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Randomization, Endogeneity and Laboratory Experiments

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Abstract

In conducting experiments with multiple trials, outcomes from previous trials can impact on current behavior. One of the most obvious cases in which this can happen, and the case considered in this paper, is in an auction market experiment, where earnings from previous auction trials alter cash balances which, in turn, can affect bidding behavior. (The most obvious mechanism for such a result, within standard theory, is if bidders are risk averse and do not have constant absolute risk aversion. One can imagine a number of non-standard reasons for such effects as well.) Use of OLS regressions with cash balances included as a right hand side variable are likely to lead to a biased estimate of the cash balance effect since the variation in cash balances is largely related to differences in bidding strategies across individuals. Fixed effect regressions can commonly control for these endogeniety problems at the potential cost of obtaining inefficient estimates, since this estimator does not exploit between-individual variation. This paper addresses this problem in two ways. First we consider an experimental design that reduces the potential bias of OLS estimates while increasing the precision of fixed effect estimates. Second, we consider instrumental variables estimation of the cash balance effect where the instruments are produced by the experimental design. To the best of our knowledge, neither of these approaches has been explored in the experimental literature.

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In this paper we investigate the role of individual cash balances on bidding behavior in affiliated private value auctions. An important, yet unresolved, question in experimental economics is whether or not cash balances play a role in multi period laboratory experiments. The typical experimental design will have a series of twenty to thirty auctions in which a winner will be declared each auction period and subjects will be paid their cumulative earnings from the experimental session. Current and past earnings will impact on subjects' current cash balances, which in turn can affect their future bidding. For example, in common value auctions, where bidders are subject to the winner's curse, legitimate arguments can be made for higher cash balances either increasing or decreasing individual bids, other things equal (Hansen and Lott, 1991; Kagel and Levin, 1991). Alternatively, in a one-shot auction low cash balances may promote more aggressive bidding as subjects are no longer liable for all of their losses. However, in a sequence of auctions low cash balances may promote less aggressive bidding as bankruptcy will result in removal from the auction and lost profit opportunities in later auctions. In first-price private value auctions, where bankruptcies are typically not a problem, there is persistent bidding above the risk neutral Nash equilibrium reference point, which may be accounted for by bidder risk aversion. To the extent that bidders are indeed risk averse, only in the case of constant absolute risk aversion will cash balances not affect bidding.[1]

The few experimental studies that explicitly consider a role for cash balances in the bid function typically treat it as an exogenous explanatory variable in a regression estimating the bid function (Hansen and Lott 1991 or Kagel and Levin 1991). There are two possible problems with this approach. First, there may be insufficient variation in the cash balances variable to identify its effect in the bid function. Moreover, the available variation in current cash balances across individuals is usually entirely related to differences in past bidding strategies across individuals. If unobserved differences in bidding behavior are correlated over time for the same individual (as is likely to be the case), then introducing cash balances as an explanatory variable is likely to lead to a simultaneous equation problem. Fixed effect

[1] There is considerable controversy surrounding the question of whether bidding above the risk neutral Nash equilibrium in first-price auctions in fact results from risk aversion or some other unexplained factors (see Kagel, 1995; also Cox, Smith and Walker, 1992 and Kagel and Roth, 1992). Nevertheless the question of potential effects of changing cash balances in private value auctions remains of interest.

regressions address the second (simultaneity) problems at the cost of accentuating the problem of insufficient variation in cash balances, since this estimator does not utilize between-individual variation.

This paper addresses the above issues in two ways. First we consider an experimental design that increases the exogenous variation in cash balances. In this design we randomly assign a bonus (which may be positive or negative) to each individual in each auction period. This randomization will reduce the potential bias of OLS estimates and increase the precision of fixed effect estimates. 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. previous signals) produced by the experimental design.

Our paper makes three contributions to the existing literature in experimental economics. Firstly, 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. Second, we demonstrate how the sample design may be altered to reduce simultaneity problems and increase the efficiency of econometric estimators. Third. we provide substantial new evidence on the effects of cash balance in affiliated private value auction experiments.

This paper is organized as follows. Section II describes the structure of affiliated private value auction experiments. In Section III, we discuss different econometric approaches to estimating the cash balance effect in standard experimental designs. In section IV, we propose a randomization strategy and discuss how this approach will affect simultaneity and efficiency problems in experiments. In section V we discuss our experimental design. Section VI contains our empirical results. We find that in standard sample sizes that the random effects and fixed effects estimators perform relatively well. They produce negative estimates of the cash balance effect which are relatively precise but which show some sensitivity to how we model the adjustment process. Instrumental variable estimates are very unstable, suggesting that standard sample sizes (50 individuals over 30 periods) are insufficient to allow the desirable asymptotic properties of IV estimation to hold. Finally, our results suggest that researcher may want to consider specifying more flexible forms of the adjustment process within an experiment. We conclude the paper in Section VII.

Section II: Structure of Affiliated Private Value Auction Experiments

We begin with a description of affiliated private auction experiments. In a affiliated private value auction each bidder has perfect information regarding her own value for the object at auction. However, private information across bidders is positively correlated, and higher values of the item for one bidder make higher values for other bidders more likely. Typically experimenters design their experiments as follows. A complete description of the structure of such an experiment is provided in Kagel, Levin and Harstad (henceforth referred to as KLH) (1987). In each auction period, a random number x_o, is drawn from a uniform distribution on the interval $[x_l, x_u]$. Each subject receives a private information signal (resale value) x_i, which is randomly drawn from a uniform distribution centered on x_o with upper bound $x_o + \varepsilon$ and lower bound $x_o - \varepsilon$.,[2] where epsilon is set by the researcher. The distribution underlying the signal values, the value of ε and the interval $[x_l, x_u]$ are common knowledge, but subjects do not know the value of x_o. The value of ε usually varies across auctions and all changes are announced. Given x_i, ε, and the endpoint values, each bidder can compute an upper and lower bound on the value of x_o.

In each period the commodity is sold to the high bidder in the period (these are first price auctions). The high bidder earns profits equal to the private signal (x_i) less the amount bid. The other bidders earn zero profits for that auction period. [3] After each round, the value of $x_{o,}$ the bids (in descending order) and the earnings of (but not the identity of) the high bidder are announced.

For private information signals in the interval $[x_l + \varepsilon, x_u - \varepsilon]$, the risk neutral Nash equilibrium bid function is $x_i - 2\varepsilon/n + Y_i/n$ where Y_i is a negative exponential and n is the number of bidders.[4] The expected RNNE profit per period is approximately equal to 2ε/N. In these models, each agent bids as if she has received the highest signal since this is when she wins and her cash balances increase. In a first-price auction, it is clear that bidders should bid below their private resale values.

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[2] In the KHL experiment ε refers to the maximum range from x_o a resale value can be created. It is symmetric and is determined by the experimenter.

[3] Bids are restricted to be nonnegative.

[4] This expression is valid only for the case where x_o is not known The variable Y_i is calculated as $Y_i = 2\varepsilon / (n + 1) * \exp -\{[n / 2\varepsilon][x_i - (x_l + \varepsilon)]\}$. This becomes negligible rapidly as x moves beyond $x_l + \varepsilon$.

Important questions of interest to previous researchers are i) how far below these resale values do subjects discount (i. e. how much to discount) and ii) what are the operating principles underlying these bids. A garden variety estimating equation for the bid function is given by

$$B_{it} = \alpha + (_1 RV_{it} + (_2 C_{it} + (_3 t^{-1} + (_4 \varepsilon_{it} + u_{it}. \qquad (1)$$

The bid (B) is a linear function of a constant, the resale value (RV), cash balances *prior* to the bid (C), half of the total range the value of ε which determines the range around x_o from which the resale value can be drawn, and a time trend (1/t) which captures the learning and adjustment process in the session. Many researchers omit cash balances as an explanatory variable. However, it is interesting to examine the effect of cash balances in this equation. If this effect is significantly different from zero, this can indicate i) deviations from constant absolute risk aversion or ii) subjects evaluating outcomes in terms of deviations from the current status quo in each auction period. Moreover, if cash balances have a significant effect on bidding behavior, one cannot treat the auction series as a collection of single shot auctions.

In a recent survey, Kagel (1995) concludes that the cash balance variable does not achieve statistical significance at anything approaching conventional levels in affiliated private value auction experiments. However, previous evidence is potentially misleading since previous studies have only limited variation in the cash balance variable. Moreover, the available variation in this variable is likely to be endogenous, since it is based on past bidding behavior, and one would expect unobservables affecting past and current bidding behavior to be correlated.[5] In the next section we discuss how standard econometric approaches to simultaneous equation bias may be employed to address the issue of endogenous cash balances. In section IV we show how endogeneity problems may be reduced and the efficiency of econometric estimation may be increased by altering the experimental design.

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[5] An additional problem with the earlier work is that regressions were not restricted to the region $[x_l + \varepsilon, x_u - \varepsilon]$ where the RNNE bid function does not change.

Section III: Problems of Efficiency and Simultaneity in Experiments

For expository purposes, assume for now that cash balances is the only variable that affects bidding behavior. (The other explanatory variables in the bid function (1) are randomly generated each period and thus are orthogonal to current cash balances. Thus this modification will not generally affect the results but will simplify our discussion). Thus we rewrite (1) as

$$B_{it} = \alpha + \gamma C_{it} + u_{it} . \qquad (2)$$

Now suppose for the moment that simultaneity is not an issue. The estimated variance of the OLS estimate of the cash balance effect in equation (2) equals

$$\mathrm{Var}(\hat{\gamma}_{ols}) = \hat{\sigma}^2[\Sigma_{it}(C_{it} - \bar{C})^2]^{-1}, \qquad (3)$$

where $\hat{\sigma}^2$ is the variance of the error term in (2).[6] 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 imprecise. As a result, one may not be able to reject the hypothesis that it is significantly different from zero, and researchers may draw the inference that cash balances do not affect bidding behavior when in fact that is the case.

Next consider the possibility that the OLS estimator may suffer from simultaneous equation bias due to correlation between cash balances and the error term in (2).[7] As noted above, current cash balances are likely to act as a proxy for lagged values of the dependent variable. Individuals start with identical cash balances, and cash balances only change as a result of profits and losses resulting from previous bidding behavior. Thus cash balances are

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[6] Here we are ignoring for simplicity the fact that the error terms will be correlated across time for the same individual, and that a random effects estimator should be used to estimate (2). However, the same argument will go through for a random effects estimator but the notation will become more complex. Alternatively, one can adjust the estimated covariance matrix for the OLS estimation of the parameters to allow for this correlation in the error structure. See Hsiao (1986) for a comprehensive discussion of estimators appropriate for panel data, including random and fixed effect estimators.

[7] Note that simultaneous equation bias will not be a problem with any of the other explanatory variables in (1) as these variables are randomly generated in the experiment.

likely to be correlated with the error term in (2), and the inconsistency in the OLS estimate is given by

$$\text{plim}(\hat{g}_{ols} - () = \text{plim}(\textstyle\sum_{it} C_{it}u_{it} / N) / \text{plim}(\sum_{it}(C_{it} - \bar{C})^2 / N), \qquad (4)$$

where N is the sample size.

Some researchers have addressed this problem by adopting an error components structure for the residual in equation (1) or (2),

$$u_{it} = \eta_i + v_{it}, \qquad (5)$$

and assuming that the cause of the correlation between cash balances and the residual is correlation between cash balances and the permanent component η_i. If one treats η_i. as a parameter to be estimated, consistent estimates can be obtained from a fixed effect (FE) estimator. However, the cost of obtaining consistency in this fashion is an increase in the variance of the estimated cash balances coefficient. This variance is now given by[8]

$$\text{Var}(\hat{g}_{fe}) = \hat{s}^2[\textstyle\sum_{it}(C_{it} - \bar{C}_i)^2]^{-1}. \qquad (6)$$

The FE estimator only considers variation around individual means and thus the expected value of the variance in (6) will be greater than the expected value of (3).[9]

An alternative to the fixed effect procedure would use an instrumental variables (IV) approach such as two stage least squares (2SLS) to estimate equation (2). To implement 2SLS estimation of (1) or (2), we need to find instrumental variables. An instrumental variable must have two properties. First, it must be uncorrelated with the error term in (1) or (2). Second, it must be correlated (preferably highly correlated) with cash balances.

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[8]For simplicity, in equation (6) we have ignored the fact that the estimate of s^2 will differ between the OLS and fixed effect estimator. Note that if we compare the fixed effect estimator to a random effects estimator, this difference will be eliminated.

[9]Hausman (1978) offers a test of whether the coefficients are being biased by adopting a random effects specification versus the fixed effects specification.

A natural instrumental variable in our setting is of the total number of high signals received prior to the current period, since individuals receiving the high signal in a given period are the most likely to have the winning bid in that period, as predicted by Nash equilibrium bidding strategy. By the same reasoning, the total number of previous periods that the individual received the second highest signal is a second potential instrumental variable. In Table 1, we present summary statistics from KHL (1987) which indicate that the individuals who drew the two highest signals won almost 99% of the auctions. Moreover, whether an individual has the highest or second highest signal is in a given period is determined randomly for each individual and will be uncorrelated the error term. (Note that these variables are also valid instruments for real bidding equation (1)). Thus we regress cash balances on the instruments in the first stage equation

$$C_{it} = A_0 + A_1 D_{1it} + A_2 D_{2itt} + w_{itt} \,, \qquad (7)$$

where D_{1it} and D_{2itt} denote the total number of highest and second highest signals received respectively in previous auction periods.[10] We then run the second stage equation

$$B_{it} = \alpha + (\hat{C}_{it} + u_{it,} \qquad (8)$$

where $\hat{C}_{it}$ is the predicted value of cash balances based on estimates of equation (7).[11] The variance of the estimated cash balance coefficient from this equation is given by

$$\mathrm{Var}(\hat{g}_{2sls}) = \hat{s}^2 [E_{it}(\hat{C}_{itt} - \bar{C})^2]^{-1} \,. \qquad (9)$$

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[10]A third instrument aims 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. An examination of this data, reveals that approximately 90% of the time that the high signal holder did not win the auction round can be found where the value of this instrument is less than 10%.

[11] In practice when estimating (1) by 2SLS, one would also include the other explanatory variables from (1) in the first stage equation. We would not expect them to play much role in explaining cash balances given that they are randomly generated.

In general, the variance of the estimated coefficient from 2SLS estimation of (9) may be larger or smaller than that for the coefficient estimated from the fixed effect model given by (6). However, the better job that the instrumental variables do in predicting cash balances in terms of the fit equation, the higher the variance of the predicted cash balances and the lower the variance of the 2SLS estimates.[12] A major advantage of using data generated from the laboratory is that these instruments are strictly exogenous since in the design of the experiment, these variables are chosen independently of the individual and cannot be affected by the individual.[13]

At this point it is worth comparing the sampling properties of the OLS, FE estimator and the 2SLS estimator. The OLS and FE estimators are unbiased in small samples if the error term in (2) (or equation (1)) is normally distributed. The OLS, FE and 2SLS estimates are consistent and asymptotically normal,.independently of whether the error term is normally distributed. However, there are two caveats concerning the instrumental variables estimates. First, larger samples are likely to be necessary for the asymptotic distribution theory to hold than for OLS or FE (see Buse 1992). Second, the instrumental variables estimates be biased if the instrument variables are weak in the sense of not doing a good job of predicting the endogenous variable. In general, the weaker the instruments the greater the bias of the IV estimate.[14]

IV. Randomization of Cash Balances

As noted above, the OLS and FE estimates will perform poorly if there is insufficient variation in cash balances. Further, the 2SLS estimator will perform poorly if the instruments are weakly correlated with the cash balances. In this section we demonstrate how the experimenter can alter the experimental design to address all of these problems. Specifically,

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[12] Just as the case with the OLS estimates, one can obtain more efficient estimates using procedures such as such as 3SLS and optimal GMM, although one can run into a small sample bias problem with such estimators - see Altonji and Segal (1994)

[13] Again, Hausman (1978) offers a test of the null hypothesis that cash balances are exogenous.

[14] See Bound, Jaeger and Baker (1993) and Staiger and Stock (1997). Staiger and Stock suggest an examination of the first stage F statistic. This statistic tests the hypothesis that the instrumental variables and all other explanatory variables do not enter the first stage regression. Bound et al focus on the joint significance of the explanatory variables which are excluded from the second stage equation.

we introduce a lottery in each period for each participant with payoff z_{it} of the following form

$$z_{it} = -a \text{ with probability } .5 \qquad (10)$$
$$z_{it} = b \text{ with probability } .5$$

where b > a so the expected payoff is positive. We keep the payoff positive to compensate individuals for the uncertainty introduced by the lottery. Define

$$Z_{it} = \sum_{0}^{t-1} z_{it}$$

In terms of our previous notation,

$$Y_{it} = C_{it} + Z_{it}$$

We rewrite equations (1) and (2) in terms of Y_{it} as

$$B_{it} = \alpha + (_1 RV_{it} + (_2 Y_{it} + (_3 t^{-1} + (_4 \varepsilon_{it} + u_{it} \qquad (1')$$

$$B_{it} = \alpha + (Y_{it} + u_{it} . \qquad (2')$$

If simultaneity is not an issue, then this randomization will increase the efficiency of OLS estimation. Now the estimated variance of the OLS estimate of the cash balance effect equals

$$\text{Var}(\hat{g}_{ols}) = \hat{s}^2[E_{it}(Y_{it} - \bar{Y})^2]^{-1} \qquad (3')$$
$$= \hat{s}^2[E_{it}[(C_{it} - \bar{C}) + (Z_{it} - \bar{Z})]^2]^{-1}$$

which will be smaller (in an expected value sense) than the previous expression in equation (3).

If simultaneous equation bias is a problem, the randomization (10) will lessen the inconsistency of the OLS estimator

$$\text{plim}(\hat{g}_{ols} - (\,) = \text{plim}(E_{it}\, C_{it}u_{it)}\, /N) \,/\, \text{plim}(E_{it}(Y_{it} - \bar{Y})^2 /N). \qquad (4')$$

In (4') we have exploited the fact that Z_{it} is uncorrelated with u_{it} by design, and thus the inconsistency in (4') is smaller than in (4).

Now consider the FE estimator after randomization. The variance of the FE estimator is now given by

$$\text{Var}(\hat{g}_{fe}) = \hat{s}^2[E_{it}(Y_{it} - \bar{Y}_i)^2]^{-1} . \qquad (6')$$

$$= \hat{s}^2[E_{it}[(C_{it} - \bar{C}_i) + (Z_{it} - \bar{Z}_i)]^2]^{-1}$$

Again the variance in (6') is smaller (in an expected value sense) than the variance of the FE estimate without randomization in (6).

Finally, consider the 2SLS estimator after the randomization in (10). By design, we are introducing an additional instrument which will be strongly correlated with cash balances Y_{it} but uncorrelated with the error term in (2') and (1'). The first stage equation for Y_{it} becomes

$$Y_{it} = A_0' + A_1'D_{1it} + A_2'D_{2itt} + A_3'Z_{it} + w'_{itt} . \qquad (7')$$

Thus randomization will improve the fit of the first stage equation and thus should reduce the variance of the 2SLS estimator, as well as improving its small sample properties.

Section V: Experimental Design

Our design involves several minor modifications to that of the affiliated private value auction experiments described in section II. In order to focus on the role of cash balances we held ε fixed at 12. The range of $[x_l, x_u]$ equaled [25,975]. This range is represents a significant increase over previous studies in an attempt to increase the availability of data for analysis.[15]

Subjects were recruited for a session consisting of a series of thirty auction periods. In each auction period, a single unit of a commodity was sold to the high bidder at the high bid price, with bidders submitting sealed bids for the item. The high bidder earned profits equal to her value less the amount bid; other bidders earned zero for the auction period. At the conclusion of the auction period all the bidders were entered in to a lottery which (as explained in the preceding section) allows for re-randomization each period. The values of a and b were set at $1.00 and -0.50¢ respectively. The subjects were told that the lottery was designed simply as a source of extra earnings and that over the course of the experiment they would earn positive average profits of 25¢ each period from the lottery. Furthermore, they were told that the outcomes in the lottery were completely unrelated to the auction outcomes (which they were).

In each auction period there were two markets in operation and the number of bidders participating in a market was constant within an experiment. Each period the subjects were randomly assigned to one of the two markets each period to avoid any possible reputation effects. Subjects were recruited from undergraduate economics classes at the University of Pittsburgh. A total of five sessions with 48 different subjects were run.

The number of bidders participating in the auction was the sole item that varied between the experimental sessions. For sessions 1, 4 and 5, eight subjects were recruited and two markets of four operated each period. The remaining sessions recruited twelve subjects overall and two markets of six operated in each period. We varied the number of bidders between sessions since theory suggests that as the number of rivals within an auction increases, individuals will bid closer to their resale value. The distribution underlying the resale values, lottery payoffs, the value of ε, the number of competing bidders, and the interval $[x_l, x_u]$ were common knowledge.

Each subject was given a starting cash balances of $7.00. In the event that an individual mistakenly entered a bid that would cause her cash balances to become negative,

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[15]As noted above, the RNNE bid function will take a different form if the signal is outside this range, and thus we discard observations for which this occurs.

she was given a new starting cash balance of $7.00 but had $5.00 subtracted from her end-of-experiment earnings. At the end of each auction period, all bids were posted from highest to lowest, along with the corresponding signal values (bidder identification numbers were suppressed) and the profits of the high bidder in their market was reported to all bidders. The subjects were given three practice periods to accustom themselves to the rules and accounting procedures. Each subject was given a $5.00 participation fee[16].

For the purposes of data analysis, we restrict the data to the interval $x_l + \varepsilon \leq x_i \leq x_u - \varepsilon$ since the RNNE bid function will change outside this interval. We also eliminate all observations which constitute bidding errors. These bidding errors include all bids above the resale value and those bids below the resale value - ($2*\varepsilon$). It should be noted that there were three individuals who bid above their resale value repeatedly as they did not understand the rules and believed it was more important to win the auction rather than make a profit[17].

Table 2 shows the relationship between average profits and number of bidders by experiment. It is interesting to note that in experiment session 1, which contained four bidders, average profits were the lowest. In fact profits across all session with four bidders were only approximately 45¢ higher when average profits in sessions where the number of bidders was six. This difference in average profits by session size is substantially less than that which is predicted by theory.

VI: Econometric Results

Table 3 presents the OLS estimates for the linear bid function given by equation (1') in column (1)[18]. Column (2) contains the random-effects estimates of (1'); these are GLS estimates for the case of the error components model (5) where η_i is treated as a component of the error term. Column (3) contains the fixed effect estimates. Note that all three estimates of the cash balance effect are negative and statistically significant at standard confidence levels, but the OLS estimate is substantially smaller in absolute value than the RE and FE

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[16] The instructions are included in Appendix 1.

[17] These individuals are subject number 1 and 10 in session 3 and subject number 5 in session 4. The latter two subjects took approximately 15 rounds to determine that making a profit was more important.

[18] In our experimental design we held , fixed at 12 in all the sessions. Thus, we remove it from all of our estimates of (1') since it is collinear with the constant.

effect estimates.[19] A Hausman (1978) test indicates that one cannot reject the random effects specification in favor of the fixed effects specification. Thus the endogeneity of cash balances does not appear to be a problem, at least after the randomization (10). Perhaps surprisingly, the number of bidder does not appear to affect bidding behavior.[20] Of course, these results may simply indicate the need for a better experimental design with respect to this variable, especially given the wide confidence interval for this coefficient implied by the parameter estimates.

Before discussing the 2SLS estimates, 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 highest signal and iii) previous net lottery earnings
Table 4 indicates that in our data individuals receiving the highest or second highest signal made the highest bid in over ninety-five per cent of the auctions. Table 5 shows the raw correlation between each instrument and cash balances. Each of the instruments has a substantial correlation with the potentially endogenous variable cash balances.

Table 6 shows three first stage equations for cash balances.. Column (1) contains the results when we use all three of instruments. Column (2) presents the results when we use only the highest signal and second highest variables as instruments, while column (3) presents the results when we use only the lottery earnings as instruments. In each specification the instruments are very statistically significant. Thus each would be considered a 'good instrument'. Table 7 presents the 2SLS estimates for the same three specifications of the instrument set. In each case the cash balance coefficient is positive and statistically insignificant. These results are in sharp contrast to those presented in Table 3 for the OLS, RE and FE estimates. The difference in the estimates between Table 3 and Table 7 may indicate that the sample size is too small to avoid bias in 2SLS estimation. However, the difference in the results may also indicate model misspecification.

[19] The standard errors for the OLS results have not been corrected for correlation across bids for the same individual, and thus should be considered approximate. We will address this issue in future work.
[20] The number of bidders variable drops out of the fixed effect specification since it is constant across individuals. However, we can use the approach of Hausman and Taylor (1981) to recover this coefficient and will report on this calculation in a future draft

We investigated two possible sources of misspecification. First, we considered the possibility that the relationship between bidding behavior and cash balances is nonlinear. by also including a term in cash balances squared. This squared term in cash balances never approached statistical significance at conventional confidence levels.

We also investigated the possibility that learning and adjustment process was misspecified since cash balances are trending upward as the number of periods increases. We included dummy variables for five groups of auction periods (after the practice periods): 1) periods 1 to5; 2) periods 6 to10; 3) periods 11 to 15; 4) periods 16 to 20; and 5) periods 21 to 25. (Thus periods 26 to 30 are the control periods.) The results for the OLS, RE and FE specification are contained in Table 8. These results indicate that only the first dummy variable (for periods 1 to 5) is significantly different from zero, suggesting that all adjustment takes place in the first five periods. Therefore we reestimated the model replacing the (inverse) time trend with a dummy variable for the first five periods. The OLS, RE and FE estimates are in Table 9. The cash balance variable is still negative for each estimation method but the RE and FE estimates fall considerably in absolute value. Further, the cash balance variable is not statistically significant when we use OLS, and the RE and FE estimates are now at the margin of statistical significance (i.e. significant at the ten per cent level but not at the five per cent level). Thus our results for cash balances are somewhat sensitive to how we model the adjustment process. Our results also suggest that experimenters may wish to consider flexible alternatives to simple time trends when analyzing bidding behavior.

We next consider 2SLS estimation with a time dummy for the first five periods. The first stage equations are contained in Table 9. We see that the instruments continue to play an extremely strong role in the first stage equations. The 2SLS estimates are contained in Table 10. Again they are positive and do not come close to being statistically significant at standard confidence levels.

VII: 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. Thus we discuss econometric estimators aimed at dealing with this problem. 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. Thus we develop and implement an experimental design which increases the variation in cash balances. This experimental design involves partially randomizing cash balances each period and will also mitigate potential endogeneity problems.

Given our experimental design, we find that random effects and fixed effect estimators generally provide negative and statistically significant estimates of the cash balance effect, although the result is somewhat sensitive to how we model the adjustment process. 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 affiliated private value auctions. Finally, we find that 2SLS estimates are imprecise and may suffer from small sample bias, even though the instruments we use are exogenous by design and strongly correlated with the endogenous regressor.

Our results suggest several avenues for additional work. First, it will be interesting to consider using larger sample sizes in estimation. Such samples may reduce bias in the 2SLS estimates as well as increasing the precision of our random effects and fixed effects estimates, particularly when we use time dummies to model the adjustment process. Second, we will consider more efficient simultaneous equation methods such as three stage least squares. Third, we are currently investigating the role of cash balances in common value auctions using estimation methods and an experimental design similar to those presented above. Fourth, it will be interesting to consider experimental designs which allow us to estimate the effect of the number of bidders with greater precision.

Table 1: Ranking of Signals Received and Auction Round Winners in KHL (1987)

Rank of Signal Received in a Given Round	Number of Auction Winners in Rounds Restricted to $x_l + \varepsilon$ ˜ x_i ˜ $x_u - \varepsilon$	Percentage of Auction Winners in All Rounds Restricted to $x_l + \varepsilon$ ˜ x_i ˜ $x_u - \varepsilon$
1 (highest)	63	73.3%
2	22	25.6%
3	1	1.1%
4	0	0
5	0	0
6 (lowest)	0	0

Table 2 Average Profits by Experiment[21]

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	$2.12 (0.87)	0.34375 (.7456727)
2	6	59	$2.16 (1.11)	0.291667 (.7498839)
3	6	47	$2.19 (1.69)	0.33333 (.7463934)
4	4	48	$3.25 (2.05)	0.3375 (.746435)
5	4	60	$2.66 (1.64)	0.2625 (.751463)

[21] The average profits and number of rounds report information from the rounds where the individual who earned the item (high bidder) bid below their resale value. Thee last column provides the average lottery earnings in the entire session.

Table 3: OLS, Random Effects and Fixed Effects Estimates of the Bid Equation (Standard errors in parentheses, N= 1350)

Specification	Ordinary least squares	Random Effects	Fixed Effects
Cash Balances	-.0184 (7.678*10E-3)	-.0304 (8.948*10E-3)	-.0321 (9.316*10E-3)
Signal (resale value)	.9992 2.363*10E-4	.9993 1.876*10E-4	.9993 1.877*10E-4
Number of Bidders	-.0046 (.0644)	-.0311 (.215)	Dropped
Time Trend (=1 / T)	-5.512 (1.412078)	-6.723 (1.299185)	-6.895 (1.323015)
Constant	-2.01 (.443)	-1.61 (1.140)	-1.70 (.2575)

Table 4: Ranking of Signals Received and Auction Round Winners

Rank of Signal Received in a Given Round	Number of Auction Winners in Rounds Restricted to $x_l + \varepsilon \sim x_i \sim x_u - \varepsilon$	Percentage of Auction Winners in All Rounds Restricted to $x_l + \varepsilon \sim x_i \sim x_u - \varepsilon$
1 (highest)	217	81.0%
2	42	15.7%
3	9	3.3%
4	0	0
5	0	0
6	0	0

Table 5: Correlation Between the Level of the Cash Balances and the Instrumental Variables (N=1309)

Instrument	Correlation
Total lottery earnings in previous periods (Z_{it}) additions to cash balances	0.5934

Total number of high signals received previously	0.6919
Total number of second highest signal received previously	0.4511

Table 6: First Stage Estimates. Dependent Variable is Level of Cash Balances Prior to the Bid (Standard errors in parentheses, N= 1309)

Variable	Specification 1	Specification 2	Specification 3
Signal	-7.92*10E-5 (6.226*10E-4)	8.93*10E-5 (7.046*10E-4)	-3.8*10E-5 (7.36*10E-4)
Time Trend (= 1 / T)	14.593 (6.055)	-14.091 (6.64)	-50.69 (4.38)
Number of bidders	-0.731 (.181)	-0.407 (.204)	-2.14 (.194)
Total lottery earnings in previous periods (Z_{it}) additions to cash balances	0.878 (0.0458)	*****	1.066 (.0529)
Total number of high signals received previously	1.952 (.0799)	2.124 (.0899)	*****
Total number of second highest signal received previously	0.4298 (0.088)	0.747 (0.0976)	*****
Constant	8.406 (1.436)	11.265 (1.616)	26.6678 (1.173)
First Stage F statistic	370.295	289.6305	297.738

Table 7: Two Stage Least Squares Estimates. Dependent Variable is Level of Bid Endogenous Variables are the level of cash balances prior to the bid (Standard errors in parentheses, N= 1309)

Variable	Specification 1	Specification 2	Specification 3
Cash Balances	4.166*10E-4 (.011)	-5.257*10E-3 (.013)	6.159*10E-3 (.016)
Signal	.9993 (2.316*10E-4)	.9994 (2.314*10E-4)	.9994 (2.373*10E-4)
Time Trend (= 1 / T)	-2.009 (1.953)	-2.680 (2.152)	-3.134 (1.963)
Number of bidders	.0686 (.0656)	.0562 (.0677)	.0475 (.0712)
Constant	-3.029 (.536)	-2.821 (.604)	.-2.95 (.659)
First Stage F statistic	370.295	289.6305	297.738
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

Table 8: Econometric Estimates of the Factors which Influence The Level of Bids. Dependent Variable is Level of Bid (Standard errors in parentheses, N= 1350)

Specification	Ordinary least squares	Random Effects	Fixed Effects
Cash Balances	-0.011 (.0083)	-0.017 (.011)	-0.0186 (.0115)
Signal (resale value)	0.9994 (2.385*10E-4)	0.9992 (1.9*10E-4)	0.9992 (1.899*10E-4)
Number of Bidders	0.0139 (.065)	4.244*10E-4 (.207)	Dropped
First Five Periods Dummy (1 –5)	-0.585 (.262)	-0.710 (.259)	-0.735 (.268)
Second Five Periods Dummy (6-10)	-0.065 (.245)	-0.173 (.230)	-0.1943 (.237)
Third Five Periods Dummy (11 –15)	0.042 (.236)	-0.0245 (.211)	-0.040 (.215)
Fourth Five Periods Dummy (16 – 20)	-0.0593 (.224)	-0.1498 (.190)	-0.163 (.192)
Fifth Five Periods Dummy (21 – 25)	-0.053 (.215)	-0.073 (.173)	-0.078 (.173)
Constant	-2.592104 (.4818305)	-2.28704 (1.131176)	-2.228582 (.3371702)

Table 9: Econometric Estimates of the Factors which Influence The Level of Bids. Dependent Variable is Level of Bid (Standard errors in parentheses, N= 1350)

Specification	Ordinary least squares	Random Effects	Fixed Effects
Cash Balances	-.011 (7.113*10E-3)	-0.013 (7.63*10E-3)	-0.013 (7.83*10E-3)
Signal (resale value)	.9994 (2.37*10E-4)	9992 (1.88*10E-4)	0.9992 (1.88-10E-4)
Number of Bidders	.0138 (.064)	8.037*10E-3 (.215)	Dropped
First Five Periods Dummy	-.5541989 (.18578)	-0.581 (.157)	-0.583 (.158)
Constant	-2.63 (.403)	-2.501 (1.119)	-2.433 (.182)

Table 10: First Stage Estimates. Dependent Variable is Level of Cash Balances Prior to the Bid (Standard errors in parentheses, N= 1309)

Variable	Specification 1	Specification 2	Specification 3
Signal	-1.402*10E-4 (6.232*10E-4)	1.551*10E-4 (7.049*10E-4)	-2.611*10E-4 (7.357*10E-4)
First Five Periods Dummy	0.684 (.566)	-0.538 (.636)	-4.689939 (.5885367)
Number of bidders	-0.824 (.176)	-0.297 (.197)	-2.119997 (.1986973)
Total randomized additions to cash balances (Z_{it})	0.857 (0.045)	*****	1.232736 (.0500252)
Total number of high signals received	1.884 (.073)	2.204 (.080)	*****
Total number of second highest signal received	0.353 (0.080)	0.839 (0.086)	*****
Constant	10.367 (1.098)	9.246 (1.241)	22.915 (1.128)

First Stage F statistic	368.3434	288.0367	267.2533

Table 11: Two Stage Least Squares Estimates. Dependent Variable is Level of Bid Endogenous Variables are the level of cash balances prior to the bid (Standard errors in parentheses, N= 1309)

Variable	Specification 1	Specification 2	Specification 3
Cash Balances	3.683*10E-3 (9.214*10E-2)	9.137*10E-4 (.0104)	0.013 (.0128)
Signal	.9994945 (2.316*10E-4)	.9994955 (2.315*10E-4)	0.9994 (2.378*10E-4)
First Five Periods Dummy	-0.216 (.202)	-0.244 (.207)	-0.307 (.216)
Number of bidders	0.076 (.064)	0.070 (.065)	0.064 (.068)
Constant	-3.234 (.431)	-3.156 (.455)	-3.331 (.509)
First Stage F statistic	368.3434	288.0367	267.2533
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

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?

Bibliography

Altonji, Joseph, and Segal, L. M. (1994). Small Sample Bias in GMM Estimation of Covariance Structures, NBER Technical Working Paper no. 156.

Arrelano, Manuel, and Bond, Stephen (1991). Some Tests of Specification for Panel Data: Monte – Carlo Evidence and an Application to Employment Equations, *Review of Economic Studies,* 58, pp. 277 – 297.

Bound, J, Jaeger, D. A. and Baker, R. M. (1995), "Problems with Instrumental Variables Estimation When the Correlation Between the Instruments and the Endogenous Explanatory Variable is Weak," *J. American Statistical Association*, vol. 90, 443-450.

Bowden, R. J. and Turkington, D. A. (1984), *Instrumental Variables,* Cambridge: Cambridge University Press.

Brundy, James M., and Jorgenson, Dale W. (1971). Efficient Estimation of Simultaneous Equations by Instrumental Variables, *Review of Economics and Statistics*, 53, pp. 207 – 224.

Buse, A. (1992). The Bias of Instrumental Variable Estimators, *Econometrica*, Vol. 60, pp. 173-180.

Chamberlain, Gary (1984). "Panel Data," in *Handbook of Econometrics*, vol. II, edited by Z. Grilches and M. Intriligator, pp. 1247 – 1318. Amsterdam: North–Holland.

Cox, James C., Smith, Vernon L., and Walker, James M. (1992). Theory and Misbehavior of First-Price Auctions: Comment, *American Economic Review*, 82, pp. 1392-1412.

Hansen, Robert G., and Lott, John (1991). The Winner's Curse and Public Information in Common Value Auctions: Comment, *American Economic Review,* 81, pp. 347 – 361.

Hausman, Jerry (1978). Specification Tests in Econometrics, *Econometrica*, 46, pp. 1251 – 1271

Hausman, Jerry, and Taylor, William (1981). Panel Data and Unobservable Individual Effects, *Econometrica*, 49, pp. 1377 – 1398

Hsiao, Cheng (1986). *Analysis of Panel Data*, Econometric Society Monographs No. 11, New York: Cambridge University Press,

Kagel, John H (1995). "Auctions," in *Handbook of Experimental Economics*, edited by John H Kagel, and Alvin E. Roth, pp. 501 - 586. Princeton: Princeton University Press.

Kagel, John H., and Roth, Alvin E. (1992). Theory and Misbehavior in First-Price Auctions: Comment, *American Economic Review*, 82, pp. 1379 – 1391.

Kagel, John H., and Levin, Dan (1991). The Winner's Curse and Public Information in Common Value Auctions: Reply, *American Economic Review*, 81, pp. 362 –369.

Kagel, John H., Harstrad, Ronald M., and Levin, Dan (1987). Information Impact and Allocation Rules in Auctions with Affiliated Private Values: A Laboratory Study. *Econometrica*, 55, pp. 1275 – 1304.

Kagel, John H., and Levin, Dan (1986). The Winner's Curse and Public Information in Common Value Auctions, *American Economic Review*, 76, pp. 894 – 920.

Matyas, Laszlo (1996). "Error Components Models" in The Econometrics of Panel Data, edited by Laszlo Matyas and Patrick Sevestre, pp. 50 – 76. Boston: Kluwer Academic Press.

Sevestre, Patrick and Trognon, Alain (1996). "Linear Models with Random Regressors" in The Econometrics of Panel Data, edited by Laszlo Matyas and Patrick Sevestre, pp. 100 – 119. Boston: Kluwer Academic Press.

Staiger, Douglas, and Stock, James (1997). Instrumental Variables Regression with Weak Instruments," *Econometrica*, 65 (3) pp. 557 - 586.