Empirical Tests of Information Aggregation

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Abstract

This paper proposes tests to empirically examine whether auction prices aggregate information away from the limit. These tests are based on 1) a combination of comparative statics with respect to the number of bidders and the dispersion of information signals and 2) comparison of actual prices to predicted Nash equilibrium prices based on observed auction parameters. When applied to eBay online auctions for computers, these tests suggest that prices partially aggregate information, but do not converge to the common value. Even partial information aggregation may represent a potential efficiency gain over one-to-one trade of used goods with uncertain common values. (*JEL* D44, D8, L81; *keywords* eBay, auctions, information)

eBay claims that they "make inefficient markets efficient for millions of users," particularly for used goods.[1] Why might their auction mechanism result in an efficiency gain for buyers and sellers in the used goods market? The value of used goods is often uncertain to both the sellers and the buyers, although they posses some private information signal about that value. In theory, this private information is revealed through the auction mechanism. Auction theory predicts that under certain conditions, the auction prices will converge to the common value (CV) of the item. The theory refers to this convergence as "information aggregation," since dispersed private information signals are aggregated into the price. This aggregation is accomplished by bidders playing Nash equilibrium strategies, where they take into account expectations over information the other bidders received. Thus, both buyers and sellers can employ the auction mechanism to resolve uncertainty over both the price and allocation of the good, rather than try to engage in a one-to-one exchange based solely on private information and potentially fail to transact due to incomplete information.

However, the information aggregation predictions of auction theory hold in the limit, as the number of bidders goes to infinity. How can we empirically test for information aggregation in commercial auctions such as eBay, where observations are likely to be away from the limit? Is there any evidence from these auctions that, away from the limit, prices become more informative as the number of bidders grows (i.e., do prices partially aggregate private information away from the limit)?

This paper presents comparative static implications for auction price behavior on the path of convergence. Some of these comparative statics describe necessary conditions for partial information aggregation. Stronger evidence for information aggregation requires knowledge of the underlying distribution of information in the auction. If the underlying distribution of information is known, and this known distribution satisfies the conditions necessary for information aggregation, then predictions can be made regarding how prices that aggregate information should behave away from the limit. If we observe convergence of predicted prices

[1] eBay presentation at 2004 Pacific Crest Technology Forum, August 10, 2004.

to the common value, then we would expect actual prices to converge as well.

Section 1 presents the auction theory on information aggregation from Wilson (1977) and Milgrom (1979) and its extension to second price auctions by Kremer (2002). It then develops comparative static implications of the theory for use in testing price behavior in a commercial auction setting. In particular, I develop comparative static implications for examining auctions with differing common values. I measure convergence in two ways: convergence of average prices to the mean of the underlying distribution of common values, and convergence of the standard deviation of prices to the standard deviation of the underlying distribution of common values.

Section 2 reviews the auction and survey data employed. I employ data from a sample of eBay auctions for computers. Work done in Yin (2005) establishes that these auctions most closely resemble common value auctions with lognormally distributed values and signals. The eBay computer auctions thus satisfy the conditions necessary for information aggregation.

In Section 3, I estimate the relevant comparative statics in my sample of eBay computer auctions. I employ the predicted Nash CV prices to identify convergence behavior in my sample. While the comparative statics do not match for average price convergence, they do match for standard deviation convergence results. eBay prices do become more informative as the number of bidders increases; however, there is insufficient evidence to conclude that they aggregate information fully in the limit. Nevertheless, even partial information aggregation by eBay auction prices suggets a potential efficiency gain over one-to-one trade of used goods with uncertain common values.

1 Conditions for Information Aggregation

This section reviews the necessary and sufficient conditions for information aggregation from auction theory. It then presents the observable implications of this theory away from the limit. These implications are translated into comparative static results for a sample of auctions with different common values.

Consider a first-price sealed-bid common value auction, with bidders indexed by i. Wilson (1977) established that if the common value v is distributed $U[\underline{v}, \bar{v}]$ and the bidder's signal x_i is iid $\backsim U[0, v]$, then as the number of bidders n goes to infinity, the winning bid p_n converges almost surely to v.

Milgrom (1979) relaxes the distribution on v, only imposing that it have finite expectation. He shows the necessary and sufficient conditions for p_n to converge in probability to v. Let bidder 1 be the bidder that receives the highest signal, denoted x_1. Then bidder 1 must be able to distinguish with high probability whether the true value of the product is equal to or less than her own signal-based estimate of v for the product. From Milgrom (1979):

Theorem 1 *Let k index every possible realization of v. $p_n \to v$ in probability if and only if for every k the event $\{v = v_k\}$ can be distinguished from $\{v < v_k\}$ using x_1.*

From Milgrom (1979), the definition of "distinguish" is the following:

Definition 1 *Let C and D be events and x be a random variable, all in the same probability space. Then by "C can be distinguished from D using x" we mean that either (i) $P(D) = 0$ or (ii) $P(C) > 0$ and $\inf_A \dfrac{P\{x \in A|D\}}{P\{x \in A|C\}} = 0$.*

Kremer (2002) analyzes information aggregation for second-price auctions. As long as distinguishing signals exist, the conditions for information aggregation from Milgrom (1979) follow through, and prices from second-price auctions are expected to converge to the common value as $n \to \infty$.

What are the observable implications of information aggregation for price behavior along the path of convergence? The expected difference between price and the common value should decrease as the number of bidders increases for large enough n. The standard deviation of prices should also decrease as the number of bidders increase for large enough n, since the x_1 will distinguish a lower bound on v by the theorem above.

Hong & Shum (2002) show that the rate of convergence is faster when the dispersion of the information signals, $\sigma_{x|v}$, is lower. So if we have a measure of the dispersion of signals in these auctions, then we may observe that prices converge more quickly when information is less dispersed.

Now consider what we would expect from the distribution of prices for a sample of auctions with different common values. Assume that the common values were distributed with mean μ_v and standard deviation σ_v. If prices aggregate information, then we should observe the average of prices from these auctions, $\overline{p_n}$, converging to μ_v as n goes to infinity. The standard deviation of the prices over these auctions, $sd[p_n]$, should converge to σ_v. Both of these types of convergence should occur at a faster rate when the dispersion of signals in the auctions is lower.

For auctions with common values drawn from the same distribution, I translate these observable implications into the following comparative statics. I denote by $\underline{n}$ the minimum number of bidders necessary for an implication to hold.

1. $\dfrac{\partial|\mu_v - \overline{p_n}|}{\partial n} < 0$ for $n > \underline{n}$.[2] The absolute value of the difference between the expected common value and average price over the auctions should decrease as the number of bidders increases for large enough n.

2. $\dfrac{\partial|sd[p_n] - \sigma_v|}{\partial n} < 0$ for $n > \underline{n}$. The absolute value of the difference between the standard deviation of prices over the auctions and the standard deviation of the distribution of common values should decrease as the number of bidders increases for large enough n.

3. $\dfrac{\partial^2|\mu_v - \overline{p_n}|}{\partial n \partial \sigma_{x|v}} > 0$ for $n > \underline{n}$. The absolute value of the difference between the average price and the common value should decrease with the number of bidders at a decreasing rate with dispersion of information signals for large enough n.

[2] Although monotone comparative statics would be more appropriate to use to describe the relationship between n and p, I treat n as a continuous variable and p as continous in n. This is consistent with the empirical application later in the paper: I will employ averages of auction characteristics to examine convergence to means and variances, and the average of n will not be constrained to integers.

4. $\dfrac{\partial |sd[p_n] - \sigma_v|}{\partial n \partial \sigma_{x|v}} > 0$ for $n > \underline{n}$. The absolute value of the difference between the standard deviation of prices and the standard deviation of common values should decrease with the number of bidders at a decreasing rate with dispersion of information signals for large enough n.

Implications $1-4$ are observable for large enough n; if only a small number of bidders is observed, then the price convergence comparative statics may not hold, even though prices aggregate information in the limit. However, consider the case where the underlying distribution of information was known and the signals were distinguishing. In addition, assume that for each auction, indexed by t, $\sigma_{x|v,t}$, v_t, and n_t were known. One could then simulate Nash CV prices, and determine whether we should expect price convergence based on the behavior of the simulated prices. In other words, we can use simulated Nash CV prices to determine whether the n we observe is greater than $\underline{n}$. If Implications $1-4$ do not hold, but the simulated prices suggest that they should, then we can conclude that prices do not aggregate information in the limit.

The next section presents the data from a sample of eBay computer auctions which will be used to test the implications from this section.

2 Data

Over 5000 new and used computers are listed daily in the personal computer (PC) category by both individuals and businesses. The eBay auction mechanism is best described as a second-price sealed bid auction. Potential bidders observe the current price and the number of bids at all times. The current price is one bid increment (as defined by eBay rules) above the second highest bid currently submitted, unless this causes the current price to exceed the highest bid currently submitted, in which case the price equals the highest bid. Although the auction runs like an English auction, the ability of bidders to enter and exit at any time and multiple times in an auction leads to uncertainty over other bidders' valuations, an environment which is best modeled as sealed bid. (Harstad & Rothkopf 2000)

A reputation mechanism on eBay reports a seller's (or buyer's) overall feedback score. This score equals the number of auctions for which she received positive feedback minus the number where she received negative feedback.

Price, seller reputation, the number of bidders, and the item description were collected for 222 eBay PC auctions held between June 24 and July 12, 2002. The price in each auction is denoted P_t. The number of bidders in the auctions is denoted N_t. The overall feedback score of the seller in each auction is denoted $SCORE_t$, and the negative feedback for the seller is recorded separately under NEG_t.

The item descriptions were used to create a survey in order to generate a measure of the common value and the dispersion of information signals in each auction. The resulting estimates employed in this paper, denoted $\tilde{\sigma}_{x|v,t}$ and $\tilde{v}_t$, are the result of work done in Yin (2005), which established that eBay personal computer auctions can be modeled as common value auctions where the common values are drawn from a common distribution. The average of $\tilde{v}_t$ over all 222 auctions, \$578.61, is used as an estimate of μ_v, denoted $\hat{\mu}_v$. The standard deviation of $\tilde{v}_t$ over all the auctions, 309.51, is used as an estimate of σ_v, denoted $\hat{\sigma}_v$. These estimates were used to simulate Nash prices, denoted here as $NASH_t$, for each auction, assuming lognormally distributed values and signals.[3] Summary statistics for these auction characteristics are reported in Table 1.

In order to empirically examine the comparative statics with respect to n from the previous section, I need observations of the average price and standard deviation of prices over auctions that share the same number of bidders. If I were to restrict my averages to auctions that had the same N_t, this would lead to only 21 observations, one for each different observed number of bidders. In addition, I would have averages based on a very small number of auctions for the higher N_t. I instead employed the auction characteristics from the 222 auctions to generate 203 observations in the following manner. I first fixed the number of auctions

[3]Robustness checks in Yin (2005) suggested that lognormal distributions for the common values generated the best fit to the distribution of prices for the sample of eBay computer auctions.

Table 1: Summary statistics for 222 eBay computer auctions

Variable	**mean**	**st. dev.**	**min**	**max**
price P_t	\$359.01	369.16	\$9.51	\$2802.00
simulated Nash price $NASH_t$	\$557.19	247.86	\$157.77	\$1519.21
overall score $SCORE_t$	680	2601	0	19456
negative score NEG_t	25.5	106	0	785
no. of bidders N_t	6.5	4	2	22
common value $\tilde{v}_t$	\$578.61	309.51	\$28.16	\$1706.36
signal dispersion $\tilde{\sigma}_{x\|v,t}$	316.64	129.95	40.14	714.87

I would use to generate average prices and standard deviation of prices at 20 auctions. I then ordered the auctions by the number of bidders, and generated a rolling average over 20 auctions. For example, the first observation was generated by taking the average and standard deviation of P_t over the first 20 auctions in my list. The second observation was generated by taking the average and standard deviation of P_t over the 2nd through 21st auction on my list, and so on. This procedure ensured that the number of bidders in the auctions used in my averages deviated by no more than ± 1 bidder.

I denote these averages by $\overline{P}_{\overline{N}}$ and standard deviations by $sd[P_{\overline{N}}]$, where the index $\overline{N}$ is the average of the N_t for that group of 20 auctions. I employ these estimates to calculate the absolute difference between average prices and the expected common value and the standard deviation of prices and the standard deviation of common values, denoted $|\hat{\mu}_v - \overline{P}_{\overline{N}}|$ and $|\hat{\sigma}_v - sd[P_{\overline{N}}]|$, respectively. Summary statistics are presented in Table 2.

Using $\overline{N}_{\overline{N}}$ as an approximation for the number of bidders in each of these constructed observations is consistent with the interpretation of N_t. N_t itself is an approximation to the number of participants in the auction, since the number of people who submit bids in the auction does not necessarily equal the number of people who were actively participating in the auction (e.g., a potential bidder may have arrived at the auction too late to submit a low bid). However, the process of limiting the standard deviation on these N_t means that I allow other auction characteristics to vary within my observations. I calculated the average and standard deviation of $SCORE_t$, NEG_t, $\tilde{\sigma}_{x|v,t}$, and $\tilde{v}_t$ as well, so that I could control for these differences across observations. The same notation conventions that applied to prices apply to these statistics.

3 Comparative Static Estimates

In this section, I estimate 2 equations. The dependent variable of the first equation is price convergence, $|\hat{\mu}_v - \overline{P}_{\overline{N}}|$. The dependent variable in the second equation is convergence of standard deviation of prices, $|\tilde{\sigma}_v - sd[P_{\overline{N}}]|$. In both cases, I am interested in determining the effect of changes in $N_{\overline{N}}$ on convergence and the interaction effect between $N_{\overline{N}}$ and the dispersion of information $\tilde{\sigma}_{x|v,\overline{N}}$ while controlling for the effect of other auction characteristics on convergence.

The results of ordinary least squares estimation for the two equations are presented in Table 3. Column 1 shows the results for average price convergence. Column 2 shows the results for convergence of standard deviation of prices. The coefficients on $N_{\overline{N}}$ and $N_{\overline{N}} \times \tilde{\sigma}_{x|v,\overline{N}}$ are significant in both models. The signs on the coefficients in Column 1 are inconsistent with the comparative statics implied by average price convergence. $\frac{\partial|\mu_v - \overline{p_n}|}{\partial n}$ is greater than 0, contrary to Implication 1 from Section 1. Likewise, $\frac{\partial^2|\mu_v - \overline{p_n}|}{\partial n \partial \sigma_{x|v}}$ is less than 0, contrary to Implication 3. The absolute difference between the average eBay prices and the estimated expected common value is increasing with the number of bidders at a decreasing rate with dispersion. However, the signs on bidder-related coefficients in Column 2 are consistent with the comparative statics implied by convergence of standard deviation of prices (implications 2 and 4 from Section 1). The absolute difference between the dispersion of prices and the dispersion of common values is decreasing with the number of bidders at a decreasing rate with dispersion.

Table 2: Summary statistics for 203 constructed auction averages

Variable	**mean**	**s.d.**	**min**	**max**
avg. price $\overline{P}_{\overline{N}}$	\$363.35	\$119.82	\$133.16	\$636.93
diff. in means $\lvert\hat{\mu}_v - \overline{P}_{\overline{N}}\rvert$	\$219.34	\$112.14	\$0.19	\$445.45
avg. sim. Nash price $\overline{NASH}_{\overline{N}}$	\$546.86	\$114.01	\$306.51	\$798.84
s.d. price $sd[P_{\overline{N}}]$	323.21	158.84	99.03	689.65
diff. in st. dev. $\lvert\tilde{\sigma}_v - sd[P_{\overline{N}}]\rvert$	130.63	90.95	3.72	380.14
avg. score $\overline{SCORE}_{\overline{N}}$	790.71	603.54	71.35	2213.25
s.d. score $sd[SCORE_{\overline{N}}]$	2044.16	1730.96	156.35	5006.00
avg. neg. score $\overline{NEG}_{\overline{N}}$	23.98	19.21	1.05	71.6
s.d. neg. score $sd[NEG_{\overline{N}}]$	80.77	70.40	1.61	212.17
avg. no. of bidders $\overline{N}_{\overline{N}}$	6.34	3.19	2	14.95
s.d. no. of bidders $sd[N_{\overline{N}}]$	0.45	0.34	0	2.48
avg. common value $\overline{\tilde{v}}_{\overline{N}}$	\$585.11	\$123.14	\$302.62	\$869.33
s.d. common value $sd[\tilde{v}_{\overline{N}}]$	272.76	84.02	101.81	421.18
avg. dispersion $\overline{\tilde{\sigma}}_{x\|v,\overline{N}}$	319.34	31.17	240.77	382.23
s.d. dispersion $sd[\tilde{\sigma}_{x\|v,\overline{N}}]$	126.23	19.32	75.49	174.54
avg. credible $\overline{\tilde{\sigma}_{x\|v,\overline{N}} \times SCORE_{\overline{N}}}$	294264	266478	26056	864903
avg. discount $\overline{\tilde{\sigma}_{x\|v,\overline{N}} \times NEG_{\overline{N}}}$	8730.94	8176.39	386.39	23626
s.d. credible $sd[\tilde{\sigma}_{x\|v,\overline{N}} \times SCORE_{\overline{N}}]$	855522	952900	62788	3.1E06
s.d. discount $sd[\tilde{\sigma}_{x\|v,\overline{N}} \times NEG_{\overline{N}}]$	30322	31893	637.68	94789
avg. dispersion² $\overline{\tilde{\sigma}^2_{x\|v,\overline{N}}}$	126.23	19.32	75.49	174.54
avg. score² $\overline{SCORE^2_{\overline{N}}}$	7.8E06	9.3E06	28501	2.9E07

Although not all implications are satisfied, we need to examine whether we should even expect to observe the implications of convergence for $n \leq 15$, the maximum of $N_{\overline{N}}$. Columns 1 and 2 of Table 4 present results from replacing $P_{\overline{N}}$ by simulated Nash prices, $\overline{NASH}_{\overline{N}}$, in the equations estimated in Columns 1 and 2 of Table 3, respectively. The signs on $N_{\overline{N}}$ and $N_{\overline{N}} \times \tilde{\sigma}_{x|v,\overline{N}}$ confirm that we should expect to observe the same comparative static signs from Implications $1-4$ in the eBay prices. I then examine the simulated Nash prices to determine whether any auctions should be expected to converge in our sample of auctions. The simulated Nash prices suggest that we should observe price convergence to the common value in 30% of the auctions. However, an examination of the absolute difference between the eBay price and $\tilde{v}_t$ for those auctions indicates that only 1 of those auctions does converge. Over all the auctions, eBay prices converge to $\tilde{v}_t$ in only 5 auctions. This evidence suggests that eBay prices do not aggregate information in the limit.

However, as apparent in Table 1, the simulated Nash prices are on average \$196.16 higher than the eBay prices. In Column 3 of Table 3, I re-estimated the standard deviation of prices equation, where I replaced $\tilde{v}_t$ by $\tilde{v}_t - 196.16$. I found that Implications 1 and 3 now hold. As a robustness check, I also estimated the equation replacing $\tilde{v}_t$ by 0. Implications 1 and 3 did not hold in this case. It seems that prices are in fact converging to a value that is lower than the expected common value.

This finding is consistent with the conclusions from Yin (2005): although bidders do take into account the winner's curse, they may be overreacting to the winner's curse on eBay. As a result, eBay prices do converge to a value, but the value is lower than the common value. This result is also consistent with theoretical predictions from Kremer & Jackson (2004). They establish that prices may converge to values less than the common value in multi-unit discriminatory auctions. If eBay bidders participate in multiple auctions over time and adjust bids so that they only win in one auction, their behavior might resemble that of multi-unit discriminatory auctions. Another possible explanation for the deviation is that computers are a mix of private and common values. The common value component could drive the convergence in dispersion, while the private value component could drive the wedge between realized prices and the common value.

Kremer (2002) notes that in the absence of distinguishing signals, second-price sealed bid auctions produce "semi-informative" prices: prices do not converge to the realized common values, but they do converge to values other than the expected common value. In this analysis of eBay computer auction prices, we have found that even in the presence of Nash equilibrium bidding behavior and distinguishing signals, we may have semi-informative prices. We can conclude that some information, although not complete information, about the common value of computers is aggregrated into prices in eBay auctions.

4 Conclusion

One of the interesting practical issues for online markets is how efficient prices are attained when information about the value of a good is dispersed among the economic agents in that market. Theory suggests that auctions may be one way to aggregate common value information without direct transfer of information between agents. The ability to achieve efficient pricing for goods of uncertain common value to both buyers and sellers may be one reason why eBay is a particularly successful market for used items and items not otherwise available through retail outlets.

However, information aggregation is a limit property. Do eBay prices actually aggregate information? This paper has identified empirical tests for information aggregation away from the limit. For a sample of auctions which share a common distribution for their common values, the average of prices over those auctions should converge to the mean of that distribution as the number of bidders increases, while the variance of prices should converge to the variance of that distribution. Convergence should occur at a faster rate if the dispersion of information signals is smaller.

If the data observed is still far from the limit, we may not observe these comparative

Table 3: Convergence of average and standard deviation of prices

Variable	Column 1	Column 2	Column 3
CONSTANT	389.308†	218.851	1348.88‡
	(215.727)	(529.53)	(356.342)
$\overline{\tilde{\sigma}}_{x\|v,\overline{N}}$	1.693	4.170	-3.219
	(1.547)	(3.798)	(2.556)
$sd[\tilde{\sigma}_{x\|v,\overline{N}}]$	0.24015	-1.17787‡	-1.07996‡
	(0.148123)	(0.36588)	(0.244672)
$\overline{N}_{\overline{N}}$	24.409†	-207.122‡	-165.523‡
	(13.014)	(31.945)	(21.497)
$sd[N_{\overline{N}}]$	11.426	-48.632‡	47.183‡
	(9.549)	(23.440)	(15.773)
$\overline{SCORE}_{\overline{N}}$	0.154†	-0.465‡	-0.755‡
	(0.086)	(0.210)	(0.141)
$sd[SCORE_{\overline{N}}]$	-0.064‡	0.075	0.165‡
	(0.025)	(0.062)	(0.042)
$\overline{NEG}_{\overline{N}}$	-0.462	6.027	25.408‡
	(3.787)	(9.296)	(6.256)
$sd[NEG_{\overline{N}}]$	0.795	-1.225	-5.926‡
	(0.841)	(2.063)	(1.388)
$\overline{\tilde{\sigma}}_{x\|v,\overline{N}} \times \overline{N}_{\overline{N}}$	-0.094‡	0.700‡	0.496‡
	(0.042)	(0.104)	(0.070)
$\overline{\tilde{v}}_{\overline{N}}$	-0.602‡	-0.071	0.087
	(0.065)	(0.161)	(0.108)
$sd[\tilde{v}_{\overline{N}}]$	-0.542‡	0.515‡	0.451‡
	(0.044)	(0.109)	(0.073)
$\overline{\tilde{\sigma}_{x\|v,\overline{N}} \times SCORE_{\overline{N}}}$	-.45E-03†	0.12E-02†	0.24E-02‡
	(0.27E-03)	(0.67E-03)	(.45E-03)
$\overline{\tilde{\sigma}_{x\|v,\overline{N}} \times NEG_{\overline{N}}}$	0.017	-0.040	-0.101
	(0.012)	(0.030)	(0.020)
$sd[\tilde{\sigma}_{x\|v,\overline{N}} \times SCORE_{\overline{N}}]$	0.13E-03‡	-0.38E-03‡	-0.56E-03
	(0.59E-04)	(0.15E-03)	(0.98E-04)
$sd[\tilde{\sigma}_{x\|v,\overline{N}} \times NEG_{\overline{N}}]$	-0.34E-02	0.93E-02	0.023‡
	(0.27E-02)	(0.66E-02)	(0.44E-02)
$\overline{\tilde{\sigma}^2_{x\|v,\overline{N}}}$	-0.20E-02	-0.013‡	-0.19E-02
	(0.27E-02)	(6.60E-03)	(0.44E-02)
$\overline{SCORE^2_{\overline{N}}}$	0.33E-05	0.16E-04‡	0.71E-05†
	(0.24E-05)	(0.58E-05)	(0.39E-05)

‡significant at 5%, †significant at 10%. Column 1 $R^2 = 0.96$, Column 2 $R^2 = 0.64$, Column 3 $R^2 = 0.76$.

Table 4: Convergence of simulated Nash prices

Variable	Column 1	Column 2
CONSTANT	$1680.43^{‡}$	-149.877
	(198.202)	(102.831)
$\overline{\tilde{\sigma}}_{x\|v,\overline{N}}$	$-8.165^{‡}$	$3.292^{‡}$
	(1.421)	(0.737)
$sd[\tilde{\sigma}_{x\|v,\overline{N}}]$	$.663222^{‡}$	$0.127^{†}$
	(0.13609)	(0.071)
$\overline{N}_{\overline{N}}$	$-100.328^{‡}$	$-18.401^{‡}$
	(11.957)	(6.204)
$sd[N_{\overline{N}}]$	$45.002^{‡}$	-4.700
	(8.773)	(4.552)
$\overline{SCORE}_{\overline{N}}$	$-5.096^{‡}$	-0.090
	(0.079)	(0.041)
$sd[SCORE_{\overline{N}}]$	$0.131^{‡}$	$0.032^{‡}$
	(0.023)	(0.012)
$\overline{NEG}_{\overline{N}}$	$16.333^{‡}$	1.44
	(3.479)	(1.805)
$sd[NEG_{\overline{N}}]$	$-4.222^{‡}$	-0.440
	(0.772)	(0.401)
$\overline{\tilde{\sigma}}_{x\|v,\overline{N}} \times \overline{N}_{\overline{N}}$	$0.274^{‡}$	$0.547^{‡}$
	(0.039)	(0.020)
$\overline{\tilde{v}}_{\overline{N}}$	$0.360^{‡}$	$-0.100^{‡}$
	(0.060)	(0.031)
$sd[\tilde{v}_{\overline{N}}]$	-0.070*	$-0.659^{‡}$
	(0.041)	(0.021)
$\overline{\tilde{\sigma}_{x\|v,\overline{N}} \times SCORE_{\overline{N}}}$	$0.16E\text{-}02^{‡}$	0.16E-03
	(0.25E-03)	(0.13E-03)
$\overline{\tilde{\sigma}_{x\|v,\overline{N}} \times NEG_{\overline{N}}}$	-0.055	0.14E-03
	(0.011)	(0.58E-02)
$sd[\tilde{\sigma}_{x\|v,\overline{N}} \times SCORE_{\overline{N}}]$	$-0.45E\text{-}03^{‡}$	-0.46E-04
	(0.54E-04)	(0.28E-04)
$sd[\tilde{\sigma}_{x\|v,\overline{N}} \times NEG_{\overline{N}}]$	$0.014^{‡}$	0.13E-03
	(0.25E-02)	(0.13E-02)
$\overline{\tilde{\sigma}^2_{x\|v,\overline{N}}}$	$0.80E\text{-}02^{‡}$	$0.55E\text{-}02^{‡}$
	(0.25E-02)	(0.13E-02)
$\overline{SCORE^2_{\overline{N}}}$	(0.22E-05)	-0.50E-06
	(0.22E-05)	(0.11E-05)

‡significant at 5%, †significant at 10%. Column 1 $R^2 = 0.90$, Column 2 $R^2 = 0.97$.

statics. Furthermore, differences in the dispersion of information in the auction and the credibility of that information will affect prices (and thus the distribution of prices in the sample) as well. The specific behavior of prices away from the limit depends on the underlying distribution of information in the auction. I generate predictions of information aggregation behavior away from the limit for the auctions in my sample, controlling for information dispersion and seller reputation. This allows me to confirm that the number of bidders in one-third of my sample is sufficiently high enough that we would expect to see evidence of convergence; the fact that we do not observe this convergence suggests that eBay prices do not aggregate information fully in the limit. However, eBay prices do converge to a value below the expected common value. The prices in eBay auctions for computers can be described as semi-informative: they partially aggregate information about the common value away from the limit. Even partial information aggregation by eBay auction prices suggests a potential efficiency gain over one-to-one trade of used goods with uncertain common values.

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