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Some Evidence on Prices as Signals of Quality

Richard Guy Cox*

Abstract. Theory indicates that prices may serve as signals of unknown product quality. The relevant implication is that prices remain above marginal cost. Price signaling may also occur when buyers have a return option or money-back guarantee. Intuitively, sellers that deviate from a price that conveys full information by setting a higher price will have their products returned and suffer losses. Absent in the literature are any empirical studies to support the theoretical findings. This paper provides empirical results from an online used computer exchange to offer support for the theory of price signaling. The data are consistent with the theory but more research is needed.

JEL Classification Codes: D00.

Key Words: Prices, signals of quality.

1. Introduction

In many circumstances firms lower their prices to attract more customers. However, in some instances customers interpret low price as a signal of low quality. In that case firms may be reluctant to lower their prices. Customers interpreting the low price as a signal of low quality don't buy, and sales may actually decline. In the industrial organization literature this is important because the asymmetry in information leads to prices above marginal cost. How does this result change when customers have the option to return the product after inspection? When customers can inspect the product it is

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* University of Arkansas at Little Rock, Department of Economics and Finance, 2801 South University Ave., Little Rock, AR 72204-1099, phone: (501) 569-8875, fax: (501) 569-8871, email: rgcox@ualr.edu.

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unclear that prices can serve as signals of quality because quality can be determined through inspection. In this paper I argue that when buyers face a small cost of returning the good, prices still serve as signals of quality. Additionally, while the previous literature establishes that prices can serve as signals of product quality there is only anecdotal evidence that consumers infer quality from price. I present some evidence from an online market for used computers that is consistent with the theory.

2. Previous Results

There are various models which show that prices can serve as signals of unknown product quality. The idea hinges on consumers' belief that if something costs more it must be better. The use of signals results from asymmetric information. The seller knows the quality of the product, but the buyer does not. Wolinsky (1983) shows that quality signaling through price can be an equilibrium result with the implication that some firms set prices above marginal cost. His model involves a small cost of obtaining the signal and no option for return. Chan and Leland (1982) employ a different model but also find that prices can serve as signals of quality. They show that informed consumers (consumers who know the true quality of the good) purchase from high quality sellers while uninformed consumers (consumers who do not know the true quality) purchase from both high and low quality sellers. Cooper and Ross (1984) find that when there are both informed consumers and uninformed consumers, price conveys information about product quality. Informed consumers provide a positive externality to uninformed consumers. In their model they suggest that "ripoffs" or low quality provided at a high price, will be infrequent when average cost rises as sales fall. Firms are unprofitable when no informed consumers buy from them.

None of the previous studies allow for the possibility of product return. However, many stores do allow for product return if the customer is not satisfied. Shieh (1996) considers a model where the seller provides a money-back guarantee. Shieh (1996) finds that with a money-back guarantee prices serve as signals of quality, but high quality firms can now set a price closer to the monopoly price than when there is no money-back guarantee. The result concerning money-back guarantees is an important extension of the literature. Still, none of the literature provides any empirical evidence that buyers interpret price to be a signal of quality.

3. Framework

The primary contribution of this paper is to present some empirical results which suggest that buyers do interpret price as a signal of quality. To do this I examine an online exchange of used computers. Before discussing the details of the particular market I explain the basic framework under which prices serve as signals of quality even when there is a costly return policy. (Shieh (1996) does not consider costly return).

A potential buyer observes a good, some of its characteristics, and its price. Many similar goods are available from other sellers. The dissimilarities in the goods may be any of the observed characteristics, some unobserved characteristic, or even the price. After a buyer purchases an item, he/she may inspect it (or try it out) and return it if dissatisfied with its quality. If the buyer returns the item he/she gets back the purchase price minus the return cost. The return cost is not necessarily monetary. The cost may simply be the cost of going back to the store and waiting for the transaction to be processed, or it could be the cost of mailing an item back to the seller. The seller also incurs a small cost if the item is returned. Again, this may simply be the cost of processing the return or mailing out a refund check.

Holding all observable characteristics constant, meaning the only dissimilarities are in the unobservable "quality" and the price, there is an equilibrium where higher prices mean higher quality. This equilibrium exists as long as the return cost is small relative to possible differences in quality. Why? Suppose all buyers believe that higher prices indicate higher quality, and sellers charge prices that are consistent with buyers' beliefs. This will be an equilibrium result if no seller has an incentive to deviate from the specified pricing rule, i.e., setting a price that reveals the true quality. There are two cases when a seller deviates from the pricing rule.

In the first case the seller sets a price that is lower than the equilibrium price given the quality of his/her item. A buyer (seeking a lower quality item) purchases the item and after inspection is satisfied. The buyer does not return the item. The seller would have had higher profit by charging the equilibrium price, so we rule out setting a lower price. In the second case a seller sets a price that is higher than the equilibrium price. A buyer purchases the item. The buyer will return the good in this case, and the seller will incur a cost associated with return. Profits will be negative, so we can rule out charging a price above the proposed equilibrium.

4. Specific Market and Data

The market is for used computers. Sales are arranged through the website www.uce.com which is maintained by United Computer Exchange (UCE).[1] The website contains a listing of primarily used computers. Buyers in the market must register with UCE before making offers to buy. Registration is free. Sellers post descriptions of the computers they are selling. The description includes the make and model of the computer as well as other characteristics. For an individual computer the seller also posts a suggested price. The suggested price is just that, and it is not necessarily the seller's reservation price. UCE does not charge the sellers a listing fee.

An interested buyer submits an offer to the seller. The offer is posted on the website. The seller then either accepts or rejects the offer. If the seller accepts the offer, UCE notifies the buyer via e-mail, and the buyer sends the offer price plus a shipping fee to UCE. The seller then ships the computer, at his/her own expense, to UCE (located in Atlanta, Georgia). UCE then inspects the computer to verify that it is the computer (make/model) listed by the seller and that it is in good condition. If there are flaws with the computer (e.g., it is dirty), UCE charges the seller certain fees and attempts to correct the problem. UCE makes no guarantee concerning the computers. It acknowledges to all parties that it might not be thorough in its inspection.

UCE then ships the computer to the buyer. The buyer has two days to inspect the computer and verify "goods as promised." During this time the buyer may ship the computer back to UCE and cancel the sale. Notice that canceling the sale means the buyer will pay an additional shipping charge. If the buyer keeps the computer, UCE sends a portion of the price to the seller and keeps a portion as commission. After the sale is complete UCE removes the listing from the website.

I recorded listings from the UCE website during the month of July 1998 for Macintosh CPUs. There were a total of 876 "offers" on 593 computers. From these observations I dropped those which were for more than one computer or something other than a CPU and those computers which were new or factory refurbished. I also dropped some observations

[1] Several features of the website have changed over the years, and all information here corresponds to the details of the exchange system at the time I collected the data.

which had unique characteristics.[2] After dropping those observations there were 723 offers on 494 computers (149 of which had no offers to buy).

For each computer I recorded the following variables:

ASK: the seller's suggested price,
BID: the offer price,
SIZE: size of the hard drive,
SPEED: speed of the computer in megahertz,
RAM: amount of random access memory,
VRAM: amount of video RAM,
NSTOR: the number of additional storage devices,
KEY: dummy=1 if keyboard comes with computer,
MOUSE: dummy=1 if mouse comes with computer,
NTWRK: dummy=1 if computer has Ethernet hook up,
MODEM: dummy=1 if modem comes with computer,
GRAPHICS: dummy=1 if computer has graphics capabilities,
AUDIO: dummy=1 if computer has audio capabilities,
COMMENT: dummy=1 if seller made a comment about the computer,
WEEKS: number of weeks the computer has been listed (up to 20).

In addition to these characteristics I also recorded the model for each computer.

UCE removes listings after the computer is sold. Accordingly, the variable BID is not a sale price but only an offer to buy. Later I discuss why actual sale prices would not likely weaken the empirical findings.

ASK is not an actual price but only a suggested price. It will be useful though as a proxy for the price that a seller sets. If buyers view price as a signal of quality then I anticipate that their offer prices, BID, will be correlated with ASK after controlling for the computer characteristics. We should note that if we do not control for the observable computer characteristics BID and ASK will clearly be correlated.

[2] In regression these characteristics would fully explain any price differences.

5. Results

Table 1 contains summary statistics for all computers and for computers with at least one offer. For computers with at least one offer the mean BID is $572 and the mean ASK was $946. Most computers come with a keyboard (83%) and a mouse (86%). Buyers made at least one offer on 70% of the computers in the sample. The decision to make an offer is not likely to be completely random, but rather is dependent upon a computer's characteristics. If relatively few people are in the market for slow computers, then slow computers will receive relatively few bids. Table 2 shows regression results for a logit and a probit model where the dependent variable is a dummy equaling 1 if the computer received at least one offer and equal to 0 if it received no offers. Table 2 also shows results from two regressions where the dependent variable is the number of offers made on a computer, one is a linear model and the other is a Poisson model. There are 70 “model” dummies not shown in the table. There were 65 computers of a unique model, these observations were pooled together in the regressions and the total number of observations is 494. Figure 1 shows the distribution of the number of bids. Most computers do not receive multiple offers.

The results of the regressions are roughly consistent with each other in terms of the signs of the estimated coefficients. The longer a computer is listed the more likely it is to receive at least one offer, and it receives more offers on average. Having video RAM also appears to attract offers. The apparent result that computers with keyboards attract fewer offers is probably an artifact of a high degree of multicollinearity.[3]

The primary question is whether or not buyers perceive higher suggested prices to be signals of higher unknown quality. Assume buyers are willing to pay more for higher quality. If higher suggested prices, on average, attract higher offers then this suggests that buyers perceive higher suggested prices to be signals of higher quality. It is important to control for the computer characteristics. Notice that faster computers (assuming speed is valuable to sellers and buyers) will have both higher suggested prices and higher offers than slower computers. One might consider a multiple regression, where the dependent variable is BID and the independent

[3] Possible ways to address the multicollinearity problem include principal components regression or dropping some of the independent variables. Either of those approaches will give biased estimates, and it will be difficult to interpret the estimated coefficients. I use principal components regression below where its economic interpretation is more facile.

variables are the computer characteristics including ASK, to estimate the effect of suggested price on offers. However, such a regression will not wholly account for the correlation between ASK and the other dependent variables. I use a different approach.

In order to control for the characteristics I first estimate a model of suggested price. The equation is

$$\mathbf{ASK}=\mathbf{XB}+\boldsymbol{\varepsilon},$$

where **ASK** is the vector of suggested prices, **X** is the matrix of characteristics, **B** is a vector of parameters, and $\boldsymbol{\varepsilon}$ is a vector of random error terms. Estimation of **B** using ordinary least squares will produce unbiased estimates but the existence of multicollinearity mentioned above may lead to unstable estimates. To resolve the multicollinearity problem I use principal components regression. The technique is described in Jolliffe (1986), and provides biased estimates of the elements of **B**. (The principal components regressions are in deviations form, but I abuse notation and let **ASK** and **X** represent the deviations matrices as well). Let $\mathbf{B}_{\mathbf{PC}}$ denote the principal components regression estimate for the parameter vector **B**. Estimates appear in Table 3. The estimated parameters of $\mathbf{B}_{\mathbf{PC}}$ are biased and regression diagnostics such as recommended in Chatterjee and Hadi (1988) reveal that the residuals do not follow a normal distribution and so significance tests may not be valid. My objective, however, is not to estimate the relationship between observed characteristics and suggested price, so that the bias is not of special concern. The use of principal components regression allows estimation of predicted suggested prices without deleting any relevant variables which are meaningful in an economic sense as prospective buyers use the observable characteristics to make assessments about what the price "should" be.

The vector of estimated suggested prices given the characteristics is

$$A\hat{S}K=\mathbf{XB}_{\mathbf{PC}}.$$

We can interpret the elements of the vector $\mathbf{XB}_{\mathbf{PC}}$ as the prices that we would anticipate the sellers to ask given the characteristics of their computers. However, a seller may ask more or less than this amount. One reason a seller may ask more is that his/her computer is well maintained or he/she may ask less knowing that his/her computer has been poorly maintained, say by exposure to extreme temperatures. Recall that a buyer has the option of returning a computer after inspection, so that a buyer paying a “high” price might decide to return a computer if after inspection it is slower than anticipated or “crashes” often.

The regression above produces a vector of error terms,

$$\mathbf{ERROR} = \mathbf{ASK} - \mathbf{XB}_{\mathbf{PC}}.$$

An entry in the vector ERROR is that part of the suggested price that cannot be explained by the computer observed characteristics. These errors do not follow a normal distribution and there are outliers. I also estimated the equation using a transformation of ASK, namely its square root. Although the resulting errors followed a better pattern they were still not distributed normal. Results for the transformed variables are also in Table 3.

The next step is to estimate the equation where BID is the left-hand-side variable and ERROR is a right-hand-side variable. If the estimated coefficient on ERROR is positive, then this suggests that buyers do perceive the suggested prices to provide information about quality. Why? ERROR is, again, that portion of the suggested price which cannot be explained by the computer observed characteristics. If buyers ignore the suggested price their offers will be correlated with computer characteristics but not with ASK. When buyers do infer quality from the suggested price they will presumably control for the computer observed characteristics and observe how the suggested price deviates from the expected suggested price given the characteristics. The relevance of computing the residuals from the first equation as opposed to simply regressing BID on ASK and the other characteristics is that ASK is correlated with the other characteristics, but the residuals are not.

Table 4 shows results from regressions where BID is the dependent variable. The regressions use Heckman's two stage procedure (Heckman (1979)). Heckman’s procedure is useful in this situation where we have possible sample selection bias. That is, not all of the computers placed for sale are used in the regressions. We only use those observations where a buyer places a positive bid. If there are systematic differences between those observations which receive a bid and those which do not, our estimates will be biased because of the sample selection process.

Heckman’s procedure consists of two steps or stages. The first stage is the computation of the probit estimates in Table 2 and using these estimates to compute the inverse Mill’s ratio (IMR) for each observation. The inverse Mill’s ratio for observation *k* is the normal density function divided by the normal distribution function evaluated at $x_k\mathbf{B}_{\mathbf{probit}}$, where x_k is the vector of observed characteristics (used in Table 2) for k and $\mathbf{B}_{\mathbf{probit}}$ are the probit estimates. The second stage is the estimation of the coefficients in Table 4 using the IMR as a dependent variable. I include the IMR to correct for sample selection bias introduced by not using observations with no offer to buy. (Refer to Greene [1997] for a discussion of sample selection bias and Heckman's two stage procedure).

Table 4 shows the estimated coefficient on ERROR in various regressions. Rows (a) and (b) show a coefficient of just over .4, and this is statistically significant at the .01 level. For every dollar above the expected suggested price that a seller lists his/her computer the high offer increases by $.46. The positive coefficient on ERROR suggests that buyers do take the suggested price to be a signal of unknown quality. However, regression diagnostics suggest that the model is not appropriate and significance test may not be valid (refer to Chatterjee and Hadi (1988) for a discussion of various diagnostics); nonetheless, the coefficients in (a) and (b) are appealing because they are easy to interpret.

A transformation of the variable BID was used in rows (c)-(f) where the dependent variable is the square root of BID. In rows (d) and (f) the residuals follow a normal distribution and these appear to be the more appropriate models. The coefficient in (f) while positive is difficult to interpret concerning its magnitude. The coefficient in (d) is also difficult to interpret because of its nonlinear nature but consider the following example. Suppose that for a given observation the predicted BID is the average of $572 in Table 1 when the predicted suggested price equals the suggested price (ERROR=0). For the same observation if instead the suggested price were $100 over the predicted price (ERROR=$100) then the predicted BID would be $609. Each of the regressions in Table 4 shows a positive and statistically significant estimated coefficient on ERROR so that the result appears robust.

6. Potential Problems and Other Explanations

I do not have any transactions prices. The offers I used for the two stage regressions were the highest offer on each computer. The highest offer is the closest to any possible transaction price on the computers I observed. How would the use of actual transactions prices possibly change the results? On average I expect transactions prices to be higher than the BIDs I used because sellers did not accept the offers I used, and I assume that on average sellers would not accept lower offers but instead higher offers. For the coefficient on ERROR to have a smaller magnitude with actual transactions prices, we would have to observe that accepted offers were lower for relatively higher values of ERROR and higher for relatively lower values of ERROR. I cannot think of a reason why this would be the case. It seems unlikely that using transactions data would provide a smaller estimate of the coefficient on ERROR.

If buyers increase their offers for every dollar above the expected suggested price a seller lists his/her computer as suggested by rows (a) and (b) in Table 4, why don't sellers set prices of say $10,000 or $100,000 or more? Any suggested price above the price of a new computer ceases to be economically meaningful. A buyer could simply buy a new computer. The listings did not have "unreasonable" suggested prices. A suggested price of $100,000 is an out of sample value. The residual it generates is also out of sample. We cannot conclude that the estimated relationship holds in that range. For example, suppose a seller sets a suggested price of $51,000 instead of $50,000. It is neither statistically nor economically meaningful to suggest that doing so will result in an increase in the high offer of $333. Additionally, the transformed model in (d) of Table 4 appears to be most appropriate.

An alternate explanation for the empirical result is that some sellers are patient while others are interested in a quick sale. For example, consider the housing market. Some sellers set prices which seem high, and others set prices which seem low given the characteristics such as square footage, school district, etc. The idea is that some sellers are willing to wait for the "right" buyer, interested in their particular home, and willing to pay a slightly higher price. Other sellers want to sell quickly, and so set a low price. In the used computer market this does not seem likely. Suppose a seller suggests a high price and is willing to wait for the right buyer. The right buyer will never come along. Buyers have options for other very similar computers or even new computers and it is difficult to conceive why any one computer has some special attribute not available in another computer. Homes, on the contrary, may have a special "charm" or other idiosyncrasies. Additionally, because of rapid changes in available computing technology computers become obsolete in a relatively short period. Waiting for the right buyer may mean that the computer falls in value as better computers become available. It is tenuous that even a patient seller would set a high price.

Another concern may relate to the fact that all observations were taken from an internet business at a time when e-commerce was fairly young. The data are valid nonetheless and similar data from the same time period have been used recently to test the notion that high asking prices results in longer waiting times until sale (see Farmer and Stango (2004)). The only potential problem is that people attracted to the internet in subsequent years may have a systematically different view of the concept that if something costs more it must be better. In that case the results here are a special case that suggests perhaps only some group of people (those that were early internet users) view prices as signals of quality.

Finally, buyers have information that the econometrician does not. For some of the characteristics I used dummy variables, but the buyers may know more about that particular characteristic than simply "there/not there." For example, if the listed computer has a keyboard, KEY takes on a value of one. However, there are different brands of keyboards. When obtaining the residuals, some keyboards may generate positive errors while others generate negative errors. This could also account for the results. I can only say then that the results here are suggestive that buyers do take prices to be signals of quality: the empirical results are consistent with the theory. Other explanations are possible.

7. Conclusion

Theory suggests that prices can serve as signals of unknown quality. This is true even in the case when there is a return policy where both buyer and seller must incur a transaction cost. To this point only anecdotal evidence supports the idea that buyers believe that if something costs more it must be better. The absence of any empirical support for these theories leaves a gap in the literature. The results here provide an initial step in filling that gap. This paper provides results from a used computer market that are consistent with the theory of price signaling. Computers with higher suggested prices received higher bids, controlling for similarities in observable computer characteristics. While these results are consistent with the theory of price signaling, they do not establish causality. We cannot rule out other possible explanations for the observed relationship between buyers' offered prices and the suggested prices. Confirmatory evidence from other markets is needed and remains an area for further research.

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Table 1: Summary Statistics

	All Computer, N=494		Computers with one or more bids, N=345	
Variable	**Mean**	**Standard Deviation**	**Mean**	**Standard Deviation**
BID			572	422
ASK	813	604	946	538
WEEKS	11	7	12	6
SPEED	86	67	103	58
RAM	38	39	45	36
VRAM	720	1185	899	1111
SIZE	950	1461	1169	1388
NSTOR	.59	.59	.69	.49
	Dummy Variables			
	Proportion		**Proportion**	
KEY	.83		.82	
MOUSE	.86		.88	
COMMENT	.75		.77	
GRAPHICS	.63		.65	
AUDIO	.67		.70	
NTWRK	.47		.52	
MODEM	.34		.33	

Table 2: Regression Results

Variable	Dependent variable=1 if computer received at least one offer		Dependent variable is the number of offers the computer received	
	Logit, estimated coefficients	**Probit, estimated coefficients**	**OLS, estimated coefficients**	**Poisson, estimated coefficients**
INTERCEPT	-1.39 (0.81)	-.773 (.463)	0.751* (.331)	-0.141 (0.219)
WEEKS	0.198* (0.303)	.113* (.016)	.083* (.010)	.059* (.007)
ASK	-5.2E-4 (5.4E-4)	-2.8E-4 (3.1E-4)	4.3E-4* (1.8E-4)	8.3E-5 (8.6E-5)
SPEED	0.008 (0.006)	4.6E-3 (3.5E-3)	2.6E-3 (1.9E-3)	0.002 (.001)
RAM	0.017 (0.009)	8.9E-3 (5.1E-3)	1.6E-5 (2.0E-3)	-9.2E-5 (.001)
VRAM	2.9E-4 (2.3E-4)	1.7E-4 (1.3E-4)	1.7E-4* (6.4E-5)	9.3E-5* (3.3E-5)
SIZE	2.7E-4 (3.4E-4)	1.8E-4 (1.9E-4)	-2.1E-5 (4.9E-5)	-1.4E-5 (2.8E-5)
KEY	-1.037* (0.501)	-.576* (.281)	-.379 (.207)	-.278 (.145)
MOUSE	0.671 (0.514)	.351 (.293)	.296 (.223)	.184 (.165)
COMMENT	-0.185 (0.368)	-..080 (.207)	-.185 (.145)	-.153 (.101)
GRAPHICS	0.523 (0.503)	.346 (.285)	.259 (.199)	.203 (.144)
AUDIO	-.580 (0.559)	0.060 (0.238)	-.087 (0.229)	-.127 (.163)
NTWRK	0.026 (0.424)	-.398 (.317)	-.054 (.165)	0.026 (.113)
MODEM	-.455 (0.386)	-.227 (.217)	-.416* (.150)	-.245* (.106)
NSTOR	0.411 (0.362)	.213 (.203)	-.157 (.126)	-.049 (.080)
FIXED EFFECTS	70 models	70 models	70 models	70 models
N	494	494	494	494
R square			.52	
Log likelihood	-149	-149		-621
Chi square Stat., d.f.=84	306*	306*		356*

Standard errors are in parentheses and * denotes statistical significance at the .05 level or better.

Table 3: Parameter Estimates From Principal Components Regressions.

Independent variable	**(3a)** **Dependent Variable = ASK**	**(3b)** **Dependent Variable= Square Root of ASK**
SPEED	271.71*	4.19*
	(24.02)	(0.339)
RAM	150.01*	1.98*
	(16.28)	(0.255)
VRAM	21.55*	0.308*
	(10.22)	(0.156)
SIZE	26.34*	0.442*
	(12.25)	(0.182)
KEY	-3.11	0.102
	(8.09)	(0.121)
MOUSE	-6.42	-.045
	(9.82)	(0.156)
COMMENT	8.16	0.267
	(14.07)	(0.202)
GRAPHICS	25.17*	0.418*
	(8.62)	(0.153)
AUDIO	-10.63	-.101
	(7.86)	(0.112)
NTWRK	11.43	-.158
	(7.41)	(0.249)
MODEM	6.97	0.254
	(9.94)	(0.157)
NSTOR	22.82	0.487*
	(11.81)	(0.176)
Fixed effects	YES-70	YES-70
N	494	494
R square	.6923	.7467
Adj. R square	.6562	.7200

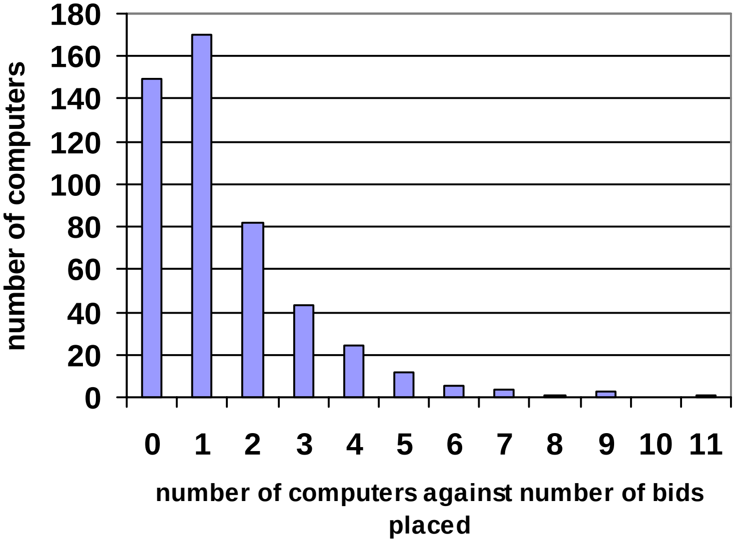
Standard errors are in parentheses, (derivation is found in Jolliffe (1986) see page 133) and * denotes statistical significance at the .05 level or better. The adj R square method was used to select the principal components. There were 52 principal components used in the first regression. The second regression has a transformed dependent variable and there were 47 principal components used. In both regressions there are multiple outliers and influential (large Welsch-Kuh statistics) observations and in neither case are the residuals well behaved, significance tests may not be valid. Parameter estimates are biased.

Table 4. Parameter Estimates For Heckman 2 Stage Regressions

	Independent Variables				R^2	adj. R^2	N
	Intercept	**ERROR**	**IMR**	**OTHER**			
(a)	642.16* (26.29)	0.420* (0.059)	-417.51* (61.69)	no	.2876	.2834	345
(b)	44.43 (50.60)	0.46* (0.035)	-58.18 (41.97)	yes	.6709	.6569	345
(c)	24.21* (0.53)	6.8E-3* (0.001)	-9.57* (1.27)	no	.3009	.2968	345
(d)	12.13* (0.97)	7.6E-3* (6.7E-4)	-2.77* (.807)	yes	.6727	.6588	345
(e)	24.148* (0.532)	0.472* (0.088)	-9.406* (1.273)	no	.2872	.2830	345
(f)	11.73* (0.97)	0.56* (0.049)	-2.45* (0.811)	yes	.6716	.6576	345

Standard errors are in parentheses and * denotes statistical significance at the .05 level or better.
OTHER independent variables are those in Table 2 without any fixed effects.
(a) dependent variable is ASK, ERROR is obtained from regression 3a in Table 3.
(b) dependent variable is ASK, ERROR is obtained from regression 3a in Table 3.
(c) dependent variable is square root of ASK, ERROR is obtained from regression 3a in Table 3.
(d) dependent variable is square root of ASK, ERROR is obtained from regression 3a in Table 3.
(e) dependent variable is square root of ASK, ERROR is obtained from regression 3b in Table 3.
(f) dependent variable is square root of ASK, ERROR is obtained from regression 3b in Table 3.
All regressions contain some outliers (observations with large studentized residuals) and influential observations (using Welsch-Kuh statistic). The residuals in (d) and (f) are well behaved and fit a normal distribution. The residuals in (a), (b), (c), and (e) are not well behaved and do not fit a normal distribution, significance tests may not be valid.

Figure 1.


180
160
140
120
100
80
60
40
20
0
number of computers
0 1 2 3 4 5 6 7 8 9 10 11
number of computers against number of bids placed