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Abstract

In repeated second-price experimental auctions, the winning bid is normally posted after each round. The posting of these winning prices after each round can result in bids submitted in later rounds to be interdependent with posted prices from earlier rounds. Several approaches in the past have tried to scrutinize their experimental data for value interdependence by regressing bids on lagged market prices or lagged bids and ignoring the inherent endogeneity problem. This paper introduces a formal test for bid interdependence in repeated second-price auctions with posted prices using a dynamic panel model. We then apply this test to formally check the presence of bid interdependence in three datasets used in previous studies.
Keywords: experimental auctions, bid interdependence, dynamic panel estimator, second-price auction

Introduction

Experimental auctions are becoming increasingly popular and are now frequently used by economists and others in eliciting valuation or willingness to pay (WTP) estimates for various goods, product attributes, value of information, etc. Normally, experimental auctions are conducted in several rounds or trials and the posting of the winning prices after each round has become a common practice (e.g., see Alfnes and Rickertsen, 2003, Buhr, et al., 1993, Fox, et al., 2002, Lusk, et al., 2004). In repeated trial experimental auctions, subjects submit bids on the same products in multiple potentially binding rounds. The winning prices after each round are then posted for subjects to see before the subsequent round. The information sent through a posted price helps bidders learn about the market mechanism and many believe that this improves valuation estimates. However, it is possible for subsequent bids to be interdependent with the posted prices and the upper support of the valuation distribution. In other words, a subject's private value may become interdependent with this upper support i.e., the chances that a bidder will bid a high value on the product are increased when one bidder values the product highly which would brake down the incentive compatibility of the mechanism (Klemperer (2004, p. 50) provides a formal mathematical definition of bid affiliation that might occur when bids are interdependent). If indeed bid interdependence develops as a result of irrational anchoring effect in repeated trial auctions, this practice could result in biased bid estimates. As it stands, however, there seems to be two camps of researchers that have different views about the issue of use of repeated trials/rounds in experimental auctions. One camp includes researchers like Harrison (2006) and Corrigan and Rousu (2006) who argue in favour of one-shot institutions rather than repeated institutions. Another camp would include researchers like Lusk and Shogren (Lusk and Shogren 2007, Shogren 2006) who tend to be supportive of repeated trials in auctions.

Harrison (2006) and Harrison et al. (2004) make the argument that posted prices can signal either the extra-experimental market price of the commodity (or a field substitute) or the quality of the commodity which would cause people's bids to become inter-dependent. Lusk and Shogren (2007) test the argument about the signal of quality by examining the bids for different qualities of beef steaks in a five-round second-price auction. When investigating the differences between each steak's bid and the average bid for all steaks, they do not reject the null of uniform bids across rounds. The interpretation is that people increase their bids for all types of steaks roughly by the same amount and do not differentiate their bids according to quality. While their finding is suggestive, there is not yet a great deal of evidence about quality signals and more research is indeed warranted. Shogren (2006) argues that if affiliation is indeed a concern, then the one-shot auctions as put forward by Harrison (2006) would not eliminate the problems. Prices are not the only value signals in experiments since subjects can also use signals such as visual cues and verbal allusions. Shogren (2006) takes it one step further and characterizes one-shot bids as naïve since the bidder lacks knowledge created by the market interactions, given that a researcher is interested in creating market experience for the subjects.

Given the above issues, it is not surprising that some researchers have used non-auction type mechanisms as an alternative to repeated auctions (Anderson, et al., 2006, Anderson, et al., 2007). However, researchers have not shied away from repeated auction institutions and repeated trials are now a standard practice in experimental auctions. In light of this practice several researchers have tried to scrutinize their data for value interdependence in order to dismiss criticisms that might arise if value interdependence is indeed a problem. For example, List and Shogren (1999) modelled the median bid in round *t* as a function of the posted price in the previous round. However, since theory does not support the use of a summary statistic in these tests, the validity of their test is to be questioned, a point also raised in Harrison (2006). Alfnes and Rickertsen (2003) use OLS in regressing the change in participant *i*'s bid from round *t-1* to *t* on the difference between the posted price and individual *i*'s bid in trial *t-1*. Similarly, Harrison *et al.* (2004) use lagged market prices as an independent variable. Including lagged market prices as a regressor, however, creates a positive correlation between the regressor and the error term, which produces inconsistent estimates and an endogeneity problem. In fact, the coefficient of the lagged market price can be attributed to individual fixed effects.

To overcome the limitations of previous approaches we propose a consistent econometric test with a dynamic panel model to assess the existence of interdependent bids in repeated second price auctions.[1] We then apply this test on

1 Although our approach can be applied to any institution with a signal of price information.

three datasets from previous studies to demonstrate the existence/non-existence of bid interdependence effects in repeated second-price auctions. We choose the second-price auction mechanism since it is a widely used mechanism in the auction literature.

We do not purport in this paper to identify the underlying mechanisms that lead bidders to revise their bids in repeated auctions. In some ways, this limits the contribution of our paper since differentiating amongst these motives and identifying the underlying rationale for bid affiliation is critical. While modest, our objective is to provide a general econometric test for bid interdependence that overcomes the limitations of previous approaches.

A dynamic panel model of bid interdependence

Let a participant's bid in a repeated auction be $BD_{i,t}$ where *i* indexes the participant and *t* indexes rounds. If there is bid interdependence then this is embedded in $BD_{i,t}$. What the experimenter really observes then is a bid $BD_{i,t}$ which includes bid interdependence plus some error term. We can then model person *i*'s bids as:

$$BD_{i,t} = BI_{i,t} + u_{i,t} \qquad (1)$$

where $BI_{i,t}$ is bid interdependence and $u_{i,t}$ is i.i.d. disturbance term with mean 0. Bid interdependence can occur when bidders incorporate signals from the previous rounds into their current bid. Bids might be interdependent for two reasons: (i) person *i* observes a posted price (e.g., the market clearing price) and will try to adjust his bid based on how much his lagged bid (i.e., bid in the previous round) differs from the posted price and (ii) an information accumulation effect occurs which relates to the repeated process of the auction and the lagged bid. Thus, we write bid interdependence as:

$$BI_{i,t} = \text{Bidding Error} + \text{Information accumulation} \qquad (2)$$

or

$$BI_{i,t} = a_1\left(BD_{t-1}^{w} - BD_{i,t-1}\right) + a_2\left(BD_{t-1}^{w} - BD_{i,t-1}\right)^2 + \ldots + b_1 t + b_2 t^2 + \ldots + \rho BD_{i,t-1} + \varepsilon_{i,t} \quad (3)$$

where BD_{t-1}^{w} is the posted price (second highest bid) of the previous round (winning bid), $\varepsilon_{i,t} \sim iid\left(0, \sigma_{\varepsilon}^{2}\right)$ and t is the time trend variable denoting rounds. What equation (3) in essence describes is that bids submitted in any round will depend on how much participant *i*'s bid differs from the posted price ($BD_{t-1}^{w} - BD_{i,t-1}$) as well as the accumulated information signals $\left(t,\ BD_{i,t-1}\right)$.

The bid affiliation function (3) can have various functional forms such as 3rd or higher order polynomial, logarithmic etc. and one could try several functional forms and

choose the best one. For simplification, however, we will proceed with a 2nd order form given that the number of instruments that are required to remove the dynamic panel bias (that will be discussed below) increases proportionally to the number of lagged variables given the number of observations. Higher order polynomial forms, however, could be more appropriate when using large datasets.
By substituting the second order polynomial form of (3) in (1) we get:

$$BD_{i,t} = a_1\left(BD_{t-1}^{w} - BD_{i,t-1}\right) + a_2\left(BD_{t-1}^{w} - BD_{i,t-1}\right)^2 + b_1 t + b_2 t^2 + \rho BD_{i,t-1} + v_{i,t} \quad (4)$$

Equation (4) offers a testable hypothesis. One could test for the joint significance of the coefficients a_1, a_2, b_1, b_2, ρ or that $a_1 = a_2 = b_1 = b_2 = \rho = 0$. A rejection of the null hypothesis would indicate the presence of bid interdependence. A separate test for the existence of either the bidding error effect or information accumulation effect is possible with our approach. One would need to test for $a_1 = a_2 = 0$ or for $b_1 = b_2 = \rho = 0$, respectively.
Besides the fact that the error term in equation (4) contains fixed individual effects, which requires the use of a panel set-up, the lagged independent variables are correlated with the fixed effects in the error term giving rise to dynamic panel bias. The disturbance term has two orthogonal components i.e. $v_{i,t} = \mu_{i,t} + m_{i,t}$. $\mu_{i,t}$ is the fixed effects component and $m_{i,t}$ are the idiosyncratic shocks with $E\left[\mu_{i,t}\right] = E\left[m_{i,t}\right] = E\left[\mu_{i,t} m_{i,t}\right] = 0$. If one uses OLS to estimate (4), as previous approaches in the literature have done, the coefficients estimates will be inconsistent. Instead, the appropriate strategy is to first transform the data to get rid of the fixed effects and then instrument the lagged variables that remain potentially endogenous. By first-differencing equation (4) we get:

$$\Delta BD_{i,t} = a_1\Delta\left(BD_{t-1}^{w} - BD_{i,t-1}\right) + a_2\Delta\left(BD_{t-1}^{w} - BD_{i,t-1}\right)^2 + b_1\Delta t + b_2\Delta t^2 + \rho\Delta BD_{i,t-1} + \Delta v_{i,t} \quad (5)$$

which removes the fixed effects. However, several of the $\Delta(\bullet)$ terms in equation (5) are correlated with the $\Delta v_{i,t}$. Natural candidate instruments could come from within the dataset. For instance, Holtz-Eakin et al. (1988) build GMM-style instruments from the second lag of the dependent variable. The result of their work was the Arellano-Bond (1991) difference GMM estimator for dynamic panels which can consistently and efficiently estimate equation (4).

The data

To test the hypothesis set forth in the previous section, we use data from three published lab valuation experiments that used repeated trials of the second price auction for four types of products: sandwiches, candy bars, mugs and beef steaks.
The first dataset comes from the study of Drichoutis et al. (2008) (hereafter DLN) which used a second price Vickrey auction with 5 repeated rounds and two treatments to test whether revealing reference price information for sandwich products (i.e. the market price of the products) changes bidding behaviour. They simultaneously auctioned three sandwich products and the binding product (and round) was chosen randomly.
The second dataset comes from the study of Corrigan and Rousu (2006) that used 10 repeated rounds of a second price auction to determine WTP values for a university logo mug and a candy bar. CR used confederate bidders to test whether high posted prices would subsequently lead to higher bids for familiar (candy bar) and unfamiliar (mugs) products. They had three different treatments, one where there were no confederate bidders in the sessions, one where the candy bar rounds had confederate bidders but the mug rounds did not, and one where both mug and candy bar rounds had confederate bidders.
The third dataset comes from Chapter 5 in Lusk and Shogren's (2007) book (hereafter LS), also used in Lusk, Feldkamp, and Schroeder (2004). The study involved valuation of five different types of meat (generic, guaranteed tender, "natural", U.S. Department of Agriculture Choice and Certified Angus Beef) and one of the mechanisms used was the second-price Vickrey auction. Five repeated rounds were used in this study.
These studies have some commonalities. For example, both DLN and CR use students exclusively and most of LS's subjects are also students2. If familiarity is defined the way CR define it, then the sandwich products can be considered a familiar product since students are likely more familiar with both the good and the extralaboratory price of it. Furthermore, both DLN and CR manipulate price information (the field price of the product in DLN and the posted price of the product in CR by using the confederate bidders). LS manipulate quality of the products by using different types of beef steaks. Therefore, these datasets provide a nice benchmark to testbed the dynamic model presented above.

Econometric Estimation and Results

We fitted equation (5) using the difference one-step dynamic panel estimator (Arellano and Bond, 1991) with the *xtabond2* module in Stata (Roodman, 2002). There are several choices involved in the use of this estimator and it is advisable to report them all (Roodman, 2006). The specification choices are reported in Tables 1 to 4. These specifications typically include the instrumental variables and lags that are going to be used and the number of instruments, which are all related with tests for the exogeneity of instruments and tests for second order serial autocorrelation. We were careful not to overfit the endogenous variables due to biases that may arise that are similar to the ones that we try to resolve.

2 Although they are from diverse cultural backgrounds, Greece for DLN and USA for CR and LS

The first choice one has to decide upon is on the instrumenting variables and lags that are going to be used. Typically, for the endogenous variables (i.e., those of lag 1), instruments of lag 2 and longer are used. The exogenous variables (t and t^2) also serve as standard instruments with one column in the instrument matrix per variable. Standard errors are robust to heteroskedasticity and arbitrary patterns of autocorrelation within individuals. Tables 1 to 4 also report tests for the exogeneity of the instruments. Since the Sargan (1958) test is not robust if the errors are non-spherical, as in robust one-step GMM, we report the Hansen (1982) statistic. The Hansen test statistic can be weakened by using too many instruments, so we took this into account when deciding on the number of instruments to use (see Roodman (2008) for a discussion on the number of instruments). In addition, Tables 1 to 4 report the Arellano-Bond (1991) test for second-order serial autocorrelation (m_2) which is applied to the residuals in differences. The test assumes no correlation in errors across individuals and that *N* is large. In essence, to check for first order serial correlation in levels, we look for second order serial correlation in differences on the idea that this will detect correlation between the v_{t-1} in Δv_t and the v_{t-2} in Δv_{t-2}.

The choice of the number of instruments is crucially dependent on the Hansen statistic and the test for serial autocorrelation. In the CR dataset and in some cases in the DLN dataset, we had to combine (collapse) instruments and use one instrument for each variable and lag distance, rather than one for each time period, variable, and lag distance to avoid the bias that arises as the number of instruments climbs toward the number of observations. Over-fitting the instrumented (endogenous) variables may lead to biases similar to the bias that results by using OLS. In general, all our estimations started with the maximum number of instruments, which we then reduced gradually based on the autocorrelation test and the Hansen statistics. Therefore, all tables report our choices on the number of instruments, lags, and form of the instrument matrix (i.e., collapsed or un-collapsed).

Tables 1 to 4 also report the coefficient estimates and three F-tests: (a) on the joint significance of all the coefficients of equation (5), (b) on the joint significance of the coefficients of the bidding error terms (a_1, a_2), (c) and on the joint significance of the coefficients of the information accumulation terms (b_1, b_2, ρ). Tables 1 and 2 report estimates using the DLN dataset. Table 1 uses the posted 2nd highest price for BD^W in equation (5) while Table 2 uses the posted field price of the product (i.e., market price of the product). The reason we estimated equation (5) using the field price of the product is because subjects in the experiment may as well have taken this price into account when determining their valuation distribution. The reason that field prices were also used when estimating the treatment for which field prices were not posted (first three columns of Table 2) is because subjects may have had an idea about the extra-laboratory prices of the products even though these were not posted during the treatment.

Table 1. GMM estimates using the Drichoutis et al. (2008) dataset (2nd highest price included in the bidding error)

Independent Variables	*Treatments without posted field prices*			*Treatments with posted field prices*		
	Sandwich 1 (1)	***Sandwich 2*** (2)	***Sandwich 3*** (3)	***Sandwich 1*** (4)	***Sandwich 2*** (5)	***Sandwich 3*** (6)
$BD^{w}_{t-1} - BD_{i,t-1}$	0.050	-0.715	-4.060	**0.756***	**0.545***	**1.563****
	(0.450)	(0.658)	(4.284)	**(0.408)**	**(0.297)**	**(0.538)**
$\left(BD^{w}_{t-1} - BD_{i,t-1}\right)^2$	0.199	**0.152***	0.381	0.028	-0.156	**-0.469****
	(0.162)	**(0.086)**	(0.536)	(0.146)	(0.108)	**(0.222)**
t	-0.292	-0.011	0.051	0.041	-0.009	-0.148
	(0.227)	(0.299)	(0.186)	(0.117)	(0.106)	(0.143)
t^2	0.036	0.009	-0.004	-0.004	0.005	0.016
	(0.027)	(0.039)	(0.024)	(0.014)	(0.013)	(0.018)
$BD_{i,t-1}$	0.737	-0.395	-3.305	**0.667****	**0.327****	**1.019****
	(0.555)	(0.386)	(3.961)	**(0.220)**	**(0.141)**	**(0.252)**
Number of instruments	20	20	20	20	20	20
Lags used	2 to 4	2 to 4	2 to 4	2 to 4	2 to 4	2 to 4
m_2	0.08	-1.16	-1.17	0.43	-0.25	0.46
(p-value)	(0.940)	(0.246)	(0.242)	(0.669)	(0.804)	(0.645)
Hansen J-statistic	21.49	18.30	8.95	11.99	13.72	13.60
(p-value)	(0.122)	(0.247)	(0.880)	(0.679)	(0.547)	(0.556)
F-test [1]	**4.17****	**16.55****	0.23	**5.36****	**3.52****	**4.86****
(p-value)	**(0.004)**	**(0.000)**	(0.945)	**(0.001)**	**(0.009)**	**(0.001)**
F-test [2]	1.06	2.13	0.48	**4.24****	1.69	**5.04****
(p-value)	(0.355)	(0.133)	(0.621)	**(0.021)**	(0.195)	**(0.0105)**
F-test [3]	**6.42****	**2.34***	0.36	**8.39****	**3.58****	**7.77****
(p-value)	**(0.001)**	**(0.088)**	(0.783)	**(0.000)**	**(0.021)**	**(0.000)**
No of observations		117			138	

[1] H0: $a_1 = a_2 = b_1 = b_2 = \rho = 0$

[2] H0: $a_1 = a_2 = 0$

[3] H0: $b_1 = b_2 = \rho = 0$

Looking at Tables 1 and 2, one can see that bidding error (i.e., how much the previous bid differs from the posted price, 2nd highest or field price) affects bidding in the current round. In addition, information accumulation (as captured by the time trend variables and the previous round bids) affects bidding behavior in the current round but not in the treatment without posted field prices. What is more important, however, is that the F-tests for the joint significance of the coefficients reject the null that all coefficients are zero. This is firm evidence that indeed bid interdependence was in effect in the DLN experiment, which used 5 repeated rounds to auction sandwich products.

Table 2. GMM estimates using the Drichoutis et al. (2008) dataset (field prices included in the bidding error)

Independent Variables	*Treatments without posted field prices*			*Treatments with posted field prices*		
	Sandwich 1 (1)	***Sandwich 2*** (2)	***Sandwich 3*** (3)	***Sandwich 1*** (4)	***Sandwich 2*** (5)	***Sandwich 3*** (6)
$BD_{t-1}^{w} - BD_{i,t-1}$	-0.491 (0.626)	-1.865 (2.089)	**1.341**** **(0.624)**	**1.060**** **(0.478)**	0.556 (0.647)	-1.681 (3.487)
$\left(BD_{t-1}^{w} - BD_{i,t-1}\right)^2$	0.303 (0.186)	0.222 (0.171)	-0.096 (0.149)	-0.030 (0.084)	-0.184 (0.237)	0.202 (0.130)
t	-0.326 (0.256)	0.139 (0.232)	0.105 (0.154)	**0.403*** **(0.215)**	0.008 (0.139)	**0.363**** **(0.171)**
t^2	0.042 (0.032)	-0.014 (0.029)	-0.015 (0.023)	**-0.042*** **(0.025)**	0.002 (0.015)	**-0.036*** **(0.019)**
$BD_{i,t-1}$	0.483 (0.352)	-1.256 (2.031)	0.933 (0.647)	**0.696**** **(0.261)**	0.258 (0.195)	-1.200 (3.284)
Number of instruments	20	20	20	11	11	9
Lags used	2 to 4	2 to 4	2 to 4	2 to 4 (collapsed)	2 to 4 (collapsed)	2 to 4 (collapsed)
m_2 (p-value)	-0.75 (0.453)	-0.53 (0.595)	-0.76 (0.445)	0.58 (0.564)	-0.07 (0.947)	-0.90 (0.369)
Hansen J-statistic (p-value)	22.01 (0.107)	14.89 (0.460)	12.76 (0.621)	7.70 (0.261)	7.42 (0.284)	4.44 (0.350)
F-test [1] (p-value)	**2.33*** **(0.061)**	**5.42**** **(0.001)**	**2.80**** **(0.029)**	**4.45**** **(0.002)**	**3.01**** **(0.020)**	**4.78**** **(0.001)**
F-test [2] (p-value)	1.98 (0.151)	1.02 (0.370)	**2.56*** **(0.090)**	**3.00*** **(0.060)**	0.39 (0.680)	**1.33*** **(0.274)**
F-test [3] (p-value)	1.19 (0.326)	1.42 (0.251)	1.27 (0.297)	**5.40**** **(0.003)**	**4.04**** **(0.012)**	**3.70**** **(0.018)**
No of observations		117			138	

[1] H0: $a_1 = a_2 = b_1 = b_2 = \rho = 0$

[2] H0: $a_1 = a_2 = 0$

[3] H0: $b_1 = b_2 = \rho = 0$

As noted before, one can conceivably separate the variables in (4) into subgroups and examine the joint significance of the coefficients separately, depending on whether one is looking to scrutinize the data for bidding error effects or information accumulation effects. For example, looking at the F-tests one can conclude that indeed some information accumulation has occurred due to repeated rounds. Since there appears to be many differences between the products, one could also conclude that bid interdependence may be product specific.

The results from the CR dataset can help us elaborate more on this point. The interesting part with this dataset is that CR clearly distinguishes between familiar (candy) and unfamiliar (mug) products based on the knowledge subjects may have on the extralaboratory price of the product[3]. It appears that there is indeed bid affiliation for both familiar and unfamiliar products with the exception of mugs in treatment two (column 4, Table 3). If one wants to separate bidding error from information accumulation, then for mugs (the unfamiliar product) we never reject the null of no bidding error or no information accumulation (but not both at the same time). Our intuition says that the choice of product could play a significant role in these results, which implies that repeated rounds and posted prices might not always create bid interdependence.

Table 3. GMM estimates using the Corrigan and Rousu (2006) dataset

Independent Variables	*No confederate bidders*		*No confederate bidders for candy bar, Confederate bidders for mug*		*Confederate bidders for both products*	
	Candy bar (1)	*Mug* (2)	*Candy bar* (3)	*Mug* (4)	*Candy bar* (5)	*Mug* (6)
$BD_{t-1}^{w} - BD_{i,t-1}$	-0.190	0.170	**-0.305***	1.367	**2.318****	-1.013
	(0.450)	(0.578)	**(0.174)**	(2.115)	**(0.959)**	(1.767)
$\left(BD_{t-1}^{w} - BD_{i,t-1}\right)^2$	-0.116	-0.067	**0.221****	-0.042	**-0.841****	0.050
	(0.223)	(0.114)	**(0.087)**	(0.094)	**(0.238)**	(0.118)
t	0.032	**0.101***	**0.062****	0.318	-0.052	0.038
	(0.029)	**(0.059)**	**(0.030)**	(0.237)	(0.031)	(0.053)
t^2	-0.002	-0.007	**-0.005****	-0.013	**0.003***	-0.002
	(0.002)	(0.005)	**(0.002)**	(0.019)	**(0.002)**	(0.005)
$BD_{i,t-1}$	-0.101	0.295	-0.076	0.430	**1.760****	-0.455
	(0.528)	(0.334)	(0.275)	(1.274)	**(0.641)**	(0.693)
Number of instruments	26	26	26	26	23	17
Lags used	2 to 9 (collapsed)	2 to 9 (collapsed)	2 to 9 (collapsed)	2 to 9 (collapsed)	2 to 8 (collapsed)	2 to 6 (collapsed)
m_2	-0.62	-0.21	0.36	0.05	0.89	0.38
(p-value)	(0.536)	(0.836)	(0.720)	(0.957)	(0.374)	(0.705)

[3] It was assumed that subjects are more familiar with candy bars since they have better knowledge of the extralaboratory price of the product while it is the opposite for mugs.

Hansen J-statistic (p-value)	21.20 (0.447)	21.56 (0.425)	26.49 (0.188)	24.78 (0.257)	24.67 (0.134)	13.62 (0.326)
F-test [1] (p-value)	**3.53** (0.013)**	**16.71** (0.000)**	**135.44** (0.000)**	1.76 (0.147)	**26.32** (0.000)**	**2.54** (0.045)**
F-test [2] (p-value)	0.46 (0.633)	0.33 (0.722)	**3.24* (0.051)**	0.29 (0.748)	**11.02** (0.000)**	0.80 (0.456)
F-test [3] (p-value)	**4.49** (0.011)**	1.22 (0.322)	1.62 (0.203)	1.79 (0.166)	**5.27** (0.004)**	0.38 (0.769)
No of observations	224		288		296	

[1] H0: $a_1 = a_2 = b_1 = b_2 = \rho = 0$

[2] H0: $a_1 = a_2 = 0$

[3] H0: $b_1 = b_2 = \rho = 0$

The LS dataset exhibits a more systematic pattern (Table 4). In almost all cases either the bidding error coefficients or the information accumulation coefficients or both are significant at conventional statistical levels. The consistency between the treatments could be attributed to the fact that subjects evaluated a rather homogeneous product differentiated only by level of quality.

Table 4. GMM estimates using the Lusk and Shogren (2007) dataset

Independent Variables	*Generic beef steak*	*Guaranteed tender beef steak*	*Natural beef steak*	*Choice beef steak*	*Certified Angus beef steak*
	(1)	(2)	(3)	(4)	(5)
$BD_{t-1}^{w} - BD_{i,t-1}$	**0.455* (0.251)**	**0.179* (0.095)**	0.131 (0.092)	**0.287** (0.122)**	**0.195** (0.052)**
$\left(BD_{t-1}^{w} - BD_{i,t-1}\right)^2$	0.040 (0.076)	0.019 (0.035)	-0.059 (0.082	0.035 (0.027)	**-0.030** (0.015)**
t	-0.018 (0.343)	0.221 (0.507)	-0.842 (0.519	0.547 (0.373)	0.121 (0.217)
t^2	0.007 (0.041)	-0.025 (0.064)	**0.121* (0.065)**	-0.018 (0.054)	-0.022 (0.029)
$BD_{i,t-1}$	**0.843* (0.464)**	0.451 (0.310)	**0.622* (0.309)**	-1.108 (1.654)	**0.529** (0.188)**
Number of instruments	18	18	18	18	18
Lags used	2 to 4	2 to 4	2 to 4	2 to 4	2 to 4
m_2 (p-value)	0.93 (0.351)	-0.71 (0.477)	-0.53 (0.596)	0.07 (0.946)	2.38** (0.017)
Hansen J-statistic (p-value)	13.96 (0.377)	18.64 (0.135)	16.77 (0.210)	4.13 (0.660)	18.61 (0.136)
F-test [1] (p-value)	**5.45** (0.001)**	**3.80** (0.007)**	**5.41** (0.001)**	**6.84** (0.000)**	**5.50** (0.001)**
F-test [2] (p-value)	**3.65** (0.036)**	2.34 (0.111)	**2.81* (0.074)**	**3.03* (0.061)**	**7.22** (0.002)**

F-test [3]	**8.05****	**5.30****	**7.84****	**5.74****	**6.36****
(p-value)	**(0.000)**	**(0.004)**	**(0.000)**	**(0.003)**	**(0.001)**
No of observations			105		

[1] H_0: $a_1 = a_2 = b_1 = b_2 = \rho = 0$

[2] H_0: $a_1 = a_2 = 0$

[3] H_0: $b_1 = b_2 = \rho = 0$

Discussion and Conclusion

The use of repeated rounds or trials in experimental auctions is now common practice. While this is done to allow subjects to receive market feedback, it can also result in breaking down the incentive compatibility of the auction. Hence, the posting of winning bids may provide a reference point for subjects with preferences that exhibit spite motives or a love of winning. To test this hypothesis, previous studies in the literature have used lagged market/posted prices and OLS regression to test whether lagged market prices affect current bids. As discussed, this approach is inherently wrong due to the endogeneity problem it creates. To date, no other study has introduced a technique that would formally assess bid interdependence. Given the increasing popularity of repeated experimental auctions, this is a significant gap in the literature.

In this paper, we presented a simple econometric procedure based on a dynamic panel model to test for bid interdependence. We then tested this procedure on three datasets from previous studies. We found that repeated rounds and posted prices create in most cases a positive correlation with bids in current rounds which is evidence of bid interdependence. Future studies can scrutinize their data from repeated auctions using the test we are proposing in this paper to formally test for the presence of bid interdependence. A caveat of the method, however, is that at least four repeated rounds are needed to econometrically estimate the model. Another constraint of the specification we are testing is that it focuses on average effects, which means that it may miss effects that are spread out in the population. If some subjects increase their bid when they see a high posted price while other subjects decrease their bid, then the net effect could be zero. Future research should put some effort in developing models that will account for subject's heterogeneity while not ignoring the econometric issues that arise with panel data, perhaps by extending the flexibility that random coefficient models give to dynamic panel estimators.

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