Engineering/Science Major	-	-	-0.1957 (1.1512)	0.6817 (0.9412)	-0.3608 (1.1712)	0.6460 (0.9394)
Economics/Business Major	-	-	-2.7464 (1.0934)	-0.5397 (0.8902)	-2.9438 (1.1106)	-0.5754 (0.8884)
Constant	8.9864 (1.0562)***	7.6498 (0.5089)***	12.0448 (1.4856)***	8.8177 (0.8890)***	11.6490 (1.5155)***	8.5119 (0.8950)***
Number of Observations	1702	3279	1702	3279	1702	3279
P-value(coefficients same in both sub-samples)(a)	0.00		0.00		0.00	

Note: Standard errors in parentheses; * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

Table A6b
Bidding Equation for Inexperienced (Week 1) Subjects
(Math Scores Used)

	No Demographics		Learning without Gender Interaction		Learning with Gender Interaction	
	Low Bankruptcy Group	High Bankruptcy Group	Low Bankruptcy Group	High Bankruptcy Group	Low Bankruptcy Group	High Bankruptcy Group
Cash Balances	0.1285 (0.0566)**	0.0962 (0.0240)***	0.1208 (0.0561)**	0.0974 (0.0239)***	0.1064 (0.0550)*	0.0961 (0.0238)***
h(x)	0.2386 (0.3196)	0.0783 (0.2401)	0.2361 (0.3181)	0.0722 (0.2393)	0.2200 (0.3131)	0.0851 (0.2389)
1/ln(t+1)	-3.0306 (0.4269)***	-0.8690 (0.2749)***	-2.9937 (0.4247)***	-0.7968 (0.2742)***	-	-
Male*(1/ln(t+1))	-	-	-	-	-1.3561 (0.5560)**	-0.1864 (0.3412)
Female*(1/ln(t+1))	-	-	-	-	-5.6608 (0.6355)***	-1.8175 (0.4220)***
Female	-	-	-2.8309 (0.9666)***	-2.3026 (0.8245)***	-0.6750 (1.0951)	-1.3051 (0.8830)
Above95th Percentile SAT/ACT	-	-	0.7854 (0.9967)	-0.0947 (0.9649)	0.8915 (1.0118)	-0.0562 (0.9627)
Below Median SAT/ACT	-	-	-0.9423 (1.3340)	-2.5690 (1.3796)*	-1.0761 (1.3514)	-2.4415 (1.3769)*
No SAT/ACT Scores	-	-	-4.8629 (1.5024)***	-0.6730 (1.0988)	-4.6793 (1.5220)***	-0.6254 (1.0963)
Engineering/Science Major	-	-	-0.4337 (1.1536)	0.6466 (1.0111)	-0.6185 (1.1708)	0.6130 (1.0088)
Economics/Business Major	-	-	-2.7889 (1.0741)***	-0.3549 (0.9396)	-3.0183 (1.0876)***	-0.3885 (0.9374)
Constant	8.9864 (1.0562)***	7.6498 (0.5089)***	11.5029 (1.4781)***	8.8004 (0.9031)***	11.0535 (1.5101)***	8.4716 (0.9099)***
Number of Observations	1702	3279	1702	3279	1702	3279
P-value(coefficients same in both sub-samples)(a)	0.00		0.00		0.00	

Note: Standard errors in parentheses; *significantatthe10%level;**significantatthe5%level;***significantatthe1%level

Table A7a
 Bidding Equation for Experienced (Week 2) Subjects
 (Verbal Scores Used)

	No Demographics		Learning without Gender Interaction		Learning with Gender Interaction	
	High Return Group	Low Return Group	High Return Group	Low Return Group	High Return Group	Low Return Group
Cash Balances	0.0409 (0.0148)***	0.1062 (0.0198)***	0.0403 (0.0148)***	0.1075 (0.0198)***	0.0398 (0.0148)***	0.1072 (0.0198)***
h(x)	-0.4490 (0.2238)**	-0.1835 (0.1958)	-0.4386 (0.2215)**	-0.1869 (0.1957)	-0.4431 (0.2215)**	-0.1869 (0.1958)
1/ln(t+1)	-0.6116 (0.2979)**	0.1941 (0.2550)	-0.5404 (0.2957)*	0.2138 (0.2550)	-	-
Male*(1/ln(t+1))	-	-	-	-	-0.2999 (0.3692)	0.2047 (0.2936)
Female*(1/ln(t+1))	-	-	-	-	-0.8677 (0.3962)**	0.2241 (0.3878)
Female	-	-	0.3856 (0.9214)	0.2519 (0.5267)	0.6478 (0.9357)	0.2421 (0.5649)
Above95th Percentile SAT/ACT	-	-	0.4154 (1.0540)	-0.1952 (0.5966)	0.4201 (1.0366)	-0.1959 (0.5945)
Below Median SAT/ACT	-	-	-1.4826 (0.9756)	-0.9929 (0.6908)	-1.4643 (0.9598)	-0.9933 (0.6884)
No SAT/ACT Scores	-	-	-1.1977 (1.3231)	-0.3669 (0.7497)	-1.1789 (1.3014)	-0.3685 (0.7473)
Engineering/Science Major	-	-	1.3333 (1.0750)	1.5696 (0.6101)***	1.3366 (1.0572)	1.5675 (0.6080)***
Economics/Business Major	-	-	-1.8720 (1.0620)*	0.8288 (0.6023)	-1.8683 (1.0446)*	0.8270 (0.6003)
Constant	11.2935 (0.4737)***	10.2982 (0.4334)***	11.4394 (1.1459)***	9.6823 (0.6826)***	11.3298 (1.1372)***	9.6922 (0.6839)***
Number of Observations	1996	2360	1996	2360	1996	2360
P-value(coefficients same in both sub-samples)	0.05		0.10		0.10	

Note: Standard errors in parentheses; * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table A7b
Bidding Equation For Experienced (Week 2) Subjects
(Math Scores Used)

	No Demographics		Learning without Gender Interaction		Learning with Gender Interaction	
	High Return Group	Low Return Group	High Return Group	Low Return Group	High Return Group	Low Return Group
Cash Balances	0.0409 (0.0148)***	0.1062 (0.0198)***	0.0399 (0.0148)***	0.1076 (0.0198)***	0.0393 (0.0147)***	0.1072 (0.0198)***
h(x)	-0.4490 (0.2238)**	-0.1835 (0.1958)	-0.4352 (0.2211)**	-0.1904 (0.1956)	-0.4394 (0.2213)**	-0.1902 (0.1956)
1/ln(t+1)	-0.6116 (0.2979)**	0.1941 (0.2550)	-0.5385 (0.2953)*	0.2188 (0.2550)	-	-
Male*(1/ln(t+1))	-	-	-	-	-0.2973 (0.3689)	0.2065 (0.2934)
Female*(1/ln(t+1))	-	-	-	-	-0.8768 (0.3958)**	0.2366 (0.3874)
Female	-	-	0.3124 (0.9400)	-0.0561 (0.5220)	0.5777 (0.9398)	-0.0698 (0.5635)
Above 95th Percentile SAT/ACT	-	-	-0.2904 (1.0003)	-1.4644 (0.5591)***	-0.2755 (0.9688)	-1.4642 (0.5604)***
Below Median SAT/ACT	-	-	-2.4471 (1.2717)*	0.4719 (1.1461)	-2.4286 (1.2318)**	0.4729 (1.1489)
No SAT/ACT Scores	-	-	-1.4242 (1.3547)	-0.5563 (0.7258)	-1.4072 (1.3116)	-0.5583 (0.7277)
Engineering/Science Major	-	-	1.2772 (1.1444)	1.9912 (0.6209)***	1.2674 (1.1075)	1.9918 (0.6224)***
Economics/Business Major	-	-	-2.1719 (1.1111)*	1.2302 (0.5963)**	-2.1581 (1.0758)**	1.2308 (0.5978)**
Constant	11.2935 (0.4737)***	10.2982 (0.4334)***	11.7210 (1.1205)***	9.7903 (0.6582)***	11.6183 (1.0977)***	9.8003 (0.6623)***
Number of Observations	1996	2360	1996	2360	1996	2360
P-value(coefficients same in both sub-samples)	0.05		0.01		0.01	

Note: Standard errors in parentheses; * significant at the 10% level;** significant at the 5% level;*** significant at the 1% level.

Additional References

- Baker, Michael and Angelo Melino 2000. "Duration Dependence and Nonparametric Heterogeneity: A Monte Carlo Study," Journal of Econometrics 96: 357-93.
- Ham, John C. and Samuel Rea Jr. 1987. "Unemployment Insurance and Male Unemployment Duration in Canada," Journal of Labor Economics 5: 325-53.
- Ham, John C., Jan Svejnar, and Katherine Terrell 1998. "Unemployment, the Social Safety Net and Efficiency During Transition: Evidence from Micro Data on Czech and Slovak Men," American Economic Review 88: 1117- 1142.
- Heckman, James J. and Burton Singer 1984. "A Method for Minimizing the Impact of Distributional Assumptions in Duration Data," Econometrica 52: 271-320.
- Ridder, Geert 1990. "Attrition in Multi-Wave Panel Data," in J. Hartog, G. Ridder and J. Theeuwes, Panel Data and Labor Market Studies, Amsterdam, North Holland.
- Ridder, Geert and W. Verbakel 1984. "On the Estimation of the Proportional Hazards Model in the Presence of Unobserved Heterogeneity," mimeo, University of Amsterdam.