Randomization, Endogeneity and Laboratory Experiments: The Role of Cash Balances in Private Value Auctions

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Abstract

From a theoretical perspective, cash balances are thought to play a role in common value auctions because of limited liability. However, they have also been found to be important in common value auctions where limited liability is not an issue. This paper investigates whether this effect carries over to private value auctions, since limited liability issues do not arise in private value auctions. We address the issue that cash balances are likely to be endogenous. We show that additional randomization can be used to reduce endogeneity problems and to improve the performance of our estimators. Further, we find that standard panel data econometric techniques are very useful in the analysis of data from laboratory experiments. Finally, we find that the cash balance effect does indeed carry over from common value auctions to private value auctions.

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1 Introduction

The most common method for conducting experiments in economics is to conduct a series of trials, or repetitions, of a given economic environment within an experimental session. It is also common when doing this to employ financial incentives (payoffs) in each trial, excluding, perhaps, a few initial trials designed to acquaint subject with the experimental procedures.[1] For example, in auction experiments the common practice is to run a series of perhaps twenty or more auctions with financial incentives in place in each trial. In most cases with repeated payoffs, the effect of accumulated earnings (cash balances) on agents behavior is ignored.

The possible impact of cash balances on bidder behavior has been hotly debated in common value auctions.[2] In common value auction experiments, fully rational bidders often have an incentive to bid more aggressively than the risk neutral Nash equilibrium once cash balances become low enough. This phenomenon arises because subjects have limited-liability for losses (i.e., it is not possible to extract money from subjects who may have negative cash balances).[3] However, it has been reliably demonstrated that limited-liability for losses cannot account for fully rational bidders overly aggressive bidding (the winner's curse) in common value auction experiments (Kagel and

[1] The alternative is to make payments contingent on one or more trials, selected at random (see, for example, Roth, Prasnikar, Okuno-Fujiwara, and Zamir 1991). Cases where this is done usually involve relatively short experimental sessions and a design in which virtually all subjects are likely to earn positive profits on each trial (e.g., in bilateral bargaining games). This is, however, not the case here. As a result random payments on a single trial or a couple of trials can impact subjects' incentives in a several ways: (1) Expected payoffs are a function of the probability of a trial being selected multiplied by the payoffs for that trial. This waters down incentives substantially for any given trial. (2) In single unit auctions of the kind studied here, only one bidder earns money in any given auction, so that effective recruitment of subjects would require a rather large fixed show-up fee relative to expected earnings. This might be expected to trivialize the incentives associated with the auctions themselves, with a resulting loss of experimental control. Finally, while these alternative procedures eliminate a role for cash balances on subjects behavior, one still faces the problem of calculating appropriate standard errors and obtaining efficient estimates of the parameters of interest, issues which are also addressed here.

[2] A common value auction is one in which the value of the item is the same to all bidders, but different bidders have different estimates of the value. The canonical example of a common value auction is the Federal government's offshore oil lease auctions.

[3] See Hanson and Lott (1991) and Kagel and Levin (1991).

Levin, 1991; Kagel and Richard, 2001; Lind and Plott, 1991). Further, Kagel and Levin (1991) conducted an experiment where, for all practical purposes, all subjects had sufficient cash balances on hand at all times so that they were fully liable for any losses that might have been incurred for deviating from the predicted (risk neutral) Nash equilibrium. They found a significant effect of cash balances that cannot be explained by limited liability arguments.

There are several reasons why cash balances may matter independent of a limited liability effect in auctions. First, in both common value and private value auctions one might postulate such effects on the basis of deviations from risk neutrality and a breakdown of constant absolute risk aversion.[4] However, the idea of a significant (standard) risk preference effect given the amount of money at stake in any given auction, no less varying risk preferences on the basis of the small deviations in wealth that occur within an auction session, are quite implausible (Rabin, 2000). Second, since experimenters investigate behavior which may not be fully rational, there are a number of *behavioral* reasons to anticipate that cash balances may impact on bidding. For example, even though there might not be a rational reason for overbidding on the basis of limited liability in common value auctions, subjects may *mistakenly* conclude that it pays to overbid since they indeed are not liable for any losses in excess of their existing cash balance. More prosaically, experimenters recruit subjects and attempt to motivate them financially. As such, subjects may have earnings targets or aspirations which affect their bidding, and which may change as their earnings accumulate and they better understand the experimental contingencies.

Of course, it can be quite difficult to formulate and test non-optimizing behavioral models that underly the behavioral explanations for cash balance effects offered above. However, we believe that we can begin to explore this issue by examining the role of cash balances in private value auctions. If cash balance effects arise because

[4] In private value auctions bidders know the value of the item to themselves with certainty. What they do not know is the valuations rival bidders place on the item. Most real life auctions have both a common value element and a private value element; e.g., in buying a painting, a collector might be motivated by both the potential resale value (the common value element) and the appeal of the painting in terms of where it might fit into the existing collection of paintings or the plans for displaying the painting.

subjects base their behavior in part on earnings targets or aspirations that are not observable to the experimenter, then cash balances should impact on bidding in private value auctions. Further, since limited liability does not play a role in private value auctions, examining cash balance effects in private value auctions separates the possible role of target earnings and/or aspirations on bids from real or mistaken responses to limited liability. On the other hand, if cash balances do not play a significant role in private value auctions, this would cast doubt on an earnings target, or aspirations, explanation of the role of cash balances in common value auctions. In this case researchers could then focus their attention on testing for cash balance effects in common value auctions in terms of bidders' mistaken beliefs about the effect of limited liability.

The study of cash balance effects has been essentially non-existent in private value auctions. Accumulated cash balances are rarely included as an explanatory variable in estimating bid functions or testing the implications of Nash equilibrium bidding theory (Kagel, 1995). Further, if cash balances impact on behavior, as has been shown to be the case in common value auctions, then omitting them in a formal statistical analysis is likely to bias important parameters of interest, such as those representing the effect of learning and the effect of numbers of bidders on bidding behavior. The use of cash balances as an explanatory variable also raises important issues of efficiency and endogeneity; issues which have generally been ignored in the statistical analysis of laboratory data.

To see the problems involved with using cash balances as an explanatory variable, consider that a typical experimental design will have a series of twenty to thirty auctions. A winner is declared each auction period and the cash balances of (only) the winner are adjusted at the end of the period. Since cash balances change only for one bidder in each period there may not be much variation in this variable. Further, what variation there is in cash balances is likely to be endogenous with respect to current bidding behavior, since it is a function of previous bidding behavior and we would expect unobservables in the bid function to be correlated over time for the same individual. For example, it is known that bidders generally bid above the risk neutral Nash equilibrium and thereby lower their profits. However, current profits simply equal current cash balances, and those who tend to bid more closely to the equilibrium bid will have tend to have higher profits or cash balances in any period. Thus we would expect to obtain a negative coefficient on cash balances in the absence of any true cash balance effect - cash balances would simply be capturing heterogeneity in bidding behavior. If one does not allow for the endogeneity of cash balances, one runs the risk of finding a cash balance effect simply because of simultaneous equation bias.

Further, variables representing learning and the number of bidders are likely to be correlated with cash balances, so that endogeneity problems with cash balances will carry over into estimating the effects of learning and the number of bidders. Researchers may turn to fixed effect regressions to address the simultaneity problem; this is the approach taken by Kagel and Levin (1991) in their study of the role of cash balances in common value auctions. However, dealing with endogeneity in this manner comes at the cost of accentuating the problem of insufficient variation in cash balances, since the fixed effect estimator does not utilize between-subject variation.

This paper addresses the above issues in two ways. First we consider an experimental design that increases the exogenous variation in cash balances. Specifically, in addition to bidding, subjects are simultaneously enrolled in a lottery which randomly assigns a payment (which may be positive or negative) to each individual in each auction period. This modification allows us to obtain a substantially more powerful test of the null hypothesis that cash balances do not affect bidding behavior.[5] Second, we consider instrumental variables estimators of the cash balance effect, where the instruments are based on these (random) bonuses and other exogenous variables (e.g. ranking of signal values) produced during the experiment.

Our paper makes four contributions to the literature in experimental economics. First, it applies simultaneous equation techniques to the estimation of economic relationships from experimental data, and notes that experiments produce a number of variables which are valid instrumental variables since they generated randomly each period and are strongly correlated with the potentially endogenous variables. Second, we demonstrate how the sample

[5] Our randomization procedure also will reduce the bias of OLS estimates (as compared to previous studies) if the cash balance variable is endogenous.

design may be altered to reduce simultaneity problems and increase the efficiency of econometric estimators. To our knowledge this is the first such application of these two techniques to experimental data. Third, we investigate the effect of sample size on the precision and stability of various econometric estimators; this investigation is of some interest to both experimenters and non-experimenters alike since the properties of many of our estimators (random effects, instrumental variables) depend on asymptotic results. Fourth, we provide substantial evidence that cash balances do indeed play a statistically significant role in bidding in private value auction experiments. Further we show that two parameters of interest to experimenters, the effect on bidding of the number of bidders and the effect of learning respectively, are substantially affected by omitting cash balances as an explanatory variable.

We note that our modification of the experimental design and estimation strategy are equally applicable when studying common value auctions. However, one also faces the problem of attrition or sample selection bias in common value auctions.[6] We are currently investigating experimental designs and estimation approaches to deal with this problem and will report on our results at a later date.

We emphasize that the problems that we deal with in a laboratory setting are very similar to those encountered by researchers using field data to estimate panel data models. The only real difference is that those working a laboratory setting can increase the exogenous variation in the explanatory variables and the sample size much more easily than those working with field data. Thus we believe there is no reason to treat the detailed statistical analysis of data from laboratory experiments any differently from the analysis of microeconomic field data. Further, laboratory data allow econometricians to develop and apply estimators in an economic setting where the assumptions underlying their estimators are much more likely to hold. Indeed, we find a number of additional results that demonstrate important principles in microeconometrics and thus our paper should have substantial pedagogical value in the teaching of this subject. First, we find a considerable gain in moving to efficient estimators such as random effects (RE) or three stage least squares (3SLS) as compared to using ordinary least squares (OLS) or two stage least squares (2SLS). Second,

[6] See Heckman (1974, 1976, 1979) and Lee (1976, 1978, 1982). Manski (2001) also notes the attrition problem in laboratory experiments.

while these efficient estimators behave relatively well in sample sizes comparable to, or slightly larger than those used in many experiments, increasing the sample size does provide more precise and stable parameter estimates (across estimators). Third, using standard regression programs to calculate standard errors for OLS or 2SLS estimates substantially underestimates the standard errors of the parameter estimates in our data. Fourth, we find that RE, fixed effect (FE) and 3SLS estimation produce parameter estimates which are quite similar to each other and stable across samples.

The paper is organized as follows. Section 2 describes the structure of affiliated private value auction experiments and introduces our randomization strategy. In Section 3 we present different econometric approaches to estimating the cash balance effect in standard experimental designs. In section 4 we discuss how our randomization strategy addresses problems of simultaneity and efficiency. Section 5 contains our empirical results. Section 6 concludes the paper and discusses the behavioral implications of our findings.

2 Affiliated Private Value Auctions

In an affiliated private value auction each bidder has perfect information about the value they place on the object to be auctioned off in each period. Each bidder then enters a bid, and the individual with the highest bid wins the auction in that period. With affiliation, the higher the value of the item for one bidder, the more likely other bidders are to have higher values as well. A simple example of an affiliated private value auction would be a business to business auction in which suppliers compete for the right to sell parts to automobile manufacturers. In such auctions, the lower the supply cost for sellers of part Z, the more likely other sellers are to have lower sales costs for that particular part as well. That is, we do not expect the costs for producing fuel injectors to be in the same neighborhood as the cost of transmissions, but that costs of different fuel injector manufacturers to be bunched in a similar neighborhood and costs of transmissions producers to be bunched in another, albeit higher priced, neighborhood.

2.1 Experimental Design

Each experiment has 30 auction periods with either 4 or 6 bidders, competing for a single unit of a commodity using a first-price, sealed-bid procedure (high bid wins and pays the price bid). Bidders' valuations for items are determined randomly in each period using the procedure described in the next paragraph. In each auction the high bidder earns a profit equal to his/her value of the item less the amount bid; other bidders earn zero profit.

Our experimental design follows that developed by Kagel, Harstad, and Levin (1987) (hereafter KHL) for studying affiliated private value auctions. Private values are determined in each auction period according to the following two step procedure: First, a random number, x_o, is drawn (with replacement) from a uniform distribution on the interval $[\underline{x},\overline{x}]$= [\$25, \$975]. Once x_o is determined, private values, x_i (one for each bidder) are randomly drawn (with replacement) from a uniform distribution on the interval$[x_o - \varepsilon, x_o + \varepsilon]$, with $\varepsilon = \$12$ throughout. Private values are independently drawn relative to x_o, but are strictly positively affiliated (Milgrom and Weber, 1982), as they are positively correlated relative to the set of possible valuations.

Prior to bidding, participants know the underlying distributions from which x_o's and x_i's are drawn, their own x_i, the number of competing bidders and the rules of the auction. They do not know the value of x_o or the value of rivals' signals. Following each auction period, the winner of the auctioned item is announced, with profits and cash balances calculated and updated as part of the computer software controlling the experiment. In addition all bids are listed from highest to lowest on each bidder's screen, along with underlying signal values. Also posted on each bidder's screen are x_o and the profits of the winning bidder. Bidder identities are suppressed throughout so that one could not identify which subject won or which subject had submitted which bid.

An important difference between our design and that of KHL is that bidders are automatically enrolled in a lottery each period with payoffsz_{it}, where

$$z_{it} = -\$0.50 \text{ with probability } .5$$

$$z_{it} = \$1.00 \text{ with probability } .5.$$

The lottery yields a positive expected payoff of \$0.25 per period. The purpose of the lottery is to provide a source of exogenous variation in bidders' cash balances, the variable of primary interest in this experiment. (Our study is the first to use such a lottery to induce additional randomization in an experiment.) We used both positive and negative payoffs to insure that cash balance would not increase monotonically over time within an experimental session. The lottery has positive expected value to insure palatability to subjects, and to avoid the distractions associated with negative payoffs. Subjects are told that the lottery is designed simply as a source of extra earnings and that over the course of the experiment they would earn positive average profits of 25¢ per period from the lottery. Further, they are told that the outcomes in the lottery are completely unrelated to the auction outcomes (which they are). Outcomes for the lottery are posted (with a delay of 15 seconds) at the bottom of bidders' screens after the results of the auction are posted. This is intended to induce a clear separation between the two events - the auction outcome and the lottery outcome.

In each experimental session there are two markets in operation simultaneously. Subjects are randomly assigned to one of the two markets in each auction period to minimize possible reputation effects. The number of bidders is the same in both markets, and constant within an experimental session.

Subjects were recruited from undergraduate economics classes at the University of Pittsburgh. At first, a total of five sessions with 48 different subjects were run. Then to examine the effect of sample size on bid function estimates, the sample size was doubled by running an additional 5 sessions with 48 more subjects.

Each subject is given a starting cash balance of \$7.00. In the event that an individual mistakenly entered a bid that caused her cash balance to become negative, she is given a new starting cash balance of \$7.00 but had \$5.00 subtracted from her end-of-experiment earnings. Subjects are given three practice periods to become accustomed to the rules and accounting procedures. Subjects also receive \$5.00 as a participation fee. In our empirical analysis, we eliminate those occasional observations involving bids above resale value and those bids below $x_i - 2\varepsilon$, as both constitute clear outliers and most likely result from bidding errors.[7]

2.2 Equilibrium Bid Functions

Theoretical models of auctions have focused on characterizing the risk-neutral symmetric Nash equilibrium (SRNNE). Restricting our analysis to values of x_i in the interval $\underline{x}+\varepsilon \leq x_i \leq \overline{x}-\varepsilon$, the SRNNE bid function where x_o is unknown is

$$\begin{aligned} b(x_i) &= x_i - \frac{2\varepsilon}{n} + \frac{Y_i}{n} \qquad (1) \\ where\ Y_i &= \frac{2\varepsilon}{n+1}\exp^{-(\frac{n}{2\varepsilon})[x_i-(\underline{x}+\varepsilon)]} \end{aligned}$$

and n is the number of bidders in the auction. The term Y_i contains a negative exponential, and becomes negligible rapidly as x_i moves beyond $\underline{x}+\varepsilon$.[8] Expected profit to the high bidder under the SRNNE is approximately $2\varepsilon/n$.

In estimating the bid function we confine ourselves to $x_i \in [60, 963]$. At this point the negative exponential term Y is .114 with $n = 4$ and .011 with $n = 6$, so that the theoretical bid function is approximately linear in this interval. In addition bidders are known (see Kagel and Richard, 1997) to be relatively insensitive to the non-linear component of the bid function, adopting a piece-wise linear rule of thumb in its place. Thus for this range of x_i it is appropriate to employ the following simplified estimating equation for the bid function for the case where n and ε are constant[9]

$$B_{it} = \gamma_0 + \gamma_1 x_{it} + \upsilon_{it} \qquad (2)$$

[7] Note that our trimming is symmetric in the sense that we are eliminating very high and very low bids. However, we are eliminating 90 high bids and only 30 low bids. In future work it would be better to trim an equal number of high and low bids. Note that we cannot use more robust techniques (LAD, quantile regression) given our emphasis on simultaneous equation bias and panel data issues. See Koenker and Hallock (2001) for a discussion of robust techniques.

*Note that this selection is on the basis of an exogenous variable.

[8] Derivation of the SRNNE bid function for our experimental design is contained in KHL (1987). They also characterize the SRNNE bid function outside the interval $\underline{x}+\varepsilon \leq x_i \leq \overline{x}-\varepsilon$.

[9] In our empirical work below we also allow for learning by allowing bids to depend on a function of t.

where x_{it} is the value of the signal for individual i in period t. In estimating the bid function we will also want to take account of the potential impact of accumulated cash balances on bids. For now we assume there is no lottery (as is true in previous papers), so that the cash balance variable includes starting cash balances plus accumulated auction earnings prior to the current auction period. Including it in (2) yields the estimating equation

$$B_{it} = \gamma_0 + \gamma_1 x_{it} + \gamma_2 C_{it} + \upsilon_{it} \tag{3}$$

where C_{it} denotes the cash balance prior to the bid in period t which changes from period $t-1$ to period t only when individual i wins the auction in period $t-1$.

3 Efficiency and Simultaneity Problems in Experiments

For expository purposes suppose for the moment that simultaneity is not an issue. Define $X'_{it} = (x_{it} - \overline{x}, C_{it} - \overline{C})$ and X'_i as the 2 by T matrix of the explanatory variables (measured as deviations from their sample means) where T is the number of auction periods and let $\gamma' = (\gamma_{1,}\gamma_2)$. Then if the error term in (2) or (3) is assumed identically and independently distributed (iid), the variance of the least squares estimator is given by[10]

$$Var(\widehat{\gamma}_{ols}) = \sigma_\upsilon^2 (\sum_{i=1}^{I} X'_i X_i)^{-1} \tag{4}$$

where σ_υ^2 is $Var(\upsilon_{it})$. Using fact that the resale value (x_{it}) is a random variable which is independently generated each period, and thus is (asymptotically) uncorrelated with C_{it}, the variance of the OLS estimator of the cash balance coefficient in equation (3) can be written as

$$Var(\widehat{\gamma}_{2,ols}) = \frac{\sigma_\upsilon^2}{I * T * Var(C_{it})} \tag{5}$$

where I is the total number of subjects. Thus the variance of the OLS estimator is (inversely) proportional to the variance in cash balances, and if there is insufficient variance in cash balances, the estimated coefficient will be

[10] All of the equations describing our estimators and their variance-covariance matrices will be very familiar to many readers. We include them here to increase the clarity of exposition and to increase the accessibility of the paper.

imprecise. As a result, one may not be able to reject the hypothesis that it is equal to zero even when this hypothesis is false, and researchers may incorrectly make the inference that cash balances do not affect bidding behavior.

Of course, the assumption that υ_{it} is i.i.d. over time for the same person is too strong (Hsiao, 1986). Instead, many researchers assume an error components structure of the form

$$\upsilon_{it} = \eta_i + v_{it} \tag{6}$$

where one treats η_i as a random effect which is i.i.d.. across individuals and v_{it} is an error term which is assumed i.i.d.. across periods for the same individual. Let V be the T by T variance covariance of an individual's vector of error terms based on equation (6). Then V is given by

$$\begin{aligned} V_{ij} &= \sigma_\eta^2 + \sigma_v^2 \text{ if } i = j \qquad (7) \\ &= \sigma_\eta^2 \qquad\quad \text{if } i \neq j \end{aligned}$$

In this case, the variance of the OLS estimator is given by

$$Var(\widehat{\gamma}_{ols}) = (\Sigma_i X_i' X_i)^{-1} (\Sigma_i X_i' V X_i)(\Sigma_i X_i' X_i)^{-1} \tag{8}$$

In our empirical work we find that the difference between (4) and (8) is substantial and that the use of (8) substantially increases the standard errors. Thus, to the extent that previous investigators have employed OLS estimation in experimental studies with a panel data structure, they are likely to have substantially overstated the precision of their estimates. However, given equation (6) or equation (8), OLS estimation is inefficient and random effects (RE) estimation (i.e. generalized least squares estimation) is appropriate. . Defining y_i as the T by 1 vector of explanatory variables, the RE estimator takes the form

$$\widehat{\gamma}_{re} = (\Sigma_i X_i' V^{-1} X_i)^{-1} (\Sigma_i X_i' V^{-1} y_i) \tag{9}$$

The variance-covariance matrix of the RE estimator is given by

$$Var(\widehat{\gamma}_{re}) = (\Sigma_i X_i' V^{-1} X_i)^{-1} \tag{10}$$

We find that the use of the RE estimator substantially increases the precision of the parameter estimates, especially when the OLS standard errors are calculated in an appropriate manner using (8). Of course, having enough variation in cash balances is still a fundamental issue whether one uses OLS or RE estimation.

The above discussion is concerned with efficiency. However, in the standard experimental design that does not utilize a lottery, the variation in cash balances across individuals or periods is generated entirely by previous bidding behavior, since individuals typically start with identical cash balances and these balances only change as a result of profits and losses in earlier periods. If the error structure is given by (6), then the OLS and RE estimators will suffer from simultaneous equation bias.[11] The inconsistency in the OLS estimator is given by

$$\text{plim}(\widehat{\gamma}_{2,ols}) = \text{plim}(\Sigma_i \Sigma_t C_{it} v_{it}/N)/\text{plim}(\Sigma_i \Sigma_t C_{it} - \overline{C})^2/N) \tag{11}$$

where $N = I * T$ is the sample size across individuals and time periods.

Note that a similar expression to (11) will apply to the RE estimator because η_i is still part of the error term; thus using RE estimation will not eliminate the simultaneity bias. For most researchers, the natural alternative to RE is the use of a fixed effect (FE) model where η_i is treated as a parameter to be estimated. (Another alternative is to use instrumental variable procedures such as two stage least squares and three stage least squares, which we discuss in detail below.) FE estimation is equivalent to OLS estimation of (3) where the dependent and independent variables are measured as deviations from the individual means. As a result, design features that vary only across groups and thus are constant across individuals cannot be directly estimated if FE estimation is used.[12] If one assumes (as is usually done in both FE and RE estimation) that the transitory component v_{it} in (6) is i.i.d. across periods for the same individual, then the variance of the fixed effect estimator is given by

$$Var(\widehat{\gamma}_{fe}) = \sigma_v^2/(\Sigma_i \Sigma_t (C_{it} - \overline{C}_i)^2) \tag{12}$$

[11] Note that simultaneous equation bias will not be a problem with xit in (3) as this variable is randomly generated each period and thus will be uncorrelated with all explanatory variables.

[12] One can recover the coefficient on such a variable using the approach of Hausman and Taylor (1981).

where $\overline{C}_i$ is the mean of C_{it} for individual i. The variance of the FE estimator in (12) will be greater than (in an expected value sense) the variance of the RE estimator in (10) in the absence of simultaneous equation bias, since the FE estimator only considers variation around individual means. (See Hsiao, 1986, section 3.4.)

An alternative to the FE procedure is to use an instrumental variables (IV) approach, such as two stage least squares (2SLS), to estimate equation (3). IV procedures have the advantage that one can assume that cash balances are correlated with both components of the error term, as would occur if there is learning which induces autocorrelation in the transitory error component v_{it}. The FE estimator assumes that the only source of endogeneity of cash balances is the permanent component of the error η_i.

To implement 2SLS estimation of (3), we need to find instrumental variables. An instrumental variable must have two properties. First, it must be uncorrelated with the error term in (3). Second, it must be correlated (preferably highly correlated) with cash balances. A natural instrumental variable in our setting is of the total number of previous periods that the subject received the high signal, since the individual receiving the high signal in a given period is the one most likely to have the winning bid in that period. By the same reasoning, the total number of previous periods that the individual received the second highest signal is a second potential instrumental variable. Moreover, whether an individual has the highest or second highest signal in a given period is determined randomly for each individual and will be uncorrelated the error term. Note that because we are in a laboratory setting, we can guarantee that the othogonality conditions for our instrumental variables hold, since the signals are generated randomly each period. In a non-laboratory setting it is generally necessary to assume that instruments are uncorrelated with the error term unless the data are generated by a social experiment.[13] These instruments are also strongly correlated with the endogenous variable, and thus the problem of weak instruments does not occur in the current setting.[14]

[13] This statement assumes that the model estimated in the non-laboratory setting is exactly identified. If it is over identified, one can test the over identifying assumptions but not the exactly identifying assumptions.

[14] If the instruments are only very weakly correlated with the endogenous variables (i.e. the correlation approaches zero), then the instrumental variables estimates will be asymptotically biased - see Bound, Jaeger and Baker (1995) and Staiger and Stock (1997).

We regress cash balances on the instruments and all the other exogenous explanatory variables from (3) in the first stage equation

$$Cit = \pi_0 + \pi_1 D_{1it} + \pi_2 D_{2it} + \pi_3 x_{it} + e_{it} \tag{13}$$

whereD_{1it} and D_{2it} denote the total number of highest and second highest signals received respectively in previous auction periods.[15] We then run the second stage equation

$$B_{it} = \gamma_0 + \gamma_1 x_{it} + \gamma_2 \widehat{C}_{it} + \upsilon_{it} \tag{14}$$

where $\widehat{C}_{it}$ is the predicted value of cash balances based on estimates of equation (13).[16] Define W_i' as the 2 by T matrix of explanatory variables measured as deviations from their respective sample means where the fitted value for cash balances from (13) is used instead of C_{it}. The 2SLS estimator is given by

$$\widehat{\gamma}_{2sls} = (\Sigma_i W_i' W_i)^{-1} (\Sigma_i W_i' y_i) \tag{15}$$

For the case where the error term υ_{it} is i.i.d. across periods for the same individual, the variance of the 2SLS estimator of the cash balance coefficient is given by

$$Var(\widehat{\gamma}_{2,2sls}) = \frac{\sigma_\upsilon^2}{I * T * Var(\widehat{C}_{it})} \tag{16}$$

which is comparable to the expression for OLS in equation (5). For the more realistic case where the error component structure (6) is appropriate, the variance-covariance matrix for the 2SLS estimate is given by

$$Var(\widehat{\gamma}_{2sls}) = (\Sigma_i W_i' W_i)^{-1} (\Sigma_i W_i' V W_i) (\Sigma_i W_i' W_i)^{-1} \tag{17}$$

[15] A third possible instrument would aim to proxy the probability that the individual who receives the highest actually wins that auction round. The instrument is calculated by taking the difference between the signal values of the highest and second highest signal received, divided by the range over which signals could be drawn in that round (2ε). We would expect that when this number is small, the second highest signal holder is more likely to win the auction round. We have not explored how this estimator will work in practice.

[16] In practice, when estimating an expanded version of (3) with additional exogenous explanatory variables by 2SLS, one would also include these other explanatory variables in the first stage equation.

While the 2SLS estimator addresses the problem of endogeneity, it will not be efficient given the error component structure (6), as demonstrated by (17). Just as efficiency gains over OLS can be achieved by using RE, one can obtain efficiency gains over 2SLS by considering the RE version of 2SLS, i.e. the three stage least squares (3SLS) estimator. This estimator is given by

$$\widehat{\gamma}_{3sls} = (\Sigma_i W_i' V^{-1} W_i)^{-1} (\Sigma_i W_i' V^{-1} y_i) \tag{18}$$

The variance covariance matrix of the 3SLS estimator is given by

$$Var(\widehat{\gamma}_{3sls}) = (\Sigma_i W_i' V^{-1} W_i)^{-1} \tag{19}$$

In practice, we find the efficiency gains from moving to 3SLS estimation from 2SLS estimation are substantial.

In general, the variance of the estimated coefficient on cash balances from 3SLS may be larger or smaller than that for the FE coefficient. However, we do know that the better the job that the instrumental variables do in predicting cash balances in terms of the fit of the first stage equation, the higher the variance of the predicted cash balances and the lower the variance of the 2SLS and 3SLS estimators.

At this point it is worth discussing the sampling properties of the various estimators. The OLS and FE estimators do not require the sample size to go to infinity as long as the error term is normally distributed. The RE estimator depends on asymptotic (large sample) arguments, since one does not know the covariance matrix V and must use a consistent estimate of it to obtain a feasible RE estimator. The 2SLS estimator also requires asymptotics in the sense that it only has desirable large sample properties. Finally, the 3SLS estimator relies even more heavily on asymptotics since it is a combination of RE and 2SLS estimation. To investigate the performance of these estimators in different sample sizes, we compare the case where standard size samples are used (48 subjects and 30 periods per subject) and a larger sample is used (96 subjects for 30 periods per subject).

4 Randomization of Cash Balances

Now consider the effect of introducing the lottery as a means of generating substantial exogenous variation in cash balances. Recall that each period we require each subject play the lottery, where they are equally likely to win one dollar or lose fifty cents. The outcome of the lottery is independent of any action on the subject's part. Introducing the lottery has three important effects. First, it reduces the bias in OLS and RE estimation by adding variation in cash balances which is independent of the error term by design; if there is no exogeneity problem randomization increases the efficiency of these estimators. Second, it increases the precision of the FE estimates by increasing the within-person variance of cash balances. Third, it increases the efficiency of 2SLS and 3SLS estimates because, as we show below, it allows one to create a powerful additional instrumental variable as well as increasing the exogenous variation in cash balances.

Define

$$Z_{it} = \sum_{r=0}^{t-1} z_{ir} \tag{20}$$

as the accumulated sum of lottery earnings for bidder i at time t. (Recall that z_{ir} is the lottery outcome in period r.) Now total cash balances take the form

$$CZ_{it} = C_{it} + Z_{it} \tag{21}$$

where C_{it} is the level of cash balances arising from the initial endowment and previous bidding behavior. Our estimating equation becomes

$$B_{it} = \gamma_0 + \gamma_1 x_{it} + \gamma_2 CZ_{it} + \upsilon_{it} \tag{(1.3')}$$

Under the null hypothesis that bidding behavior is not affected by cash balances, the variance of CZ_{it} must be greater than C_{it}, since C_{it} and Z_{it} are independent under this null hypothesis. In the absence of endogeneity problems, OLS and RE estimators will be more efficient. If bidding behavior is affected by cash balances and C_{it} and Z_{it} are correlated, we have the familiar expression

$$Var(CZ_{it}) = Var(C_{it}) + Var(Z_{it}) + 2Cov(C_{it}, Z_{it})$$

Thus the variance in CZ_{it} unless will be greater than the variance of C_{it} unless there is a strong negative correlation between C_{it} and Z_{it}.[17] As a practical matter, we find that C_{it} and Z_{it} are positively correlated in all our samples and that the variance in CZ_{it} is always greater than the variance of C_{it}. Specifically, the variance in CZ_{it} is 49%, 50% and 51% larger than the variance in C_{it} in the first, second and combined sample respectively.

Further, Z_{it} is uncorrelated with the error term by construction, and thus the lottery must reduce the inconsistency in OLS estimation under the null hypothesis that cash balances do not affect bidding behavior. (It increases the denominator in (11) but does not affect the numerator.) Moreover, even if cash balances do affect bidding behavior, from equation (11) randomization decreases the inconsistency in OLS or RE estimation in our data because the variance in CZ_{it} is larger than the variance of C_{it}.

With the lottery, the variance of the fixed effect estimator of the cash balance coefficient now equals

$$Var(\widehat{\sigma}_{fe}) = \sigma_v^2/(\Sigma_i\Sigma_t(CZ_{it} - \overline{CZ}_i)^2) = \sigma_v^2/(\Sigma_i\Sigma_t(C_{it} - \overline{C}_i)^2 + (Z_{it} - \overline{Z}_i)^2) \tag{22}$$

In our sample the variance in (22) is smaller than the variance of the FE estimate without randomization given by (12), since randomization increases the variance in CZ_{it} (around the individual specific means) as compared to C_{it} (around the individual specific means) by 101%, 93% and 97% in the first, second and combined sample respectively.

Finally, consider 2SLS and 3SLS estimation after the introduction of the lottery. By design, we are introducing an additional instrument Zit which will be strongly correlated with cash balances CZ_{it} but uncorrelated with the error term in (3). The first stage equation for CZ_{it} becomes

$$CZ_{it} = \pi_0' + \pi_1' D_{1it} + \pi_2' D_{2it} + \pi_3' x_{it} + \pi_4' Z_{it} + e_{it}' \tag{23}$$

[17] To see how a negative correlation could cause problems, take the extreme case where C_{it} and Z_{it} are perfectly negatively correlated, and the variance of CZ_{it} equals zero.

Thus randomization will improve the fit of the first stage equation and thus should reduce the variance of the 2SLS and 3SLS estimators.

Finally, independent of which estimator we use, equation (3') implicitly assumes that Z_{it} and C_{it} affect bidding behavior in exactly the same way. To test this assumption we rewrite the bidding equation ((1.3')) as

$$B_{it} = \gamma_0 + \gamma_1 x_{it} + \gamma_2 C_{it} + \gamma_3 Z_{it} + \upsilon_{it} \tag{(1.3")}$$

and test whether $\gamma_2 = \gamma_3$. For the case of IV estimation we use D_{1it} and D_{2it} as excluded instruments to identify the coefficient on C_{it}.

5 Empirical Results

In our empirical work we specify that the bid function is a linear equation in the value of the signal, cash balances, a dummy variable equal to one when the number of bidders equals six and a time trend measured as $1/t$ to capture any learning/adjustments on the part of bidders, (where t represents the auction period).[18] This time trend specification is preferable to a linear time trend on theoretical grounds as one would expect any learning/adjustment process to asymptote out rather rapidly over time rather than to continuously increase at a constant rate.

We estimate all equations on three samples: i) the original sample of 48 subjects; ii) the second sample of 48 subjects; and iii) the combined sample.[19] Table 1 presents the OLS estimates for these samples.[20] Specifically, in column (1) we present our results for the first sample when the standard expression from equation (4) is used for the standard errors. In column (2) we correct the standard errors for correlation across time in the residuals for the

[18] Thus we are adding i) a dummy equal to one when we have six bidders and ii) a term equal to 1/t to equation (3').

[19] Summary statistics on the average profit of the winning bid and average lottery earnings are presented in Table A1.

[20] To carry out the IV estimation we need to drop the first period, and to make the estimates from different estimation approaches comparable, we drop the first period for all estimators. We recalculated the RE and FE estimates including the first period and obtained essentially the same results as with the first period deleted, except that the time trend increased in absolute value with the first period included. See Table A3.

same person using equation (8). The standard errors increase considerably for all but the signal coefficient when we make this correction. The same thing happens for sample 2 and the combined sample.

The cash balance term is statistically significant at standard confidence levels in one of our samples of size 48, and is even more significant in our combined sample of 96. Focusing on the combined sample, increases in cash balances reduce bids. We also find that, consistent with theory, the number of bidders does have a positive coefficient, although the coefficient on this variable only approaches statistical significance for the combined sample once we correct the standard errors. (Note that it is quite significant in the second sample.)

As noted above, OLS estimation is not efficient once we allow for correlation across residuals for the same individual, while RE estimation takes this correlation into account. Thus RE is the appropriate estimation method if one treats cash balances as exogenous. Considering the case where cash balances are endogenous, one can use either FE or 3SLS. We have placed the RE estimates of the cash balance coefficient in row (3) of Table 2, while placing the full set of estimates in Appendix Table A2. (Rows (1) and (2) contain the OLS estimates from Table 1 for comparison.) From row (3) we see that the RE estimates of the cash balance effect is quite significantly negative, even in the smaller samples, and the estimates are very stable across samples.[21] Using the RE estimator as compared to the OLS estimator (with corrected standard errors) for the full sample cuts the standard error of the estimate approximately in half. Further, the RE cash balance coefficient for either of the sub-samples is more precisely estimated than that for the full sample under OLS. Also note that the RE estimates are quite stable across samples, in marked contrast to the OLS estimates. This suggests that if efficiency is the only concern and thus RE estimation is appropriate, it often may not be necessary to go to larger sample sizes to obtain precise parameter estimates if one uses RE estimation instead of OLS estimation.

[21] The instability in the OLS estimates may simply reflect the large sampling variation as indicated by the standard errors in row (2). To see this note that the estimates in columns (1) and (2) are independent, and thus the variance in the difference of the coefficients is simply the sum of the variances. In column two the difference in the coefficients is 4.39 but the standard error of this difference is 3.41. Thus the estimates in columns (1) and (2) of row (2) are not significantly different.

We next consider the possibility that cash balances are endogenous because some of the variation in cash balance is a result of past bidding behavior. Our first means of addressing this issue is to use a FE estimator to estimate the bidding equation. The results for the cash balance coefficient are given in row 4 of Table 2. (The full set of estimates are also in Appendix Table A2.) From row 4 we see that the FE and RE coefficients are very similar in columns 1 and 3, while they are somewhat different in column 2. Indeed one can test for the exogeniety of cash balances by testing the null hypothesis that the RE and FE estimates are equal using a Hausman-Wu test (see Hausman 1978). Consider first a test based only on the cash balance coefficient. Under the null hypothesis of exogeneity, the test statistic is distributed as a standard normal random variable and the test statistics for columns 1, 2 and 3 are .89, 2.1 and .55 respectively. Thus we reject the null hypothesis that total cash balances are exogenous only in column two. Considering a test based on all coefficients, now the test statistic is distributed as a Chi-square random variable with two degrees of freedom[22], and the critical value at the 5% level is 5.99. The test statistics for columns 1, 2 and 3 are 2.31, 1.64, and 0.17 respectively. Thus the null hypothesis of exogenous cash balances would not be rejected at the 5% level in any sample. Overall we find very little evidence against the null hypothesis of exogenous cash balances. (We would expect to get much larger test statistics absent the exogenous variation in cash balances that we introduced into our experimental design.) In any case, the FE estimates again suggest that cash balances have a significant negative effect on bids, although note that the estimates are not quite as stable across samples as the RE estimates.

The other way to address the potential endogeniety of cash balances is to use an instrumental variables estimator such as 2SLS or 3SLS. Before discussing the point estimates produced by these estimators, we present some summary information on the instruments. To review, we are using as instruments: i) the number of previous periods that an individual received the highest signal; ii) the number of previous periods that an individual received the second

[22] We noted above that the signal will not be affected by the endogeneity (since it is randomly generated in each period) and thus we consider a test based on only the cash balance coefficient and, the time trend (The dummy variable for six bidders drops out of the FE estimation.)

highest signal and iii) previous net lottery earnings. In our data individuals receiving the highest or second highest signal made the highest bid in over ninety-five per cent of the auctions in all samples. Furthermore, each of the instruments has a substantial correlation with the potentially endogenous cash balances variable. We consider three sets of instruments: 1) all three instruments together; 2) instruments (i) and (ii); and 3) instrument (iii) by itself. Note that instruments (i) and (ii) are available in all experimental auction data. Table 3 contains the first stage regressions. In each specification of the instrument set, each relevant instrumental variable is highly statistically significant.

Looking back at Table 2, the 2SLS estimates of the effects of cash balances are in rows 5 - 7 for the different instrument sets. (The full set of estimates are in Table A4.) In each case and in each sample, the 2SLS estimate of the cash balance effect is statistically insignificant. (Note we are using the corrected standard errors here.)

Of course 2SLS is an inefficient estimation procedure when the error terms across the same individual are correlated. This is analogous to the inefficiency of using OLS instead of RE when cash balances are treated as exogenous. Thus, instead we use a 3SLS estimator which is the RE version of 2SLS.[23] Rows 8-10 present these estimates. (Table A5 contains the full set of estimates.) First, there is a huge efficiency gain over 2SLS. Second, all but one of the estimates show a significant negative effect of cash balances on bids. Third, there is some moderate sensitivity to the instrument set used in conjunction with the sample used. However, in the combined sample these estimates are quite stable across instrument sets. Further, when we use the full set of instruments, the estimates are stable across samples. Fourth, as one would expect, the estimates using all instruments are more precise than those using fewer instruments.

Note one can also test for the exogeniety of cash balances by comparing 3SLS with the RE estimates, again

[23]Note, if there is, contrary to our approach, no correlation across periods for the same individual we would not expect: (i) the standard errors to change when we correct the OLS standard errors, (ii) RE estimation to show an efficiency gain over OLS estimation; and (ii) for 3SLS to give an efficiency gain over 2SLS. All of these things happen in our data set, thus casting strong doubt on the i.i.d. assumption for the overall error.

using a Hausman-Wu test. We do so using the 3SLS estimates based on all three instruments. Considering the cash balance coefficient, the test statistics are .34, .78, and .99 for columns 1-3 respectively. Since these statistics are distributed N(0,1) under the null hypotheses, in no case do we reject the null hypothesis of exogenous cash balances. Considering all the coefficients jointly the test statistic under the null hypothesis is a Chi-square random variable with three degrees of freedom, and thus its critical value at the five per cent level is 7.82. The actual test statistics are 1.08, 3.84 and 0.17 in the first, second and combined respectively, and thus in no case do we reject the exogeneity of cash balances at standard significance levels.

The quantitative impact of cash balances is substantial. We evaluate this quantitative impact in terms of the bid factor; i.e., the reduction of bids relative to the signal value. For the case of $n = 4$ the overall bid factor is the value of the intercept of the bid function, plus the mean value of cash balances times its coefficient (in terms of their absolute value). For example, with $n = 4$, for our RE estimates the portion of the bid factor represented by the intercept is \$1.76, while the portion due to cash balances is \$0.60. With $n = 6$ the intercept portion is \$1.27 and the cash balance portion is \$0.43.

As noted above, our randomization and estimation strategy are based on the assumption that bidders treat profits from previous auctions and winnings from previous lotteries equivalently. We can test this assumption by freeing up the coefficients on these two components of cash balances using equation (3") and testing the null hypothesis that the two coefficients are the same. The results of this exercise for the RE, FE and 3SLS estimates (all instruments) are shown in Table 4. We see that the coefficients on auction winnings are larger in absolute value than those on lottery earnings in Sample 1, while they are much closer in Sample 2 and the combined sample. Further, from the second last line of Table 4, we see that the test statistic for the null hypothesis of equal coefficients (which is distributed N(0,1) under the null) is less than the critical value at the 5% level in all cases with the exception of 3SLS in the first sample. Thus in general we cannot reject the null hypothesis of equal coefficients on the two components of cash balances.

All of our analysis so far indicates that cash balances have a significant negative effect on bids. We now consider what, if any, effect it would have on our estimates of the other coefficients if we followed the usual policy of omitting cash balances as a RHS variable. Table 5 reports this exercise for the combined sample and our preferred estimators RE, FE and 3SLS (all instruments). To gain some intuition on the results in Table 4, consider our expanded regression equation

$$B_{it} = \gamma_0 + \gamma_1 x_{it} + \gamma_2 CZ_{it} + \gamma_3 D6_{it} + \gamma_4(1/t) + \upsilon_{it} \tag{24}$$

with cash balances included and

$$B_{it} = \beta_0 + \beta_1 x_{it} + \beta_3 D6_{it} + \beta_4(1/t) + \upsilon_{it} \tag{25}$$

with cash balances excluded.

Finally, consider the auxiliary regression of cash balances on the other explanatory variables

$$CZ_{it} = \delta_0 + \delta_1 x_{it} + \delta_3 D6_{it} + \delta_4(1/t) + e_{it} \tag{26}$$

Assume that we are using least squares to estimate (24) and (25) since this will provide the appropriate intuition in the simplest manner. Then the relationship between the expected value of the coefficients in (25) when we omit cash balances and the expected value of the other coefficients is given by the Theil-Griliches specification error result[24]

$$\beta_0 = \gamma_0 + \gamma_2\delta_0 \tag{1.27a}$$

$$\beta_1 = \gamma_1 + \gamma_2\delta_1 \tag{1.27b}$$

$$\beta_3 = \gamma_3 + \gamma_2\delta_3 \tag{1.27c}$$

$$\beta_4 = \gamma_4 + \gamma_2\delta_4 \tag{1.27d}$$

[24] Note that (1.27a) - (1.27d) will also hold for the OLS estimates of (24) - (26).

Now consider the effect of omitting the cash balance variable in (25) on the private value coefficient β_1. Since the private values x_{it} are randomly generated, the expected value of δ_1 is zero. Thus the private value coefficient should be unaffected by omitting cash balances and indeed we find this to be the case in Table 5. Next consider the coefficient on the dummy variable indicating 6 bidders instead of 4. From Table 5 we see that the coefficient on this variable rises when we omit cash balances. We would expect that δ_3 is less than zero since with more bidders, both the expected and realized profit per auction is reduced, resulting in lower cash balances. Since γ_2 is less than zero, equation (**??**) would indeed predict that the dummy for 6 bidders rises when we omit cash balances. Intuitively, number of bidders has both a direct effect (γ_3) and indirect effect ($\gamma_2\ \delta_3$) on the bid function. The indirect effect combines the effects of more bidders lowering cash balances ($\delta_3 < 0$) and the fact that with lower cash balances, other things equal, subjects bid more aggressively ($\gamma_2 < 0$). When we include cash balances we only get the direct effect (γ_3), which is what most tests of auction theory are after.

Next consider the effect on the time trend coefficient of omitting cash balances; from Table 4 we see that this coefficient falls in absolute value when we omit cash balances. When we omit cash balances we can again think of the trend having a direct and indirect effect, as indicated by (1.27d). The direct effect of the time trend variable ($\gamma_4 < 0$) indicates more aggressive bidding over time. (Recall that our time trend variable is $1/t$.) The indirect effect ($\gamma_2\ \delta_4$) is positive, since cash balances are growing over time ($\delta_4 < 0$) and increasing cash balances results in less aggressive bidding ($\gamma_2 < 0$). Thus the indirect effect arising from omitting cash balances dampens the direct effect of the time trend.

Finally, omitting the cash balance variable increases the absolute value of the constant. The constant represents the discounting of bids relative to signal values with four bidders. Thus, the larger absolute value when cash balances are omitted represents greater discounting (less aggressive bidding). When you omit cash balances, the constant takes credit for the cash balance effect ($\gamma_2\delta_0 < 0$).

6 Conclusion

In this paper we investigate the role of individual cash balances on bidding behavior in affiliated private value auctions. We argue that previous studies have suffered from two problems. First, cash balances are likely to be endogenous in standard experimental designs. Second, standard experimental designs are likely to produce insufficient variation in cash balances to enable researchers to precisely estimate the effect of this variable on bidding behavior. We discuss econometric estimators aimed at dealing with this problem. We also develop and implement an experimental design which increases the exogenous variation in cash balances. This experimental design involves partially randomizing cash balances each period and will also mitigate potential endogeneity problems. It is applicable in many experimental designs.

Given our experimental design, we find that random effects, fixed effects and three stage least squares estimators generally provide stable, negative, and statistically significant estimates of the cash balance effect. Since we do not have comparable experimental data which does not involve randomization, we cannot precisely isolate the effect of randomization. However, it is interesting to note that our results using randomized data suggest a much stronger role for cash balances than previous work in private value auctions (Kagel, 1995).[25]

Cash balances have a small but significantly negative effect on the level of bids in private value auction experiments. During these sessions subjects begin by immediately increasing their bids to improve their odds of winning and increasing their earnings. However as play continues, this drive to increase bids tails off, while increasing cash balances serves to reduce bids, other things equal. These results are remarkably similar to those reported for common value auctions (Kagel and Levin, 1991). Thus, there seems to be evidence of target income earnings and/or income aspirations on bidding in both common value and private value auctions.

The precise mechanism underlying these effects has not been revealed by our experiment. We conjecture that

[25] Unfortunately past data for auctions without exogenous variation in cash balances is not directly comparable to the data reported here. The lack of such a control treatment is an important deficiency which we intend to correct in further research on this topic.

within the framework of private value auctions, bidders enter the auction with some target earnings in mind and they quickly recognize that they must win an auction to realize these earnings. This in turn promotes higher bidding at first (the learning/adjustment affect observed in the data). However, as cash balances accumulate, subjects come closer to any target earnings they might have in mind. This, in turn, may induce them to take a chance on a bigger score through lowering their bids, even though this reduces the probability of winning. This story is consistent with the bid patterns reported here. Nevertheless the above description of the exact mechanism underlying the cash balance effect is largely conjectural at this point.

Finally, note that the lower bidding with larger cash balances does not result in bidding so low as to be unlikely to win the auction. In general, subjects bid above the risk neutral Nash equilibrium benchmark in first-price private value auctions (Kagel, 1995 surveys these results). Bidding in our experiment is no exception to this rule.[26] At the same time other research shows quite clearly that it is *not* a best response to bid higher than the risk neutral Nash equilibrium bid function in response to bids above the risk neutral benchmark by ones rivals (Selten and Buchta, 1999; Kagel and Richard, 2001). Further, individual bidder cash balances are never high enough in these auctions that, on the basis of the RE estimates of the bid function, predicted bids would be below the risk neutral benchmark. Thus, what bidders are actually doing with larger cash balances is coming closer to, rather than further from, best responding to rivals' bids.

[26]The risk neutral bid factor here is \$6 with n = 4 and \$4 with n = 6, compared to bid factors of \$2.36 and \$1.70 for n = 4 and 6 reported here for RE estimators at the mean value of cash balances.

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Table 1: OLS Estimates of the Bidding Equation With and Without Correcting the Standard Errors.

	Original Sample		Second Sample		Combined Sample	
	Uncorrected Standard Errors	Corrected Standard Errors	Uncorrected Standard Errors	Corrected Standard Errors	Uncorrected Standard Errors	Corrected Standard Errors
CZ_{it}*10E-2 (Cash Balances)	-1.500 (0.758)	-1.500 (2.021)	-5.891 (0.837)	-5.891 (2.746)	-3.726 (0.565)	-3.726 (1.379)
Signal X_{it} (resale value)	0.999 (2.4*10E-4)	0.999 (2.1*10E-4)	0.999 (2.2*10E-4)	0.999 (3.0*10E-4)	0.999 (1.6*10E-4)	0.999 (1.5*10E-4)
Time Trend (=1 / t)	-4.037 (1.708)	-4.037 (2.688)	-8.400 (1.621)	-8.400 (3.382)	-6.424 (1.193)	-6.424 (1.767)
Dummy variable =1 for 6 bidders	0.070 (0.127)	0.070 (0.426)	0.818 (0.126)	0.818 (0.312)	0.466 (0.091)	0.466 (0.280)
Constant	-2.310 (0.278)	-2.310 (0.649)	-0.994 (0.283)	-0.994 (0.501)	-1.683 (0.200)	-1.683 (0.433)
Sample size	1291	1291	1234	1234	2525	2525

Note: Standard errors in parentheses.

Table 2: Summary of cash balance effects on bidding

Method	Original Sample	Second Sample	Combined Sample
OLS Uncorrected Standard Errors	-1.500 (0.758)	-5.891 (0.837)	-3.726 (0.565)
OLS Corrected Standard Errors	-1.500 (2.021)	-5.891 (2.746)	-3.726 (1.379)
Random Effects	-3.062 (0.904)	-3.228 (0.989)	-3.050 (0.667)
Fixed Effects	-3.291 (0.940)	-2.542 (1.042)	-2.937 (0.697)
2SLS (All three instruments)	0.125 (2.752)	-3.174 (2.328)	-1.865 (1.923)
2SLS (Highest and 2nd Highest Signal Instruments)	-0.319 (3.362)	-1.995 (3.126)	-1.025 (2.424)
2SLS (Only Randomized Instrument)	1.170 (4.529)	-3.987 (3.422)	-2.578 (3.007)
3SLS (All three instruments)	-3.319 (1.186)	-4.004 (1.387)	-3.670 (0.903)
3SLS (Highest and 2nd Highest Signal Instruments)	-4.986 (1.459)	-4.547 (1.837)	-4.854 (1.143)
3SLS (Only Randomized Instrument)	-1.456 (2.026)	-5.148 (2.036)	-3.442 (1.447)

Note: Standard errors in parentheses. The two stage least squares standard errors are corrected for correlation across observations for the same individual..

Table 3: First Stage Estimate of Cash Balances.

Variable	Original Sample			Second Sample			Combined Sample		
	IV Set 1	IV Set 2	IV Set 3	IV Set 1	IV Set 2	IV Set 3	IV Set 1	IV Set 2	IV Set 3
Signal * 10E-4	0.070 (0.639)	0.207 (0.723)	-0.356 (0.770)	0.028 (0.570)	-0.288 (0.651)	-0.487 (0.654)	0.029 (0.429)	-0.122 (0.490)	-0.443 (0.507)
Time Trend (= 1 / t)	15.020 (6.107)	-13.825 (6.695)	-63.375 (5.548)	3.959 (5.472)	-19.652 (6.102)	-56.639 (4.688)	9.669 (4.118)	-16.370 (4.576)	-60.771 (3.625)
Dummy variable =1 for 6 bidders	-1.403 (0.368)	-0.764 (0.415)	-4.391 (0.400)	-3.638 (0.323)	-3.661 (0.369)	-5.826 (0.338)	-2.510 (0.246)	-2.202 (0.672)	-5.118 (0.263)
Previous lottery earnings (Z_{it})	0.881 (0.046)	-----	1.032 (0.055)	1.032 (0.053)	-----	1.198 (0.059)	0.936 (0.034)	-----	1.087 (0.039)
Total number of high signals received	1.949 (0.081)	2.127 (0.091)	-----	1.726 (0.089)	1.923 (0.101)	-----	1.850 (0.059)	2.035 (0.067)	-----
Total number of second highest signals received	0.441 (0.089)	0.753 (0.099)	-----	0.147 (0.088)	0.481 (0.099)	-----	0.300 (0.063)	0.626 (0.070)	-----
Constant	5.292 (0.951)	9.491 (1.046)	19.226 (0.748)	8.492 (0.855)	12.083 (0.954)	19.306 (0.635)	6.854 (0.642)	10.757 (0.715)	19.377 (0.489)
Sample size	1291	1291	1291	1234	1234	1234	2525	2525	2525

Table 4: Estimates of the Bidding Equation Allowing Lottery Earnings and Auction Earnings to Have Separate Coefficients.

Variable	Original Sample			Second Sample			Combined Sample		
	3SLS	Random Effects	Fixed Effects	3SLS	Random Effects	Fixed Effects	3SLS	Random Effects	Fixed Effects
Z_{it} *10E-2 (Previous lottery earnings)	0.472 (2.158)	-0.315 (2.106)	-0.426 (2.206)	-4.721 (2.666)	-4.878 (2.506)	-5.994 (2.682)	-1.927 (1.660)	-2.496 (1.598)	-2.599 (1.693)
C_{it} *10E-2 (Previous auction profits)	-6.154 (1.794)	-3.970 (1.099)	-4.268 (1.159)	-3.405 (2.402)	-2.683 (1.244)	-1.336 (1.353)	-5.086 (1.445)	-3.234 (0.824)	-3.055 (0.880)
Signal	0.999 (1.8*10E-4)	0.999 (1.8*10E-4)	0.999 (1.8*10E-4)	0.999 (1.9*10E-4)	0.999 (1.9*10E-4)	0.999 (1.9*10E-4)	0.999 (1.4*10E-4)	0.999 (1.3*10E-4)	0.999 (1.3*10E-4)
Time Trend (= 1 / t)	-6.273 (1.791)	-5.336 (1.658)	-5.614 (1.691)	-6.795 (1.919)	-6.388 (1.639)	-6.048 (1.671)	-4.233 (2.316)	-5.932 (1.163)	-5.897 (1.187)
Dummy variable =1 for 6 bidders	-0.117 (0.423	-0.016 (0.437)	_____	1.055 (0.385)	0.967 (0.312)	____	0.385 (0.282)	0.480 (0.266)	____
Constant	-1.518 (0.473)	-1.885 (0.418)	-1.797 (0.280)	-1.497 (0.521)	-1.641 (0.366)	-1.284 (0.282)	-1.433 (0.349)	-1.768 (0.276)	-1.519 (0.197)
Normal Test Statistic for Equality	-2.101	-1.446	-1.436	0.311	-0.718	-1.397	-1.255	–0.381	-0.219
Sample size	1291	1291	1291	1234	1234	1234	2525	2525	2525
Instruments Utilized	- Total number of high signals received - Total number of second highest signal received			- Total number of high signals received - Total number of second highest signal received			- Total number of high signals received - Total number of second highest signal received		

Table 5: Random Effects, Fixed Effect and Three Stage Least Squares Estimates of the Bidding Equation, With and Without Cash Balances Prior to the Bid Included as a Regressor.

	Original Sample		Second Sample		Combined Sample	
	Random Effects					
	With cash balances	Without cash balances	With cash balances	Without cash balances	With cash balances	Without cash balances
Signal (resale value)	0.999 (1.8*10E-4)	0.999 (1.8*10E-4)	0.999 (1.9*10E-4)	0.999 (1.9*10E-4)	0.999 (1.3*10E-4)	0.999 (1.3*10E-4)
Time Trend (=1 / t)	-6.158 (1.557)	-2.489 (1.124)	-6.065 (1.574)	-2.675 (1.182)	-6.069 (1.106)	-2.630 (0.813)
Dummy variable =1 for 6 bidders	0.023 (0.432)	0.153 (0.426)	0.947 (0.310)	1.156 (0.322)	0.488 (0.265)	0.652 (0.257)
Constant	-1.827 (0.414)	-2.679 (0.326)	-1.642 (0.366)	-2.514 (0.262)	-1.762 (0.275)	-2.598 (0.208)
	Fixed Effects					
	With cash balances	Without cash balances	With cash balances	Without cash balances	With cash balances	Without cash balances
Signal (resale value)	0.999 (1.8*10E-4)	0.999 (1.8*10E-4)	0.999 (1.9*10E-4)	0.999 (1.9*10E-4)	0.999 (1.3*10E-4)	0.999 (1.3*10E-4)
Time Trend (= 1 / t)	-6.449 (1.588)	-2.500 (1.124)	-5.415 (1.608)	-2.742 (1.180)	-5.978 (1.129)	-2.663 (0.813)
Constant	-1.725 (0.275)	-2.575 (0.131)	-1.293 (0.282)	-1.896 (0.135)	-1.514 (0.196)	-2.242 (0.131)
Sample size	1291	1291	1234	1234	2525	2525
	3SLS (IV Set 1)					
	With cash balances	Without cash balances	With cash balances	Without cash balances	With cash balances	Without cash balances
Signal (resale value)	0.999 (1.8*10E-4)	0.999 (1.8*10E-4)	0.999 (1.9*10E-4)	0.999 (1.9*10E-4)	0.999 (1.3*10E-4)	0.999 (1.3*10E-4)
Time Trend (= 1 / t)	-6.398 (1.794)	-2.489 (1.124)	-6.886 (1.884)	-2.675 (1.182)	-6.730 (1.296)	-2.630 (0.813)
Dummy variable =1 for 6 bidders	0.007 (0.419)	0.153 (0.426)	0.893 (0.314)	1.156 (0.322)	0.451 (0.275)	0.652 (0.257)
Constant	-1.749 (0.461)	-2.679 (0.326)	-1.422 (0.453)	-2.514 (0.262)	-1.584 (0.327)	-2.598 (0.208)
Sample size	1291	1291	1234	1234	2525	2525

Note: Standard errors in parentheses. With cash balances excluded, 3SLS reduces to random effects.

Appendix Table A1: Average Profits by Experiment

Experiment Number	Number of Bidders	Number of rounds	Average Profits per Round Standard deviation in parentheses	Average Lottery Earnings per Round Standard deviation in parentheses
1	4	59	\$2.122 (0.877)	0.344 (0.746)
2	6	56	\$2.186 (1.058)	0.292 (0.750)
3	6	47	\$2.194 (1.698)	0.333 (0.746)
4	4	48	\$3.255 (2.059)	0.338 (0.746)
5	4	60	\$2.664 (1.654)	0.263 (0.751)
6	6	58	\$1.081 (0.678)	0.229 (0.751)
7	4	54	\$3.946 (2.171)	0.269 (0.751)
8	6	48	\$2.067 (0.878)	0.200 (0.749)
9	4	56	\$1.873 (0.960)	0.250 (0.752)
10	4	50	\$1.901 (1.264)	0.282 (.751)

Note: The average profits and number of rounds report information from the rounds where the individual who earned the item (high bidder) did not bid above their resale value. The last column provides the average lottery earnings in the entire session.

Appendix Table A2: Random Effects and Fixed Effect Estimates of the Bidding Equation.

Specification	Original Sample		Second Sample		Combined Sample	
	Random Effects	Fixed Effects	Random Effects	Fixed Effects	Random Effects	Fixed Effects
CZ_{it}*10E-2 (Cash Balances)	-3.062 (0.904)	-3.291 (0.940)	-3.228 (0.989)	-2.542 (1.042)	-3.050 (0.667)	-2.937 (0.697)
Signal X_{it} (resale value)	0.999 (1.8*10E-4)	0.999 (1.8*10E-4)	0.999 (1.9*10E-4)	0.999 (1.9*10E-4)	0.999 (1.3*10E-4)	0.999 (1.3*10E-4)
Time Trend (=1 / t)	-6.158 (1.557)	-6.449 (1.588)	-6.065 (1.574)	-5.415 (1.608)	-6.069 (1.106)	-5.978 (1.129)
Dummy variable =1 for 6 bidders	0.023 (0.432)	-	0.947 (0.310)	-	0.488 (0.265)	-
Constant	-1.827 (0.414)	-1.725 (0.275)	-1.642 (0.366)	-1.293 (0.282)	-1.762 (0.275)	-1.514 (0.196)
Sample size	1291	1291	1234	1234	2525	2525

Appendix Table A3: Random Effects and Fixed Effect Estimates of the Bidding Equation. Including the First Period.

Specification	Original Sample		Second Sample		Combined Sample	
	Random Effects	Fixed Effects	Random Effects	Fixed Effects	Random Effects	Fixed Effects
CZ_{it}*10E-2 (Cash Balances)	-3.082 (0.906)	-3.268 (0.939)	-4.166 (1.029)	-3.674 (1.077)	-3.591 (0.680)	-3.514 (0.708)
Signal X_{it} (resale value)	0.999 (1.9*10E-4)	0.999 (1.9*10E-4)	0.999 (2.1*10E-4)	0.999 (2.1*10E-4)	0.999 (1.4*10E-4)	0.999 (1.4*10E-4)
Time Trend (=1 / t)	-6.855 (1.308)	-7.041 (1.332)	-9.663 (1.330)	-9.288 (1.355)	-8.262 (0.932)	-8.209 (0.949)
Dummy variable =1 for 6 bidders	-0.058 (0.434)	-----	0.912 (0.335)	-----	0.432 (0.272)	-----
Constant	-1.780 (0.405)	-1.693 (0.261)	-1.294 (0.378)	-0.912 (0.282)	-1.532 (0.275)	-1.301 (0.191)
Sample size	1332	1332	1280	1280	2612	2612

Appendix Table A4: Two Stage Least Squares Estimates of the Bidding Equation.

Variable	Original Sample			Second Sample			Combined Sample		
	IV Set 1	IV Set 2	IV Set 3	IV Set 1	IV Set 2	IV Set 3	IV Set 1	IV Set 2	IV Set 3
CZ_{it}*10E-2 (Cash Balances)	0.125 (2.752)	-0.319 (3.362)	1.170 (4.529)	-3.174 (2.328)	-1.995 (3.126)	-3.987 (3.422)	-1.865 (1.923)	-1.025 (2.424)	-2.578 (3.007)
Signal X_{it} (resale value)	0.999 (2.4*10E-4)	0.999 (2.1*10E-4)	0.999 (2.2*10E-4)	0.999 (2.0*10E-4)	0.999 (2.0*10E-4)	0.999 (2.0*10E-4)	0.999 (1.5*10E-4)	0.999 (1.5*10E-4)	0.999 (1.5*10E-4)
Time Trend (= 1 / t)	-2.122 (1.960)	-2.644 (4.150)	-0.890 (5.437)	-5.520 (2.723)	-4.271 (3.513)	-6.382 (2.233)	-4.335 (2.296)	-3.391 (2.848)	-5.136 (3.444)
Dummy variable =1 for 6 bidders	0.141 (0.435)	0.121 (0.443)	0.186 (0.463)	0.997 (0.338)	1.075 (0.368)	0.943 (0.376)	0.568 (0.291)	0.614 (0.303)	0.529 (0.317)
Constant	-2.762 (0.840)	-2.638 (0.996)	-3.053 (1.311)	-1.738 (0.683)	-2.060 (0.889)	-1.515 (0.969)	-2.198 (0.572)	-2.431 (0.704)	-2.001 (0.856)
Sample size	1291	1291	1291	1234	1234	1234	2525	2525	2525
Instruments Utilized	- Total number of high signals received - Total number of second highest signals received - Total randomized additions to cash balances	- Total number of high signals received - Total number of second highest signals received	- Total randomized additions to cash balances	- Total number of high signals received - Total number of second highest signals received - Total randomized additions to cash balances	- Total number of high signals received - Total number of second highest signals received	- Total randomized additions to cash balances	- Total number of high signals received - Total number of second highest signals received - Total randomized additions to cash balances	- Total number of high signals received - Total number of second highest signals received	- Total randomized additions to cash balances

Note: Adjusted standard errors in parentheses. Endogenous regressor is the level of cash balances (CZ_{it}) prior to the bid.

Appendix Table A5: Three Stage Least Squares Estimates of the Bidding Equation.

Variable	Original Sample			Second Sample			Combined Sample		
	IV Set 1	IV Set 2	IV Set 3	IV Set 1	IV Set 2	IV Set 3	IV Set 1	IV Set 2	IV Set 3
CZ_{it}*10E-2 (Cash Balances)	-3.319 (1.186)	-4.986 (1.459)	-1.456 (2.026)	-4.004 (1.387)	-4.547 (1.837)	-5.148 (2.036)	-3.670 (0.903)	-4.854 (1.143)	-3.442 (1.447)
Signal	0.999 (1.8*10E-4)	0.999 (1.8*10E-4)	0.999 (1.9*10E-4)	0.999 (1.9*10E-4)	0.999 (1.9*10E-4)	0.999 (1.9*10E-4)	0.999 (1.3*10E-4)	0.999 (1.3*10E-4)	0.999 (1.3*10E-4)
Time Trend (= 1 / t)	-6.398 (1.794)	-8.389 (2.060)	-4.196 (2.632)	-6.886 (1.884)	-7.474 (2.276)	-8.098 (2.456)	-6.730 (1.296)	-8.084 (1.520)	-6.471 (1.807)
Dummy variable =1 for 6 bidders	0.007 (0.419)	-0.067 (0.421)	0.090 (0.426)	0.893 (0.314)	0.859 (0.328)	0.815 (0.327)	0.451 (0.275)	0.387 (0.279)	0.463 (0.281)
Constant	-1.749 (0.461)	-1.285 (0.518)	-2.271 (0.651)	-1.422 (0.453)	-1.275 (0.561)	-1.107 (0.610)	-1.584 (0.327)	-1.255 (0.380)	-1.646 (0.452)
Sample size	1291	1291	1291	1234	1234	1234	2525	2525	2525
Instruments Utilized	- Total number of high signals received - Total number of second highest signal received - Total randomized additions to cash balances	- Total number of high signals received - Total number of second highest signal received	- Total randomized additions to cash balances	- Total number of high signals received - Total number of second highest signal received - Total randomized additions to cash balances	- Total number of high signals received - Total number of second highest signal received	- Total randomized additions to cash balances	- Total number of high signals received - Total number of second highest signal received - Total randomized additions to cash balances	- Total number of high signals received - Total number of second highest signal received	- Total randomized additions to cash balances

Note: Endogenous regressor is the level of cash balances (CZ_{it}) prior to the bid.

Appendix 1: Instructions

This is an experiment in the economics of market decision making. Funding for this research has been provided by the University of Pittsburgh. The instructions are simple, and if you follow them carefully and make good decisions you may earn a CONSIDERABLE AMOUNT OF MONEY which will be PAID TO YOU IN CASH at the end of the experiment.

1. In this experiment we will create a market in which you will act as buyers of a commodity in a sequence of trading periods. A single unit of the commodity will be auctioned off in each trading period. There will be several trading periods.
2. Your task is to submit bids for the commodity along with several other buyers. In each trading period you will be assigned a RESALE VALUE for the commodity. This indicates the value to you of purchasing the item. This value may be thought of as the amount you would receive if you were to resell the unit. The process of determining the resale values will be described in Sections 7 and 8 below.
3. The high bidder earns the item and makes a profit equal to the difference between his/her resale value and the high bid. That is

   (Resale Value) – (High Bid) = Profits

   for the high bidder. If you do not make the high bid on the item, you neither gain nor lose money from bidding on the item. Note that bids in excess of your resale value will result in losses if you earn the item. Also note that if you earn the item at a price equal to its (your) resale value your profit will be zero.
4. At the end of each trading period you will automatically be entered in to a lottery where you have a 50 – 50 chance of either earning $1.00 or losing 50¢. Over the course of the experiment you should earn positive average profits of 25¢ each auction period. Earnings from the lottery are totally unrelated to the auction outcomes. They are just a source of extra earnings.
5. You will be given a starting cash balance of $7.00. Your earnings from the auction and your lottery earnings will be added to this starting cash balance with your end of experiment balance paid to you in CASH at the end of the experiment. In addition you will receive $5.00, as promised, for participating in the study.
6. During each auction period you will be bidding in a market in which 4 other participants are also bidding. There will be two separate markets operating simultaneously in each auction period. The market to which you are assigned is randomly determined prior to the start of each auction period so that the other bidders in your market will change between auction periods.

7. Resale values will be assigned as follows. First we will randomly draw a number between $25 and $975 inclusively. Call this number D*. For each auction any value between $25 and $975 has an equally likely chance of being drawn as D*.
8. Once D* is determined, resale values will be selected from an interval whose lower bound is D* - 12, and whose upper bound is D* + 12. Any value within the interval has an equally likely chance of being drawn and being assigned to one of you as your resale value. For example, suppose that D* is $648.50. Then each of you will receive a resale value which will consist of a randomly drawn number between $636.50 (D* - 12 = 648.50 – 12) and $660.50 (D* + 12 = 648.50 + 12). Any number in this interval has an equally likely chance of being drawn as D*.
9. Your resale values are strictly private information and are not to be revealed to anyone else. At the end of each trading session all of the bids in your market will be presented on your computer screen in descending order along with the resale values that correspond to these bids. You will also be told the profits of the high bidder in your market.
10. As already noted your cash profits depend upon your ability to buy a unit at a price below your resale value. There are clear tradeoffs in deciding what to bid: the lower you bid relative to your resale value, the higher your profits should you be the high bidder, but the lower your chances are of being the high bidder. Further, the exact nature of this tradeoff depends on what other bidders are doing in terms of these tradeoffs also.
11. No one may bid less than $0.00 for the item. Bids must be rounded to the nearest penny to be accepted. In the case of ties for the high bidder, the computer will randomly determine who will earn the item.
12. You are not to reveal your bids, or profits, nor are you to speak to any other subject while the experiment is in progress. This is important to the validity of the study and will not be tolerated.
13. As promised, everyone will receive $5 irrespective of their earnings for participating in the experiment.
14. We will have three practice periods to familiarize you with the procedures and accounting rules. This will be followed by 30 periods played for cash.
15. Review. Let's summarize the main points:
    - The high bidder in each period receives a profit equal to his/her resale value minus the bid. Everyone else in the period earns $0.
    - Profits from the auctions and lottery earnings will be added or subtracted from your cash balances.

- All bids must be greater than $0.00
- D* in each market will be between $25 and $975. Resale values will be drawn between D* - 12 and D* + 12.
- You will be randomly assigned to one of two markets each period.
- There will be 6 bidders in total in your market.

Are there any questions?