

# Information Dispersion and Auction Prices

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November 20, 2006

## Abstract

Do bidders behave as auction theory predicts they should? How do bidders (and thus, prices) react to different types of information? This paper derives implications of auction theory with respect to the dispersion of private information signals in an auction. I conduct a survey of non-bidders to construct a measure of information dispersion that is independent of bidding data. This permits joint tests of Bayesian-Nash equilibrium bidder behavior and information structure (common vs. private value) in a sample of eBay auctions for computers. The measure also allows me to separately estimate the price effects of seller reputation and product information. eBay prices appear consistent with Bayesian-Nash common value bidding behavior. Uncertainty about the value of goods due to information dispersed over auction participants plays a larger role than uncertainty about the trustworthiness of the sellers, but both are significant drivers of price. Thus, seller reputation complements, rather than substitutes for, information provided in the auction descriptions by lending credibility to that information, creating an incentive for sellers to reduce uncertainty in their auctions.

(*JEL* C42, D44, D8, D82, L14, L15, L86)

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<sup>0</sup>I would like to thank Pat Bajari, Tim Bresnahan, Susan Athey, Ed Vytlacil, Ali Hortaçsu, and three very helpful anonymous referees; Paul Hartke for scripting; Adam Juda, Tiffany Chow, Yi-Xuan Huynh, Steve Yuan, and the many survey respondents for their research assistance; and The John M. Olin Foundation through the Stanford Institute of Economic Policy Research and Stanford School of Humanities and Sciences Graduate Research Opportunities Grant for their financial support. Any mistakes in the paper are completely my own; comments and suggestions are very welcome.

This paper addresses two important and challenging questions about the use of auctions in commercial markets: “Do bidders behave in the way that theory predicts they should?” and “What are the effects of different types of information on prices?” These questions are relevant to both government and industry, who have traditionally employed auctions to price and allocate assets and contracts with high but unknown value, and the millions of people have been able to participate via the Internet in auctions for goods that are often of unknown value (e.g., used goods, unknown brands). The answers to these questions suggest the appropriate conditions under which auctions can be employed most effectively.

In theory, by solving sophisticated Bayesian-Nash (Nash) equilibrium bidding strategies, auction participants have benefited from the ability of the auction mechanism to elicit prices which reflect the true but unknown common value of the good from bidders who only possess private information signals about the value of the good. (Wilson 1977) These strategies involve accounting for the dispersion of information signals and number of bidders. Bidders that fail to do this may suffer the “winner’s curse,” where the highest bidder wins the auction at a price greater than the common value of the good. The challenge to determining whether commercial auctions are consistent with theory is that tests thus far have had to assume either that bidders a) play these equilibrium strategies or b) treat their private information as having common value rather than treat it as a reflection of their private value for the good. The assumption that participants solve complex bid functions may be particularly suspect for participants in mass-market online auctions.

This paper produces a procedure for testing both assumptions concurrently by examining price responses to changes in information dispersion and the number of participants in auctions. The procedure involves testing implications of auction theory with respect to information dispersion that are derived using results from Milgrom & Weber (1982, henceforth referred to as MW). These tests require a measure of information dispersion that does not rely on assumptions about bidder strategies or whether the setting is private or common values. I constructed an “external” measure of information dispersion by conducting a sur-

vey among non-bidders. The survey asked people to view product descriptions of auctioned items and report what they thought was the most the item was worth. I used the standard deviation of responses for each auction description to estimate the dispersion of information in each auction.

In practice, the bidder deals with different types of information: information about the seller and information about the good (as provided by the seller and as gathered from the bidder's own experiences). Seller-rating mechanisms offer natural measures for reputation, but information about a good is challenging to quantify. As a result, while a growing empirical literature has exploited seller reputation in online auctions and focused on information asymmetry between bidders and sellers as a barrier to trade, the role of product information and the price effects of uncertainty over the value of a good due to information dispersed over all auction participants has largely been ignored.<sup>1</sup> If this type of uncertainty is important, the previous work may suffer from omitted variable bias. The survey-based measure of information dispersion serves as a measure of amount of product information available to the bidder, permitting estimation of price effects that distinguish between seller reputation and product information. This permits estimation of the importance of information dispersion relative to information asymmetry in these markets. Empirical work on this topic has found that reputation and product information can be substitutes. (Anand & Shachar 2004a, 2004b) By estimating the interaction effect of these two types of information, it is also possible to determine whether the same holds true in these markets.

I apply my process for measuring information dispersion to a sample of eBay online auctions to test theory and estimate the price effects of different types of information. I find that eBay prices are consistent with Nash equilibrium behavior in a common values setting and that winners do not suffer from the winner's curse. I find evidence that information dispersion is more important than information asymmetry in these markets, since changes

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<sup>1</sup>In general, this work has found the price effect of reputation to be small. (Reiley, Bryan, Prasad & Reeves *forthcoming*; Houser & Wooders 2006; Melnik & Alm 2002; McDonald & Slawson, Jr. 2002; Livingston 2005; Eaton 2002; Resnick, Zeckhauser, Swanson & Lockwood 2004; Jin & Kato 2004) A summary of the empirical work appears in Resnick, Zeckhauser, Swanson & Lockwood 2004.

in product information provided by the seller have a larger effect on price than reputation, but both are important. Reputation complements, rather than substitutes for, information dispersion on eBay: a good reputation lends credibility to the information provided by the seller. There is an incentive for sellers to both build good reputations and provide more information in their auction descriptions, reducing uncertainty in these markets.

The source of privately dispersed common value information in this market is the differing private information that bidders possess about the reliability of a particular model of computer or its components. Private value information (e.g., heterogenous preferences over computers) is likely dispersed in this market as well. Fortunately, my tests allow me to distinguish Nash equilibrium behavior in a common values setting (Nash CV) from the alternatives of naïve bidding in a common values setting (naïve CV) and bidding in a private values settings (PV), so I do not need to make any assumptions about whether the CV or PV component dominates this market. Sellers provide product descriptions in the auction listing that may decrease the level of information dispersion by sharing private information publicly. The level of detail in those descriptions differs across auctions, so the level of information dispersion varies across auctions in my sample. This variation helps identify the effect of changes in information dispersion on price.

This approach has several advantages compared to other approaches in the literature which test for Nash behavior or common versus private values, but rarely both.

Some experimental literature has tested equilibrium bidding behavior by directly controlling the primitives. Kagel, Levin & Harstad (1995) find that while prices rise as predicted by theory when information is publicly released in CV auctions with fewer bidders, prices fall in larger auctions.<sup>2</sup> Although bidders may be attempting to play Nash equilibrium strategies, they may not get the magnitudes right. However, contrary to Nash CV, increasing the

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<sup>2</sup>In experimental auctions with 4-5 and 6-7 bidders, Kagel, Levin & Harstad (1995) provide bidders with a private signal on a common value item, and then release a public signal after a first round of bids on the item and allow bidders to update their bids.

number of bidders does not change the bids.<sup>3</sup> Most analogous to my work is a study by Goeree and Offerman (2002), who test the reaction of prices when the range of signals is compressed. Prices fall with increased dispersion, but by less than theory predicts.<sup>4</sup>

Studies of commercial auctions have not yet employed tests exploiting information dispersion. As a result, the majority of the literature has focused on either testing for common versus private values or testing for rational bidding behavior, but not both concurrently. The literature testing for Nash equilibrium behavior has often assumed a common or private values setting, allowing authors to relate ex post values to ex ante bids to draw inferences about strategic bidding.<sup>5</sup> In only a few cases have ex post values been used, and these values are typically estimated.<sup>6</sup> Even with these assumptions and ex post information on values, the underlying parameters are just identified, so any further tests of bidder behavior or comparative static estimates cannot be conducted.<sup>7</sup>

The literature testing between common value and private value settings has often assumed Nash equilibrium behavior.<sup>8</sup> Authors have then explored how variation in the number of bidders can be used to test between private and common value settings, since the winner's curse

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<sup>3</sup>Bidders also fail to account for the winner's curse in ascending oral auctions. (Kagel & Levin 1991) Other experimental tests (Kagel & Levin 1991, Lind & Plott 1991, Cox & Smith 2001) suggest that this failure is not the result of strategic considerations with respect to budgets. Even experienced commercial bidders may fail to shade correctly in experiments, as found in Dyer, Kagel & Levin (1989) which employs construction industry bidders as subjects.

<sup>4</sup>Goeree & Offerman (2002) conduct auctions with low and high distributions of signals for 3 bidders, but only conduct high distributions of signals for auctions with 6 bidders. They thus are not able to fully study the interaction effect between variance and the number of bidders.

<sup>5</sup>McAfee, Takacs & Vincent (1999) use ex post values to test the information aggregation properties of auction prices. (McAfee, Takacs & Vincent 1999) In their seminal paper, Hendricks & Porter (1988) showed that bidders with superior information make a profit in auctions, whereas uninformed bidders account for the winner's curse and get zero profits. Athey & Levin (2001) show that bidders respond strategically to private information about the species composition in timber auctions.

<sup>6</sup>In fact, different conclusions regarding whether bidders actually avoided the winner's curse as evidence of equilibrium bidding behavior in oil tract lease auctions has been attributed to measurement error. (Capen, Clapp & Campbell 1971; Mead, Moseidjord & Sorensen 1983; Hendricks, Porter & Boudreau 1987, etc.)

<sup>7</sup>Li, Perrigne & Vuong (2000) also show that the joint distribution of signals and values is identified under some additional functional form assumptions *and* if all bids are observed. Athey & Haile (2002) show that identification fails unless all bids are observed, but that ex post information on the common value combined with partial bid information can identify the primitives in a common value auction. See also Laffont & Vuong (1996); Guerre, Perrigne & Vuong (2000); Li, Perrigne & Vuong (2002).

<sup>8</sup>This empirical literature has been predicated on an extensive theoretical literature identifying empirically testable conditions for private value and common value settings, e.g. Donald & Paarsch (1993); Elyakime, Laffont, Loisel & Vuong (1994); Laffont, Ossard & Vuong (1995); Pinske & Tan (2000).

is more severe with more bidders.<sup>9</sup> (Paarsch 1992; Haile, Hong & Shum 2003, Athey & Haile 2002). The challenge to these approaches (and my approach as well) is that the true number of participants may be unobserved and/or endogenously determined. Another approach imposes Nash bidding behavior in order to estimate the joint distribution of information signals and values and determine whether the distributions correspond to common or private values. (Hong & Shum 2002, Bajari & Hortacısu 2003) The paper most closely related to my work is Hendricks, Pinkse & Porter (2003). They first test whether bids are consistent with Nash equilibrium in a first-price sealed-bid setting, assuming a common values setting. They then exploit ex post information on values to back out the distribution of signals and show that bidder profit margins appear unreasonable under the PV assumption and are more consistent with a CV assumption. Their method does not assume Nash equilibrium behavior. However, it relies on calculated magnitudes rather than comparative statics to distinguish between the CV and PV settings.

My survey data provides information about the distribution of signals independent of the bidding data, so I avoid expending the identifying power of the information available on recovering the distribution of private information signals from the bid data. This allows me to 1) simultaneously distinguish between common and private value settings using comparative statics without imposing Nash equilibrium bidding behavior, 2) distinguish between Nash and naïve bidding behavior using comparative statics without assuming a PV or CV setting, 3) employ only price data from the auctions as opposed to all bids, 4) utilize extra identification power to estimate any potential bias between my measures of dispersion and the true values and estimate other comparative statics of interest. Since I base my assessment of bidding behavior on comparative statics, my benchmark for whether bidders exhibit Nash CV behavior does not require bids to exactly match Nash CV predictions. My benchmark simply requires that bidders react strategically to the number of bidders and dispersion in the direction that theory predicts, and thus permits Nash CV bidder behavior to involve

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<sup>9</sup>Laffont & Vuong (1996) show that bidding data alone with a fixed number of bidders is insufficient to distinguish common value settings from affiliated private value settings.

errors in magnitude (which I can then estimate).

The rest of the paper proceeds as follows: Section 1 presents the theoretical model from which the testable implications of information dispersion are derived. Section 2 describes the auction and survey data. Section 3 presents the empirical results. Section 4 estimates the potential winner's curse in these auctions and conducts counterfactual analysis of changes in reputation and information dispersion. The last section draws conclusions.

## 1 Theory and Empirical Implications

This section presents a theoretical model of Nash CV prices from second-price sealed-bid auctions. Using this model as a benchmark, this section then presents comparative static implications that will be used to test whether eBay computer auctions exhibit behavior consistent with the Nash CV model or a PV/naïve CV model, as well as hypotheses to test regarding reputation and information dispersion (as a measure of product information).

A single, indivisible item is put up for auction. The item has the same, unknown value  $v$  to all  $n$  risk-neutral bidders, indexed by  $j$ .<sup>10</sup> Bidders know the density of  $v$ ,  $f_V(v)$ . Each bidder also observes a private signal  $x_j$  from a distribution around  $v$ . Consider the form of the mineral rights model, where  $X_j$  is independently and identically drawn from a distribution centered around  $v$  such that the signals  $X_j$  are affiliated with the values  $V$ . This distribution has commonly known density  $f_{X|V}(x_j|v)$ .

In a second-price auction, the person who submits the highest bid wins the auction, and pays the amount submitted by the second highest bidder. Losing bidders get zero payoff. Under risk neutrality, the optimal Nash equilibrium bid  $b(x_j)$  for symmetric bidders in a

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<sup>10</sup>Risk-aversion in the common values setting can be modeled as reductions in bids in response to higher uncertainty (information dispersion). This will not change the sign of any comparative static implications of Nash CV vs. PV/naïve CV.

sealed-bid auction is

$$(1) \quad b(x_j) = E[v|x_j, \max X_{k \neq j} = x_j],$$

where  $X_{k \neq j}$  denotes the set of all signals excluding  $x_j$ . (Milgrom and Weber 1982)

The expected winning price is the expected value of the second order statistic of Equation 1. Let  $X^{n-1:n}$  denote the 2nd highest signal from a set of  $n$  signals. I can approximate the expected winning price by a function, denoted  $p$ , of  $n$  and parameters describing  $f_{X|V}(x|v)$  and  $f_V(v)$ . For distributions which can be characterized by scale and location, I denote the standard deviations of  $f_{X|V}(x|v)$  and  $f_V(v)$  by  $\sigma_{X|V}$ , and  $\sigma_V$ , respectively. The means of  $f_{X|V}(x|v)$  and  $f_V(v)$  are  $v$  and  $\mu_V$  by construction, respectively.

$$(2) \quad E[b(x^{n-1:n})] = p^{cv}(n, v, \sigma_{X|V}, \mu_V, \sigma_V, r),$$

where  $r$  represents any other factors in the auction that may affect bidding in an empirical application of the auction model but do not appear in the theoretical auction literature ( $r$  will be defined more precisely later). I use the function  $p^{cv}$  to establish comparative static results from auction theory in the following subsection.

The second-price, sealed-bid model is more appropriate than the English auction model as a benchmark for testing Nash CV in eBay auctions for several reasons. During the eBay auctions, bidders can see the current price: the second-highest bid plus one increment. The winner is the bidder who submits the highest bid. Bidders are free to enter and exit at any time as well as update and resubmit their bids before the close of the auction. Harstad & Rothkopf (2000) found that English auctions with re-entry are more closely approximated by second-price sealed bid models. Empirical observations of the timing of bids on eBay indicate that the majority of auctions in all categories experience a flurry of bidding during the last minutes.<sup>11</sup> To the extent that insufficient time exists to view all the information

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<sup>11</sup>Bajari & Hortacısu (2004) review empirical findings in online auction settings.

contained in those bids before the close of the auction, the auction tends to operate like the second-price sealed-bid model. Despite this circumstantial evidence in favor of modeling eBay computer auctions as CV auctions, I will nevertheless test whether eBay prices reflect behavior more consistent with CV than PV.

## 1.1 Implications of Nash CV auctions

MW showed that in equilibrium, if the seller publicly reveals a signal drawn from the same distribution as those of the bidders' signals, then prices will rise in a second-price sealed-bid common value auction.<sup>12</sup> Public revelation is equivalent to a seller providing more information in the auction description. The effect of publicly revealing more information is a reduction in information dispersion, reflected in  $\sigma_{X|V}$ . For example, as soon as bidders see "Computer Brand A" in the auction description, their signals will be dispersed due to differences in private information about the fan noise and clear wiring for Computer Brand A. However, if the auction description also says "fan is noisy, clear wiring makes it easy to install more memory", the differences in information have been reduced, and so their signals become less dispersed around  $v$ . For  $n > 2$ , prices fall in Nash equilibrium, where bidders account for the less narrow distribution of signals around the common value by shading more.

1.  $\frac{\partial p^{cv}}{\partial \sigma_{X|V}} < 0$ . The Nash CV price decreases if the dispersion of information signals increases.<sup>13</sup>

Although prices converge to something higher than  $\mu_V$  as  $n \rightarrow \infty$  (2002), if not fully to the common value (Wilson 1977, Milgrom 1979), prices may be decreasing or increasing

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<sup>12</sup>MW assume that the signals and common value are affiliated, and that bidders are symmetric and behave rationally. They also assume the existence of some mechanism, such as reputation, which makes the additional information credible to the bidders. The MW public information result will not necessarily hold in first price auctions. (Perry & Reny 1999)

<sup>13</sup>This result is translation of Theorems 8 and 12 of MW. McMillan & Kazumori (2002) prove this result for distributions satisfying affiliation. Rothkopf (1969) discussed the disclosure of information as a way to improve the estimating accuracy of bidders, thus causing procurement prices to fall in first price auctions.

in  $n$  away from the limit. As  $n$  increases, the expected value of the highest signal drawn increases. Under Nash CV, bidders should shade more to account for this increase. Whether the draw of a higher signal will overcome the amount of bid shading depends on both  $n$  and the distribution of signals. As a result, prices will be decreasing with respect to  $n$  for some values of  $n$  and  $\sigma_{X|V}$ , but increasing for other values.

## 1.2 Implications of PV and naïve CV auctions

In second-price auctions, the Nash strategy is to bid one's signal, so prices equal the second highest signal under PV. Therefore, the expected winning price in the PV case can be analogously modeled to that of the CV case, Equation 2 as follows:

$$(3) \quad E[x^{n-1:n}] = p^{pv}(n, v^{pv}, \sigma^{pv}, r),$$

where  $v^{pv}$  and  $\sigma^{pv}$  now simply describe the average and standard deviation of private values among auction participants.

I define naïve CV as a common value setting where bidders ignore  $n$  and  $\sigma_{X|V}$ , and just bid their signal plus some absolute amount or percentage adjustment. By this definition of naïve CV, I distinguish between Nash versus naïve bidding by whether bidders react to  $n$  and  $\sigma_{X|V}$  such that prices increase or decrease as predicted by Nash, not by whether bidders generate prices exactly equal to the Nash prediction. Therefore, I allow Nash equilibrium behavior to involve errors in magnitude.

I derived the following comparative static implications from analysis of expected values of order statistics under symmetric (e.g. uniform, normal) and lognormal distributions.<sup>14</sup>

2.  $\frac{\partial p^{pv}}{\partial \sigma^{pv}} > 0$  for symmetrically distributed signals. PV and naïve CV prices increase with

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<sup>14</sup>Result derived from analysis of order statistics. (Mood, Graybill & Boes 1974; Balakrishnan & Chen 1999)

Table 1: Comparative statics from auction theory

<b>Model</b>	$\frac{\partial p}{\partial \sigma}$	$\frac{\partial p}{\partial n}$
PV/naïve CV	-/+*	+
Nash CV	-	-/+

\*+ for symmetrically distributed signals.

the dispersion of signals for symmetrically distributed signals. Prices could increase or decrease for lognormally distributed signals.

3.  $\frac{\partial p^{pv}}{\partial n} > 0$ .<sup>15</sup> PV and naïve CV prices increase with the number of bidders.<sup>16</sup>

### 1.3 Summary of Predictions

Table 1 summarizes the comparative statics predictions which would permit us to empirically distinguish the auction model generating the data, where  $p$  now generically represents expected prices and  $\sigma$  generically represents the dispersion of signals from either a CV or PV model. Each row designates a different model of bidding behavior and information structure. Each column designates a comparative static. Each box in the grid indicates the predicted sign for each comparative static under each model.

The Nash CV model is uniquely identified if prices are decreasing in dispersion and decreasing in the number of bidders. If prices increase with dispersion and in the number of bidders, then the PV/naïve CV model applies. I do not measure Nash CV behavior by whether or not bids exactly match Nash CV predictions but by whether prices suggest that bidders react to the number of bidders and dispersion in the way that they should strategically. So I allow Nash CV bidder behavior to involve errors in magnitude.

Bidders valuations of computers may be composed of a mix of common and private values.

<sup>15</sup>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 continuous in  $n$ . This is consistent with the empirical application later in the paper: bidders and the econometrician must estimate  $n$ , and so they may not be constrained to integers.

<sup>16</sup>Thanks to John Morgan for his notes on order statistics.

Goeree and Offerman (2003) derive implications for prices under mixed CV and PV, and find that prices increase as information dispersion is reduced and increase as the number of bidders increases. Therefore, if I observe prices decreasing with the number of bidders, I am able to distinguish Nash CV from a Nash mixed values model. If I observe prices increasing with dispersion, I am able to distinguish PV/naïve CV from the Nash mixed values model.

## 1.4 Hypotheses about Information Asymmetry

MW model public revelation of information as credible statements by a seller of her signal of the object's  $v$ . In real-world auctions, sellers can describe the objects in greater detail. Real-world sellers also vary in reputation and therefore in the credibility of their descriptions of objects. Reputation can affect price in two ways: by raising or lowering the expected value of an item (i.e., a reputation premium) and by affecting the way bidders perceive the dispersion of information (i.e., credibility). Reputation may also behave as a substitute for product descriptions: bidders may find that reputation of the seller provides sufficient information about the value of the product. This would be particularly true if information asymmetry was a much larger source of uncertainty than information dispersion.

Work by Akerlof(1970), Klein & Leffler (1981) and Shapiro (1983) suggest that prices should rise with better reputation under non-auction conditions. A seller with a reputation for good transactions may be signaling that she auctions better products. I now define parameter  $r$  in Equations 2 and 3 as reputation, and consider expected prices  $p$  from either the CV or PV cases.

4.  $\frac{\partial p}{\partial r} > 0$ . The expected price is directly increasing in reputation.

A reputation for good transactions may also signal that the seller auctions products that meet bidder expectations based on the auction description. The value of the product may be lower, but the seller reveals this information. Holding  $v$  constant, I hypothesize that in the CV setting, a seller with a good reputation who reduces information dispersion will reap

higher prices as a result of credible reduction in  $\sigma_{X|V}$ . Even if truthful revelation causes bidders to estimate a lower  $v$  than if the seller had remained vague about the faults of the item, the reduced information dispersion means that bidders will not shade their bids even lower. An interesting implication of this hypothesis is that credible sellers should also suffer a more negative price effect from high  $\sigma_{X|V}$  than sellers with worse reputations. A seller with a good reputation who provides minimal product information may be perceived by bidders as trying to hide something. For a seller with no credibility, reducing information dispersion makes no difference, because bidders discount the value of information provided by that seller. Under PV/naïve CV, no interaction effect is expected between  $\sigma^{pv}$  and  $r$ . Consequently, I hypothesize that CV Nash prices will fall with dispersion at a faster rate with better reputations.

5.  $\frac{\partial^2 p^{cv}}{\partial \sigma_{X|V} \partial r} < 0$ . In Nash CV auctions, the expected price is decreasing in the level of information dispersion generated by the seller at an increasing rate with the seller's good reputation.

The alternative hypothesis would reverse the sign on this interaction, suggesting that reputation could compensate for the negative effect of poor product information (high information dispersion) on price. This effect would be consistent with findings by Anand & Shachar (2004a, 2004b) that reputation can substitute for product information.

## 2 Dataset

Over 5000 new and used computers are listed daily in the personal computer (PC) category by both individuals and businesses. Prices, the eBay-defined overall score for the seller, the number of bidders, and the auction description were collected for the 250 most recently closed eBay single-unit PC auctions with 2 or more bidders that did not terminate via “Buy It Now,” a feature which allows a bidder to pay a list price for the item and end the auction. The sample size was made large enough to ensure variation in the sellers' overall feedback

scores, but limited in size due to an inability to test competitive bidding with less than 2 bidders and in order to gather more survey responses per auction and reduce depreciation issues by minimizing the time between which all auctions were held. These auctions spanned the period between June 24 and July 12, 2002. The auction descriptions were used to create a survey. Due to technical bugs, only 222 auctions ended up being surveyed. This section defines the regressors that were drawn directly from the auction data and those generated by the survey.

## 2.1 eBay Auction Data

Each computer auction is a unit of observation. The auction operates as follows: a seller lists a computer for auction on eBay, setting the minimum bid and the duration of the auction in days, and providing a description of the item being auctioned. She may also choose to set a reserve price, below which the item does not sell, and she may choose to pay for special listing features that could increase the visibility of her auction.

During the auction, potential bidders can observe all of the auction details set by the seller except for the value of the reserve price. They can also observe the seller's overall feedback score, which is the number of unique parties from which she received positive feedback minus the number from whom she received negative feedback. By clicking on that score, bidders may view the breakdown of positive, negative, and neutral feedback that any eBay user has received and whether these feedback were for sales or purchases of items. Bidders may also click on the number of bids thus far to observe who has already bid in the auction and how many times, and all the losing bids to that point.

Bidders observe the current price at all times. When bidders submit bids, the price rises by one bid increment (as defined by eBay rules) above the second highest bid currently submitted. If the increment causes the price to be higher than the highest bid, then the price only rises to the highest bid. Bidders may submit bids at any time and more than once while the auction is still open. In the case of tied bids, the earliest bidder wins.

Table 2: Summary statistics for 222 eBay computer auctions

<b>Variable</b>	<b>mean</b>	<b>median</b>	<b>st. dev.</b>	<b>min</b>	<b>max</b>
price: $P_t$	\$359.01	\$255.00	369.16	\$9.51	\$2802
overall score: $SCORE_t$	680	27	2601	0	19,456
negative score: $NEG_t$	25.5	2	106	0	785
no. of bidders: $N_t$	6.5	6	4	2	22

The summary statistics of data collected from my sample of auctions are presented in Table 2. The price in each auction is denoted  $P_t$ , where  $t$  indexes the auctions. The number of bidders observed in the auctions is denoted  $N_t$ . The overall feedback score of the seller in each auction is denoted  $SCORE_t$ , and the total negative feedback for the seller, including multiple negative feedback from the same party, is recorded separately under  $NEG_t$ . The regressors used to capture the effect of the number of bidders and reputation on price will be  $N_t$  and a linear combination of  $SCORE_t$  and  $NEG_t$ . The quadratic term  $SCORE_t^2$  is also included to account for diminishing returns to a large feedback score.

## 2.2 Survey Data

To obtain a measure of the mean and dispersion of private signals received by bidders in the auctions, I created a web-based survey. Anyone could respond the survey, except for the actual bidders in my sample of auctions. The survey was distributed to acquaintances by word of mouth during July and August, 2002. I asked people to read the computer auction descriptions from my sample and then answer the following question: “If a friend wanted to buy the computer described below, what is the most she should pay for it?” (see Appendix A). These descriptions only contained the information provided by the seller in the “descriptions” section. Information listed by eBay about the bids, reservation values, number of bidders, and the seller’s identity and reputation were removed. As a result, my survey data is designed to illicit a signal of the computer’s value from the survey participants.

I also collected background data on survey respondents, asking them about their expe-

Table 3: Summary statistics for survey on 222 auctions

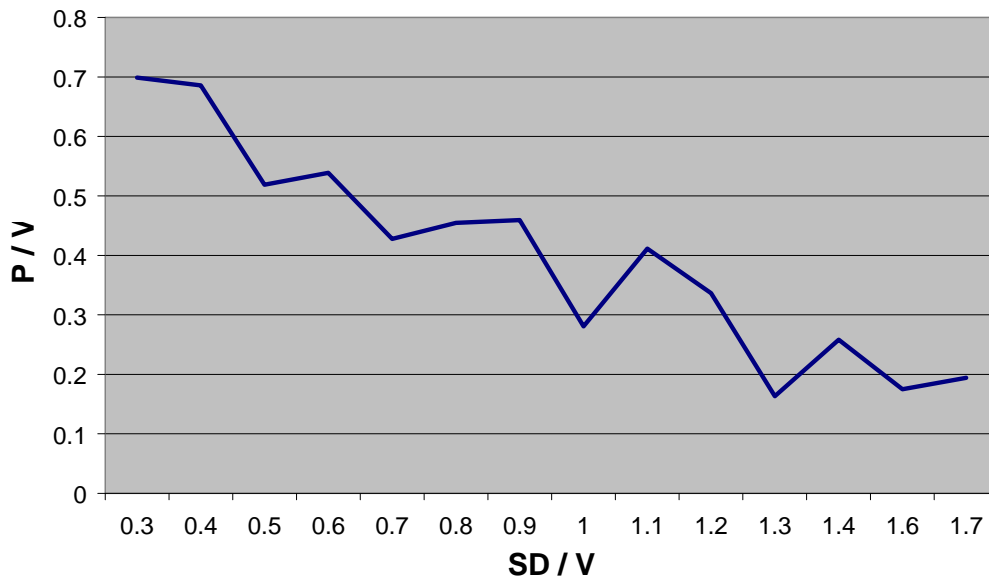
<b>Variable</b> <b>(831 respondents)</b>	<b>mean</b>	<b>st. dev.</b>	<b>min</b>	<b>max</b>
no. of responses/auction	46	6	25	65
average: $V_t$	\$666.43	317.28	\$101.48	\$1,816.98
standard deviation: $SD_t$	472.38	153.94	163.57	980.50
average experienced: $V_t^e$	\$603.76	351.43	\$46.11	\$1923.08
... inexperienced: $V_t^i$	\$682.48	317.59	\$95.97	\$1782.50
st. dev. experienced: $SD_t^e$	317.25	171.17	0	1429.78
... inexperienced: $SD_t^i$	492.03	168.31	138.94	1074.15

rience working with computers, purchasing computers, and purchasing computers in online auctions (see , 2006 for a full description of the survey procedure). I refer to respondents who have had experience with eBay online auctions for computers as “experienced.” Approximately 20 percent of the responses in each auction were from experienced respondents. I refer to the rest of my respondents as “inexperienced.”

On average, I collected 46 responses per auction. The average of the responses for each auction, denoted  $V_t$ , is a measure of the common value (or average private value)  $v$  in each auction  $t$ . The absolute value of the standard deviation of the responses in each auction, denoted  $SD_t$ , is a measure of  $\sigma_t$ . (See Yin (2006) for analysis of  $V_t$  and  $SD_t$  as measures of  $v_t$  and  $\sigma_t$ ). I also define  $V_t^e$  and  $V_t^i$  and  $SD_t^e$  and  $SD_t^i$  as the average and standard deviation of responses from the experienced and inexperienced respondents, respectively. Summary statistics from the survey are presented in Table 3.

Figure 1 graphs the unconditional correlation between  $P_t$  and  $SD_t$ . To control for differences in computers, I normalized both  $P_t$  and  $SD_t$  by dividing them by  $V_t$ . I then ordered the auctions by increasing normalized  $SD_t$  across the horizontal axis and divided the auctions into bins, each representing 0.1 difference in normalized  $SD_t$ . Normalized prices were then averaged over the auctions in each bin and plotted on the vertical axis. Prices are falling as my measures of information dispersion increases, a pattern MW predicted for Nash CV

Figure 1: Normalized eBay prices  $P_t$  vs. normalized information dispersion  $SD_t$ . For each auction, eBay prices  $P_t$  and standard deviation of survey responses  $SD_t$  were divided by the average of survey responses  $V_t$ . The auctions were ordered by increasing normalized  $SD_t$ , then divided into bins representing 0.1 changes in normalized  $SD_t$ . Average normalized  $P_t$  were calculated within each bin and reported along the vertical axis. Interpreting  $SD_t$  as a measure of information dispersion, the resulting graph shows that prices are negatively correlated with dispersion of information.



auctions. However, since high value items might be correlated with the lowest information dispersion, regression analysis is necessary to control for value before determining the relationship between prices and information dispersion. In the next section, I control for value and the other determinants of price and correct for any measurement bias in the survey data in order to formally test whether the Nash CV model is appropriate for eBay online auctions for computers.

### 3 Estimation

I employ four estimation procedures to test the bidding behavior and information structure in these eBay auctions for computers. In each case, I estimate the price equation, Equation 2. The first case is OLS estimation of the price equation. Results are presented in Column

1 of Table 4.

I specify a polynomial functional form for the price equation that includes quadratic and interaction terms which will allow me to examine the comparative static implications of auction theory.<sup>17</sup> For these estimates, I use  $N_t$  as a measure of  $n_t$ ,  $V_t$  as a measure of  $v_t$ , and  $SD_t$  as a measure of  $\sigma_t$ . I also include  $SCORE_t$ ,  $SCORE_t^2$ , and  $NEG_t$  as measures of reputation. Their interaction with  $SD_t$  will capture the effect of credibility of information dispersion on price if I am in a Nash CV setting. I first assume that *a priori* beliefs about the distribution of computer values are the same for all computers in my sample (I relax and test this assumption for  $\mu_v$  later). As a result, I do not include any measures for  $\mu_V$  and  $\sigma_V$ .

There are several reasons why I use parametric rather than non-parametric estimation. I use parametric estimation in order to include covariates in a parsimonious manner. I wish to test hypotheses and comparative static implications of auction theory involving those covariates. I also do not have the number of observations necessary to undertake non-parametric estimation. Finally, having a polynomial functional form approximation for the price equation further simplifies estimation and facilitates the counterfactual analysis I conduct in the next section.

All the signs correspond to predictions of Nash CV bidding. Prices fall with  $SD_t$  and  $N_t$ , which is inconsistent with PV and naïve CV settings. The negative coefficient on  $N_t$  further rules out mixed CV and PV as a model. Although the estimates are not statistically significant, they still indicate that within this sample, prices are negatively correlated with  $SD_t$  and  $N_t$  controlling for everything else in the regression. The positive interaction effect between  $N_t \times SD_t$  is not large enough to reverse the negative effects on price of either  $N_t$  or  $SD_t$  in my sample.

The statistically significant coefficients on  $SCORE_t$  and  $SCORE_t \times SD_t$  confirm that while a better reputation increases price, a better reputation also exacerbates the effect of information dispersion on price. Since reputation is composed of positive and negative

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<sup>17</sup>I examined the robustness of various orders of polynomials and found no significant improvements from adding higher order terms, including interaction terms.

feedback in this case, I expect the signs on  $NEG_t$  and  $NEG_t \times SD_t$  to be the reverse of the signs on  $SCORE_t$  and  $SCORE_t \times SD_t$ . The marginal effect of a single negative feedback is a magnitude larger than that for a single positive feedback. Although those coefficients are not statistically significant, prices decrease with worse reputations in the sample, but a worse reputation also diminishes the effect of dispersion on price.

The significant coefficients estimated for  $SD_t$  and  $SCORE_t$  indicated that there is enough variation between the two to estimate separately their effects on price. If reputation were a sufficient statistic for the information set that bidders employ when determining their bids, then I would expect the coefficient on  $SD_t$  to be estimated imprecisely or zero. These estimates suggest that product information and reputation both have significant price effects, so information dispersion over auction participants is another important source of uncertainty in addition to information asymmetry between the buyer and the seller.

I would expect prices to be directly proportional to changes in the value of the item. Recall that the survey respondents could not view prices when submitting their valuations. The significance and magnitude of the coefficient 1.05 on  $V_t$  suggests that the survey was able to capture the relative value of the auctioned items: prices react dollar-for-dollar to an increase in the survey's estimated value of the item.

The next set of estimates measures how well the survey was able to capture the absolute value of the items. It allows  $V_t$  to be a biased measure of  $v_t$ , and  $SD_t$  to be a biased measure of  $\sigma_{X|V,t}$ . It then estimates the amount of bias.

Note that the predictions of auction theory only depend on the signs of the comparative statics. Even if  $V_t$  and  $SD_t$  were biased measures of  $v_t$  and  $\sigma_{X|V,t}$ , as long as the measures are correlated with the true values, the signs on the results in Column 1 are still valid. Analysis of survey results in Yin (2006) suggests that  $V_t$  and  $SD_t$  are correlated with  $v_t$  and  $\sigma_t$ .

### 3.1 Correcting for potential bias in $V_t$ and $SD_t$

$V_t$  and  $SD_t$  are potentially biased measures of  $v_t$  and  $\sigma_t$ . I model and estimate the potential bias as follows: I treat the responses  $X_{q,t}$  from each of my survey respondents  $q$  as potentially biased draws of signals  $X_{j,t}$  that the auction participants draw about  $v_t$ . Thus,  $X_{q,t}$  are drawn from a potentially different distribution than the one that the auction participants face. I model the responses from my inexperienced respondents, denoted  $X_{q,t}^i$ , as draws from a distribution whose mean may differ from  $v_t$  by a shift factor  $\gamma_0$  and a scale factor  $\gamma_1$  and whose variance may be different as well:  $X_{q,t}^i \sim (\gamma_0 + \gamma_1 v_t, \sigma_t^i)$ . I assume that the experienced survey respondents are more similar to the auction participants. I model their responses as being drawn from a distribution whose mean only differs from  $v_t$  by a shift factor  $\theta_0$  and whose variance may be different:  $X_{q,t}^e \sim (\theta_0 + v_t, \sigma_t^e)$ . An unbiased estimate of  $v_t$  can then be written as

$$(4) \quad \hat{v}_t = \frac{Q_t^e}{Q_t} (V_t^e - \theta_0) + \frac{Q_t^i}{Q_t} \left( \frac{V_t^i - \gamma_0}{\gamma_1} \right),$$

where  $Q_t^e$  is the number of experienced survey responses in each auction and  $V_t^e$  is their average value for the item in auction  $t$ ,  $Q_t^i$  is the number of inexperienced survey responses in each auction and  $V_t^i$  is their average value, and  $Q_t$  is the total number of survey responses to each auction. The parameters to be estimated are  $\theta_0$ ,  $\gamma_0$ , and  $\gamma_1$ . They capture the amount of bias in the responses.

I employ the same process to model the potential bias in  $SD_t$  as a measure of  $\sigma_{X|V,t}$ . I assume that my experienced respondents draw from a distribution with variance  $(\sigma_t^e)^2 = \eta_0 + \sigma_t^2$ , whereas my inexperienced respondents draw from a distribution with variance  $(\sigma_t^i)^2 = \delta_0 + \delta_1 \sigma_t^2$ . The resulting unbiased estimate of the information dispersion faced by the auction participants is as follows:

$$(5) \quad \hat{\sigma}_t = \sqrt{\frac{Q_t^e}{Q_t} ((SD_t^e)^2 - \eta_0) + \frac{Q_t^i}{Q_t} \left( \frac{(SD_t^i)^2 - \delta_0}{\delta_1} \right)}.$$

The parameters to be estimated are  $\eta_0$ ,  $\delta_0$ , and  $\delta_1$ . They capture the amount of bias in the dispersion of responses.

I can use a moment condition to identify  $\theta_0$ ,  $\gamma_0$ , and  $\gamma_1$ . I set the standard deviation of the experienced survey responses equal to the definition of the sample standard deviation, replacing  $V_t^e$  with  $\hat{v}_t + \theta_0$ . The following moment condition is then estimated simultaneously with a price equation that includes  $\hat{v}_t$  as a regressor:

$$(6) \quad SD_t^e = \sqrt{\frac{\sum_{q,t}^{Q_t^e} (X_{q,t}^e - (\hat{v}_t + \theta_0))^2}{Q_t^e - 1}}.$$

Column 2 presents the results of simultaneously estimating the price equation and the moment condition in Equation 6. I remove the constant from the price equation since  $\theta_0$  and  $\gamma_0$  now serve to estimate the intercept. I now estimate  $v_t$  and  $\sigma_t$  in the price equation by  $\hat{v}_t$  and  $\hat{\sigma}_t$ , respectively.

Overall, I get the same signs and magnitudes as for the corresponding coefficients in Column 1. These results confirm the Nash CV model as appropriate to describe my sample of auctions and confirm my hypothesis about the credibility of information.

The scale parameters on  $V_t^i$  and  $(SD_t^i)^2$  are both positive ( $\gamma_1 = 1.03$ ,  $\delta_1 = 1.83$ ), confirming that the inexperienced responses are correlated with the experienced responses, which I assume to be perfectly correlated with the signals drawn by the auction participants. As expected, the coefficient on  $\hat{v}_t$  is equal to 1 and statistically significant from 0. Since the coefficient on  $V_t$  in Column 1 was already equal to 1, this seems to indicate that there was not much need for bias correction of the survey measure. Indeed, the estimate of the scale bias in  $V_t^i$  of 1.03 indicates that even the inexperienced responses are able to capture relative values of items. The inexperienced respondents tend to overestimate the value of the items by \$83.61. Just as one would expect from more knowledgeable survey respondents, the experienced respondents are closer to  $v_t$  and overestimate by only \$27.04.

The variance for the inexperienced respondents tends to be twice as large in scale and

shifted upwards compared to  $\sigma_t^2$ . Translating this into standard deviation terms,  $SD_t^i$  is approximately 1.35 ( $= \sqrt{1.83}$ ) times larger than  $\sigma_t$  and overestimates  $\sigma_t$  by 276.37 ( $= \sqrt{76381.0}$ ). Since inexperienced respondents might not understand all the details of the auction description, I would expect that the amount of information they would gather from those descriptions would be less than what auction participants would acquire. A bit surprising is the finding that experienced respondents underestimate  $\sigma_t$  by 245.40 ( $= \sqrt{60222.6}$ ). Under Nash CV, this is consistent with the concept that those who have participated in eBay auctions have learned how to interpret auction descriptions better because of their experience. It suggests that my experienced survey respondents may be even more experienced than the average participant in my sample of auctions. Despite these differences, the magnitude of the coefficients on  $\hat{\sigma}_t$ ,  $\hat{\sigma}_t^2$ , and  $\hat{\sigma}_t \times N_t$  are not that different from their counterparts in Column 1. For the purposes of estimating changes in price with respect to dispersion,  $SD_t$  seems to work sufficiently well despite biases.

### 3.2 Instrumental Variables Estimation

I present an alternative empirical specification in Column 3 of Table 4 that addresses the potential endogeneity and measurement error from using  $N_t$  as a measure of the number of participants in the auction. I consider these results to be a robustness check on the previous section. The endogeneity and errors may not have generated severe bias in Columns 1 and 2, so employ potentially weak instruments may not yield more accurate estimates.

Much of the empirical work on auctions faces the problem of an endogenous number of bidders. The auction participants who chose to bid may have been attracted by some aspect of the item being auctioned that is not captured in the other regressors or is unobservable to the econometrician. If this aspect is correlated with price, then I need to instrument for the number of bidders. One of the advantages of a survey measure of  $v_t$  is that survey readers will tend to pick up the same idiosyncratic aspects of items that affect a participant's valuation in an auction. Thus,  $\hat{v}_t$  controls for the omitted item characteristics that usually

cause the error term in the price equation to be correlated with  $N_t$ . However, if the actual participants in eBay computer auctions are better equipped than my survey respondents to spot a good deal on eBay, then  $N_t$  may still be correlated with unobservable determinants of price.

The number of bidders observed in the auction may not equal the number of participants who drew signals about the auctioned item’s value. I will not observe bids from auction participants arriving late to the auction who draw a signal about the value, but find that the price has already been bid above their valuation.<sup>18</sup> In addition, “bottom feeders” on eBay may submit extremely low bids on the off chance that no one else enters the auction. These bidders may not be taken seriously as a participant who is drawing a signal about the valuation of the item. It is possible that the net effect of these sources of measurement error is negligible, in which case instrumenting may be worse than using  $N_t$  directly.

To produce the estimates in Column 3, I again simultaneously estimate the price equation as modeled in Column 2 and the moment condition. However, I treat  $N_t$  as endogenous and instrument for  $N_t$ . I use the conventional instruments that determine access to the auction (e.g., length of auction, time of auction) as well as some instruments unique to eBay and my survey data. While these instruments are uncorrelated by construction with the error term in the price equation, they are fairly weak instruments since they are not highly correlated with  $N_t$ . Summary statistics of instruments for  $N_t$  are presented in Appendix B, Table 8.

The weakness of the instruments is reflected in numerous insignificant coefficients in Column 3. Nevertheless, I get the same signs as in Columns 1 and 2, with the exception of the statistically insignificant sign on  $NEG_t \times \hat{\sigma}_{X|V,t}$ . The magnitudes are essentially the same for corresponding coefficients across all three columns, with the exception of the statistically insignificant coefficient on  $N_t$  and statistically insignificant estimates of some of the bias

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<sup>18</sup>The number of auction participants who draw signals is the important factor for evaluating the winner’s curse, not the number of bidders, since the winner uses this information to determine how much higher than  $v_t$  her signal might be if her signal was the highest among all those draws.

parameters ( $\eta_0$ ,  $\delta_0$ , and  $\theta_0$ ). After correcting for potential endogeneity and measurement error from using  $N_t$  as a measure of  $n$ , the conclusions of Column 1 remain. Prices are declining with the number of bidders and dispersion of information, indicative of Nash CV behavior.

### 3.3 Modeling $\mu_{v,t}$

In my specifications thus far, I assumed that all bidders faced a common  $\mu_V$  over all auctions. However, a bidder may be in the market for a certain brand or speed of computer, so she may search eBay for computers that match those criteria. This means that the bidder will only view and draw signals from a selected number of auctions. It is likely that these criteria will cause the bidder to draw from a different  $\mu_V$  than a bidder who searches by a different set of criteria. To check the restrictiveness of this assumption, I modified the specification for the price equation to include  $\mu_{V,t}$  separately from  $\hat{v}_t$  and examine whether estimates were significantly different from just using  $\hat{v}_t$  alone. Results are presented in Column 4 of Table 4.

First, I constructed a set of regressors describing the technical specifications of computers that could be plausible search criteria. These regressors are described in detail in Appendix C. I then constructed an equation that regressed  $\hat{v}_t$  on those regressors. I designated the fitted value from this regression as an estimate of  $\mu_{V,t}$  for each auction. I added this fitted value as a regressor to the price equation. I then used  $\hat{v}_t$  as my measure of  $v_t$ . I simultaneously estimated the price equation, moment condition, and the  $\mu_{V,t}$  equation. I again used  $N_t$  as a measure of  $n_t$  and  $\hat{\sigma}_{X|V,t}$  as a measure of  $\sigma_{X|V,t}$ .

The coefficient on  $\mu_{V,t}$ , while statistically significant, is relatively small (0.11) compared to that on  $\hat{v}_t$  (1.96). This seems to indicate that the assumption of common  $\mu_v$  across all auctions does not significantly change estimates. The use of  $\hat{v}_t$  to control for detailed product variation across auctions has a larger influence on price than any differential effect that product categories might have on price. Again, all the signs and magnitudes are approx-

imately the same as in Columns 1 and 2, except for some of the survey bias parameters ( $\gamma_0$ ,  $\gamma_1$ , and  $\eta_0$ ) and the coefficient on  $\hat{v}_t$ . However, the estimate of  $\gamma_1$  and coefficient on  $\hat{v}_t$  are approximately equal (2.39 and 1.96, respectively), so they roughly cancel each other out when substituted back into the price equation. It is not surprising that these results are twice the size of the corresponding values in the other columns. I essentially include  $\mu_{V,t}$  twice in the equation: once as a regressor, and once as part of  $\hat{v}_t$ . A joint F-test of the significance of  $\mu_{V,t}$  and  $\hat{v}_t - \mu_{V,t}$  instead of  $\hat{v}_t$  failed. To arrive at the partial effect of  $\hat{v}_t$  on price, I should divide its coefficient in half (= 0.98). The resulting effect on price from  $v_t$  is thus equivalent across all columns. Likewise, I should then divide the parameter  $\gamma_1$  in half to get the effect of  $V_t^i$  on price (= 1.19).

All approaches confirm that the data in eBay online auctions for computers is consistent with Nash CV auctions. Prices fall with dispersion at a decreasing rate. Prices also fall with the number of bidders in this sample of auctions. Reputation determines the credibility of information dispersion: higher reputations cause prices to rise more when information is less dispersed and fall more when information is more dispersed.

## 4 Analysis

Thus far, tests of Nash equilibrium behavior have been based on comparative static signs. In this section, I rely on magnitudes of estimated coefficients and introduce assumptions about the shape of the distribution of common values and information signals in order to determine the actual difference between theoretically predicted prices and eBay prices. I also rely on magnitudes to estimate the potential winner's curse in these markets and compare the price effects of reputation, information dispersion, and the credibility of information. I use the coefficients from Column 2 of Table 4 for my analysis.

Table 4: Simultaneous equation estimates of price equation

Parameter	Column 1	Column 2	Column 3	Column 4
$\theta_0$		27.039 <sup>‡</sup> (0.407)	1.772 (156.267)	289.748 <sup>‡</sup> (0.544)
$\gamma_0$		83.611 <sup>‡</sup> (0.397)	60.405 (162.560)	-76.906 <sup>‡</sup> (1.289)
$\gamma_1$		1.033 <sup>‡</sup> (2.72E-04)	1.029 <sup>‡</sup> (0.050)	2.392 <sup>‡</sup> (1.015E-03)
$\eta_0$		-60222.6 <sup>‡</sup> (803.752)	-9259.78 (302009)	78034.3 <sup>‡</sup> (997.537)
$\delta_0$		76381.0 <sup>‡</sup> (268.241)	58047.6 (1557071)	5247.51 <sup>‡</sup> (397.027)
$\delta_1$		1.83103 <sup>‡</sup> (7.64E-03)	2.488 (1.760)	1.396 <sup>‡</sup> (7.57E-03)
<b>Variable</b>				
Constant	69.301 (120.627)			
$\hat{v}_t$	1.046 <sup>‡</sup> (0.059)	1.086 <sup>‡</sup> (3.85E-04)	1.172 <sup>‡</sup> (0.104)	1.960 <sup>‡</sup> (7.63E-04)
$\hat{\sigma}_{X V,t}$	-1.483 <sup>‡</sup> (0.450)	-1.48479 <sup>‡</sup> (3.45E-03)	-1.448 <sup>‡</sup> (0.692)	-1.446 <sup>‡</sup> (5.50E-03)
$\hat{\sigma}_{X V,t}^2$	1.20E-03 <sup>‡</sup> (4.26E-04)	1.73E-03 <sup>‡</sup> (7.07E-06)	1.79E-03 (1.20E-03)	0.16E-02 <sup>‡</sup> (-8.85E-06)
$N_t$	-11.811 (11.145)	-9.120 <sup>‡</sup> (0.047)	-21.819 (23.900)	-8.423 <sup>‡</sup> (0.053)
$N_t \times \hat{\sigma}_{X V,t}$	0.021 (0.022)	0.024 <sup>‡</sup> (1.35E-04)	0.012 (0.059)	0.018 <sup>‡</sup> (1.31E-04)
$\text{SCORE}_t \times \hat{\sigma}_{X V,t}$	-1.16E-04 <sup>†</sup> (6.68E-05)	-1.38E-04 <sup>‡</sup> (4.78E-07)	-7.05E-05 (4.82E-04)	-1.29E-04 (4.97E-07)
$\text{NEG}_t \times \hat{\sigma}_{X V,t}$	1.39E-03 (1.73E-03)	1.52E-03 <sup>‡</sup> (1.05E-05)	-6.56E-04 (0.015)	1.41E-03 <sup>‡</sup> (1.08E-05)
$\text{SCORE}_t$	0.091 <sup>‡</sup> (0.038)	0.079 <sup>‡</sup> (1.66E-04)	0.079 (0.125)	0.086 <sup>‡</sup> (1.96E-04)
$\text{NEG}_t$	-0.901 (0.816)	-0.731 <sup>‡</sup> (3.39E-03)	-0.281 (4.202)	-0.780 <sup>‡</sup> (4.08E-03)
$\text{SCORE}_t^2$	-1.12E-06 (1.15E-06)	-1.10E-06 (5.76E-09)	-2.13E-06 (3.03E-06)	-1.24E-06 (5.79E-9)
$\mu_{V,t}$				0.114 <sup>‡</sup> (1.69E-03)
$R^2$	0.72	0.72	0.69	0.71

<sup>‡</sup>significant at 5 percent, <sup>†</sup>significant at 10 percent.

## 4.1 Differences between Nash CV & eBay prices

The price equation estimated in Section 3 is an approximation to the true price function. The functional form chosen for  $p$  did not impose any particular auction model; the comparative statics identified the Nash CV model as appropriate to describe eBay computer auction prices. Thus, the estimated parameters and coefficients in Table 4 are free of any assumptions about bidder behavior or CV versus PV. To quantify how close eBay prices are to Nash CV prices as predicted by auction theory, I simulated Nash CV prices based on the  $n_t$ ,  $v_t$  and  $\sigma_{X|V,t}$  I had estimated for the eBay prices.

I employed the estimated survey bias parameters from Column 2 by plugging them back into  $\hat{v}_t$  and  $\hat{\sigma}_{X|V,t}$  to generate a  $\tilde{v}_t$  and  $\tilde{\sigma}_{X|V,t}$  for each auction. I then calculated the mean and standard deviation of  $\tilde{v}_t$  and treated these as estimates of the common  $\mu_V$  and  $\sigma_v$  over all  $t$  auctions. I tried several measures for  $n_t$ , including the first stage fitted value from instrumental variables and  $N_t \pm 20$  percent,  $\pm 50$  percent, and  $+100$  percent. There was not much difference in the resulting simulated Nash CV prices, so I present the results from simply using  $N_t$  as a measure of  $n_t$ .

I drew the second highest signal out of  $N_t$  draws made from a lognormal distribution with mean  $\tilde{v}_t$  and standard deviation  $\tilde{\sigma}_{X|V,t}$ .<sup>19</sup> I generated the Nash CV price for each auction using these values and a numerical approximation to the theoretical Nash CV price (see Appendix D).<sup>20</sup> I repeated this process 1000 times for each auction. The average over these prices is the simulated Nash CV price for auction  $t$ . I then adjusted the expected price for reputation effects and interaction effects between reputation and dispersion based on the estimates from Column 2 of Table 4. Simulated naïve CV prices were generated by taking the average over the draws of the second highest signal and then adjusting for reputation effects.

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<sup>19</sup>I also simulated prices for normal distributions, but the shape of those distributions did not fit the eBay price data as well. The lognormal and normal distributions most closely matched the observed distribution of survey responses.

<sup>20</sup>The Gauss-Hermite quadrature method is outlined in Judd (1998). I corrected for an error in the translation presented in the text for lognormally distributed signals.

Figure 2 plots simulated prices based on lognormally distributed signals and actual prices from eBay for each auction in my sample. Along the horizontal axis, auctions are presented in increasing order by the simulated Nash CV prices. Simulated prices are plotted as diamonds, while the associated eBay price is plotted as circles.

The scatterplot shows that eBay prices track the slope and curvature of the Nash CV simulated prices very closely. eBay prices tend to be lower than the Nash CV predictions by about 35 percent. Figure 2 confirms that eBay prices react to changes in  $N_t$  and  $\hat{\sigma}_{X|V,t}$  in the manner predicted by Nash CV, although prices may not exactly replicate the magnitudes of those changes.

The difference between the simulated and actual prices suggests that bidders may be over-reacting to the winner's curse. Alternatively, information contained in auctions outside of my sample or information passed between the seller and auction participants that is not posted in the auction description may be affecting auction participants' estimates of  $v_t$ . The estimates in the previous section do not take into account the effects of multi-auction behavior or of private information revelation, which would affect the magnitude of the estimates, but not the sign. Kremer & Jackson (2005) establish that as  $n \rightarrow \infty$ , 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. Evidence for this is documented in Zeithammer (2006) and Juda (2006) . Away from the limit, this behavior might result in prices that are consistently lower than simulated Nash CV prices.

## 4.2 Winner's Curse

If the difference between prices from naïve bidding behavior and the value of the auctioned items are not that large, then it may not matter if auction participants play Nash CV strategies. How much is really at risk if participants do not account for the winner's curse? I can answer this question by considering the prices the winning bidder would have paid

Figure 2: eBay prices vs. simulated Nash CV prices

The theoretical Nash CV price is simulated for each auction. Auctions are ordered by simulated prices along the horizontal axis. The simulated prices as well as the eBay prices in each auction are plotted along the vertical axis. eBay prices are highly correlated with simulated Nash CV prices.

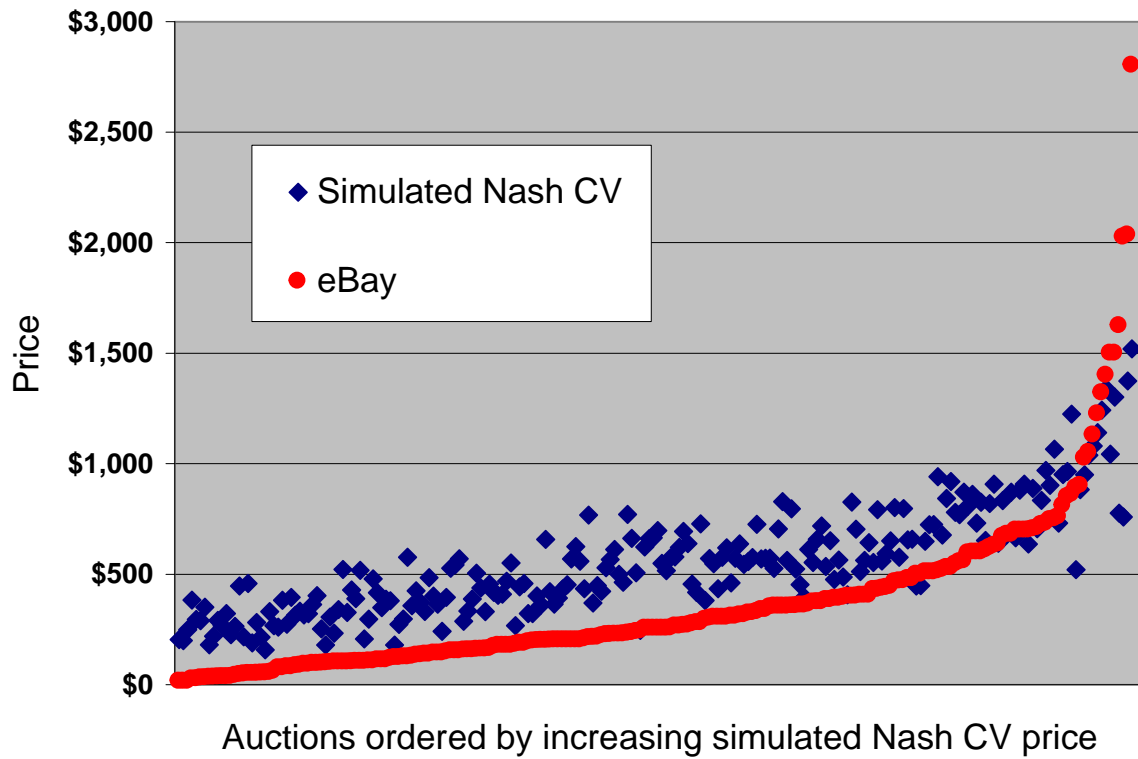


Table 5: Potential winner’s curse

<b>Prices</b>	<b>average</b>	<b>diff. w/ naïve</b>	<b>diff. w/ <math>\tilde{v}_t</math></b>
simulated Nash CV	\$557.19	-\$191.29	-\$21.42
simulated naïve CV	\$748.48	0	\$169.87
eBay	\$361.02	-\$387.46	-\$217.59

if auction participants had employed naïve CV bidding behavior. I can also examine the difference in prices if auction participants ignored changes in the number of participants, dispersion, and their interaction effects.

The first column of numbers in Table 5 reports the summary statistics over all auctions for the simulated Nash CV prices, simulated naïve CV prices, and eBay prices. The average difference between simulated naïve CV prices and the simulated Nash CV and eBay prices are presented in the middle column of numbers. The last column presents the difference between the estimated common value of the items and the simulated Nash CV, simulated naïve CV, and eBay prices.

eBay winners pay a lot less for their items than they would if they had behaved naïvely: naïve CV prices are 34 percent higher than Nash CV prices, and more than double eBay prices. The winner’s curse would be \$169.87 on average, since naïve auction winners would have paid that much more over the value of the item. Instead, the consumer surplus in these auctions is \$217.59 on average.<sup>21</sup> However, as suggested in the previous section, it is likely that the eBay bidders over-react to the winner’s curse, and therefore bid less than predicted by Nash CV. The average consumer surplus that would be predicted by Nash CV is \$21.42.

I further decompose the effects of naïve bidding into the loss from ignoring changes in information dispersion and the loss from ignoring changes in the number of auction participants. For each auction, I consider three scenarios: an increase in information dispersion by 1 unit, an increase in the number of auction participants by 1 person, and both changes.

<sup>21</sup>eBay winners paid more than  $\tilde{v}_t$  in less than 5 percent of the auctions in my sample. These auctions were characterized by higher than average  $\tilde{v}_t$ ,  $\tilde{\sigma}_{x|v,t}$ ,  $SCORE_t$ , and  $NEG_t$ .

Table 6: Price effects of naïve behavior

<b>Behavior</b>	<b>Price change from</b>		
	<b>incr. <math>\sigma_{X V,t}</math> by 1</b>	<b>incr. <math>n_t</math> by 1</b>	<b>both</b>
Nash CV	-\$0.30	-\$1.63	-\$1.05
ignore $\sigma_{X V,t}$	0	-\$9.12	-\$9.12
ignore $n_t$	-\$0.46	0	-\$0.46
naïve CV	0	0	0

The columns of Table 6 present the results from each scenario. I then calculate how much prices would change under the Nash CV model based on the estimates in Column 2, Table 4. I report those results in the first row. I also calculate how much the price would change if auction participants were naïve with regard to dispersion, naïve with regard to the number of auction participants, or both. Those calculations are made by setting the coefficients on dispersion, the number of auction participants, and interaction terms in Column 2 of Table 4 to 0, respectively. The results for each of those models of bidding behavior are presented in the remaining rows of Table 6.

Comparing the first two rows in Column 1, I can see that if all auction participants ignored the effect of a 1 unit increase in dispersion, prices would be \$0.30 higher than Nash prices. If all auction participants ignored  $n_t$  but not the increase in dispersion, then they would not take into account the interaction effect between  $n_t$  and  $\sigma_{X|V,t}$ . Prices would be \$0.16 ( $=\$0.46-\$0.30$ ) lower than Nash prices. A bidder who did not ignore changes in  $n_t$  could thus profitably win against the other bidders in this auction by bidding any amount between the Nash CV price and Nash CV price minus \$0.16.

The second column of numbers shows price changes under each model when an additional auction participant enters the auction. Failure to account for that participant leads to prices \$1.63 higher than Nash prices. The failure to account for the interaction effect between  $n_t$  and  $\sigma_{X|V,t}$  will result in prices \$7.49 ( $=\$9.12-\$1.63$ ) lower than Nash prices.

The last column of numbers presents price changes if both dispersion and the number of

auction participants increase. Ignoring the number of auction participants alone will lead to prices \$0.59 higher (=\$0.46-\$1.05) than Nash. Ignoring dispersion alone will lead to prices \$8.07 (=\$9.12-\$1.05) below Nash.

To place these counterfactual scenarios in context, consider an auction from my sample whose item description generated a level of information dispersion in the top quartile of my sample,  $\tilde{\sigma}_{X|V,t} = 420.46$  and attracted less than the average number of auction participants in the sample,  $N_t = 3$ . The winning price was \$137.50 for this item. Holding all else equal, if the auction participants had ignored the fact that this auction attracted 3 auction participants and simply assumed that the number of auction participants equaled the average  $N_t$  in my sample of 6, then the winning bidder would have overpaid by \$2.47. Holding all else equal, if the auction participants had ignored the fact that dispersion was 103.96 higher than the average in my sample, and simply acted as if dispersion was 316.64, then the winning bidder would have overpaid by \$18.30. If the auction participants had ignored both of these facts, then the winning bidder would have overpaid by \$17.62

In this sample of auctions, the declining prices as  $n_t$  rises are countered by the interaction effect with dispersion. By appropriately accounting for changes in the number of auction participants and dispersion, bidders avoid paying more than is necessary (i.e., more than the Nash equilibrium price) to win in some auctions, or they avoid losing the auction at a price less than the predicted Nash price.

### 4.3 Information Dispersion, Reputation, and Credibility

What do these estimates mean for seller strategies on eBay? Table 7 examines how prices will change with dispersion and reputation.

A seller who invests in acquiring and publishing more information in the auction description to reduce dispersion will earn a return that depends on her reputation and current level of information dispersion. The return from decreasing dispersion by 1 unit is \$0.23; for the average seller, the credibility in the reduction of dispersion due to their reputation adds an-

Table 7: Price effects of credibility

Partial effect	Price change from		
	decr. $\sigma_{X V,t}$ by 1	incr. $SCORE_t$ by 1	both
$\frac{\partial p_t}{\partial SCORE_t} *$	-	\$0.08	\$0.08
$\frac{\partial p_t}{\partial \sigma_{X V,t}} *$	\$0.23	-	\$0.23
$\frac{\partial^2 p_t}{\partial \sigma_{X V,t} \partial SCORE_t}$	\$0.11	-\$0.04	\$0.06
<b>Total effect</b>	<b>\$0.34</b>	<b>\$0.04</b>	<b>\$0.38</b>

\*These partial effects exclude the interaction effects with respect to reputation.

other \$0.11 to the price. The \$0.08 premium from increasing reputation by 1 unit is mitigated by the -\$0.04 interaction effect with dispersion. A better reputation increases credibility, and therefore increases the penalty on price for having high information dispersion.

Direct comparisons of the importance of these effects is difficult, since the units are not the same. To place these counterfactual changes in context, consider a seller from my sample who had no reputation ( $SCORE_t$  and  $NEG_t$  both equal 0) and posted an item description that generated the median level of information dispersion among all the samples in my auction,  $\tilde{\sigma}_{X|V,t} = 321.50$ . The seller in this case sold the item for \$255.07. If the seller had the median reputation,  $SCORE_t = 68$ , then holding all else equal, she would have sold the item for \$5.36 more. If the seller instead had posted an item description that generated a level of information dispersion equivalent to the levels of those posting in the lowest quartile of  $\tilde{\sigma}_{X|V,t}$ ,  $\tilde{\sigma}_{X|V,t} = 218.51$ , then holding all else equal, she would have sold the item for \$46.79 more. Based on these estimated price effects, uncertainty about the value of a good due to information dispersion over auction participants seems to be a more important source of uncertainty than information asymmetry between the buyer and the seller. If both the seller's reputation had increased and dispersion had decreased, the seller would have sold the item for \$50.16 more.

Empirical analysis of eBay auction prices which ignores the breakdown of the direct

effect from reputation and the interaction effect of reputation may lead to the conclusion that reputation has a negligible effect on price. Because of this interaction effect, a seller has an incentive to both decrease dispersion and increase her reputation, reducing uncertainty about the value of computers in eBay markets.

## 5 Conclusion

The results in this paper are unattainable without employ theory, econometric modeling, and external survey data. From auction theory, I derive implications of different auction models when information dispersion and the number of bidders are observable with error. These implications permit joint testing of the information structure (CV or PV) and bidding behavior (Nash or naïve strategies) in these auctions.

To measure information dispersion and unobservable item values, market data is augmented by survey data. By harnessing the dispersion of information in the non-eBay market, I am able to generate a measure that is independent of bidding data. Although dispersion could be derived from knowledge of all the bids in an auction or knowledge of some bids and the true common value, one would have to assume a PV or CV setting to test for Nash bidding behavior or assume Nash bidding behavior to identify the information structure. The highest bid is not observed in the eBay data, and ex-post valuations for the goods are not readily available. The survey data provides extra identification power to 1) simultaneously distinguish between CV and PV without imposing Nash equilibrium bidding behavior, distinguish between Nash and naïve bidding behavior without assuming a PV or CV setting, employ only price data from the auctions as opposed to all bids, and estimate any potential bias between my measures of dispersion and the true common value and dispersion of information. My estimates indicate that eBay auctions for computers are best described as CV auctions where prices reflect Nash equilibrium bidding behavior. They also indicate that my survey measures provide reasonably accurate approximations for the true values.

The survey data also permits treatment of information about the item being sold as distinct from information about the seller. I identify two different effects of reputation: the mean shift that a reputation premium may have on the expected common value and the credibility reputation lends to changes in the dispersion of information in an auction. The estimates indicate that uncertainty about the value of a good due to information dispersion over auction participants seems to be a more important source of uncertainty than information asymmetry between the buyer and the seller. Empirical analysis of eBay auction prices which ignores the effect of information dispersion on price may inadvertently conclude that reputation has a negligible effect on price, but both are important. Sellers with a good feedback score have an incentive to provide precise descriptions, since they benefit from the complementarity between reputation and product information.

I adjust for potential bias in my survey measures and quantify the potential winner's curse in this market. Auction participants on eBay account for the winner's curse, pay less than the common value on average. Rough calculations of naïve bidding models indicate that there is potential for a large winner's curse. Even in the pedestrian market of online computer auctions, prices exhibit the equilibrium behavior predicted by sophisticated bidding strategies.

## **A Survey Description**

Auction descriptions were edited to remove all bids and identities (other than seller identification within the auction description itself) and reputations involved. A CGI script was developed by Paul Hartke to translate PostScript graphics of these auctions into web-viewable formats, and automate a process to assign unique ID numbers to survey respondents and record which auctions were viewed and respondents' values. A separate Formage script was written to solicit background information on the respondents. The following solicitation was sent to friends of the author and posted to relevant newsgroups:

“Could you please help my friend, Pai-Ling , <http://www.stanford.edu/~p>, in her PhD economics research project to determine the distribution of commonly held values for products? Just fill out a short survey asking you to look at the descriptions of 10 computers and giving your estimate of how much they are worth. Even if you are not familiar with computers and their prices, your best guess will still be useful to Pai-Ling. So send this on to your grandparents, parents, siblings, cousins, friends, and co-workers for extra chances at winning!

“All completed surveys will be entered in a drawing for two \$1,000.00 prizes and thirty \$60 prizes. For each friend you get to do the survey, you get an extra chance to win. Deadline for all submissions is 11:59pm, July 20, 2002. E-mail [p@stanford.edu](mailto:p@stanford.edu) if you can’t make the deadline but still want to participate.

“Thanks very much! Email [p@stanford.edu](mailto:p@stanford.edu) if you have questions. Privacy will be honored; no names or emails will be released except for the winners (posted at the survey site after 1/1/03).”

#### PRIZE DETAILS:

“As a reward for participating, a drawing will take place on January 1, 2003, over all completed surveys and referrals. Two people will win checks for \$1,000.00. Odds of winning depend on the number of times you participate and the total number of surveys completed.

“As an incentive to think sincerely about your estimates, fifteen \$60.00 prizes will be awarded to the people whose estimates are closest to the average of all other estimates in the same auction, and fifteen \$60 prizes will be awarded to the people whose estimates are closest to a set of estimates provided by a panel of computer sales people. This allows both computer experts and non-experts to have a chance at winning.”

#### BACKGROUND:

1. Please enter your e-mail address. This will be used only to contact you if you win.

Please use the same e-mail if you participate more than once.

Did someone refer you to this survey? Please enter his/her e-mail address:

2. Are you involved in work or hobbies that cause you to be very familiar with the prices of computers and computer components? YES/NO

3. Have you been shopping for a computer in the last 6 months? YES/NO

4. How many computers have you bought in the past 6 months (either for personal use or for work)? 0/1/2+

If you bought a computer, did you buy it/them through (check all that apply):

an auction process (does not include using “Buy It Now”)?

a retailer (includes using “Buy It Now” to buy the computer at a set price rather than at the winning auction price)?

a wholesaler (someone who normally sells computers to stores, not directly to consumers)?

5. Have you ever looked at computers on an online auction website? YES/NO

On eBay? YES/NO

6. In how many online computer auctions have you participated in your life?

0/1/2-5/6+

How many were on eBay? NONE/SOME/ALL

How many of the computer auctions did you win? NONE/SOME/ALL

“After you hit the submit button, you will be given descriptions to evaluate, one at a time. You will be given 1 chance to win prizes for every 10 auctions you complete.

“You may want to copy your answers for each auction on some paper so that you can compare auctions.

“You can use the ‘Back’ and ‘Forward’ buttons on your browser to compare descriptions; if you want to change answers, you can use the back button as well, but make sure to click

”Send” to register the change. Then click ‘Send’ on the subsequent pages to return to the auction you left off with.

“Send e-mail to p@stanford.edu if you have any problems, want to change an answer after exiting, or want to confirm your entries. Please make sure the above answers are correct before you click ‘Send’, so that you don’t have to backtrack to this page to change any answers.

“Please wait a few seconds while the computer description loads...

“Assume that your friend is interested in buy the computer described below. Taking into account all information that you see (including shipping and insurance costs), what is the MOST she should be willing to pay for this computer (NOT how much she should bid!)? Even if you don’t understand some of the description, please do your best to be consistent (better computers cost more). Feel free to look at ads or websites to help you make better recommendations, but please DO NOT look at online auction sites to get a sense of prices. Scroll ALL the way down to enter your value at the bottom of the description.”

## **B Instruments for $N_t$**

Instruments should be correlated with the number of bidders, but, conditional on other covariates (in particular, the mean of the survey responses), not correlated with unobservable determinants of price.

Many sellers utilize “webcounter” software to track the number of times their auctions were accessed by a web browser. This number was designated as  $COUNTER_t$ . It is an upper bound on the number of participants active in that auction, since it includes repeat site access by the same user. A signal of the item’s value cannot be drawn before viewing the auction website. Therefore,  $COUNTER_t$  is uncorrelated with the value of the item being auctioned. For those auctions without counters, the average of  $COUNTER_t$  across all auctions is used.

Table 8: Summary statistics for bidder instruments

<b>Variable (222 auctions)</b>	<b>mean</b>	<b>st. dev.</b>	<b>min</b>	<b>max</b>
webcounter hits $HITS_t$	249.67	167	38	1215
webcounter dummy $NOHITS_t$	0.33	-	0	1
minimum bid $MINBID_t$	58.25	112.95	0.01	650.00
auction end time $ENDHOUR_t$	15	5	1	24
auction end day $ENDDAY_t$	4	2	1	7
auction duration $LENGTH_t$	3.45	1.1	1.5	7
item listed by photo $GALLERY_t$	0.33	-	0	1
item at top of list $FEATURE_t$	0.16	-	0	1
$N_t$ from similar auctions $ALTN_t$	6.60	1.85	3	11.8

Different ending times of the auction,  $HOUREND_t$  and  $ENDDAY_t$ , and the length of the auction in days,  $LENGTH_t$ , will change the potential number of participants in the auction but are unlikely to be correlated with the value of the item.  $GALLERY_t$  and  $FEATURE_t$  indicate whether an item was included in the photo gallery or listed at the top of the webpage listings. These characteristics should influence the number of people that enter the auction by changing the item's visibility.

I assume that changing the minimum bid,  $MINBID_t$ , only affects price by changing the number of participants entering the auction. Anecdotal evidence suggests that sellers like to generate interest in their auctions by lowering starting bids, so it is not necessarily a reflection of the value of the item.

$OTHERN_t$  is an instrument that is independent of any seller actions. It is the average number of bidders observed participating in the ten other auctions which received the closest  $V_{e,t}$ . This instrument should be correlated with the number of participants in the market for computers of equivalent value to the one listed in auction  $t$  without being correlated with any specific product characteristic of the computer in auction  $t$ .

Table 9: Summary statistics for regressors for a priori value

<b>Variable (222 auctions)</b>	<b>mean</b>	<b>st. dev.</b>	<b>min</b>	<b>max</b>
recognizable computer $BRAND_t$	0.27	-	0	1
quality of brand of $PROCESSOR_t$	2.14	1.11	0	3
processor $SPEED_t$	1088	684.88	0	2530
$RAM_t$ memory capacity	210.77	196.04	0	1100
$HARDDRIVE_t$ memory capacity	27724	27755	0	160000
device for $INTERNET_t$ access	1.31	0.83	0	2
includes $MONITOR_t$	0.21	-	0	1
includes $CD_t$ or DVD drive	0.83	-	0	1
includes $FLOPPY_t$ drive	0.66	-	0	1

## C Regressors for $\mu_{v,t}$

I constructed a set of hedonic characteristics of the computers to be used as regressors for determining  $\mu_{v,t}$ . The expected value of a computer satisfg certain criteria before a bidder has seen the auction description is captured in  $\mu_{v,t}$ , while  $v_t$  measures the value of a computer after having seen the auction description. Summary statistics are presented in Table 9.

The dummy variable  $BRAND_t$  indicates whether the computer had a recognizable brand name (Toshiba, Dell, Hewlett-Packard, IBM, Compaq) or not. A ranking of the processor brands in  $PROCESSOR_t$  ranged from no mention of processor brand (= 0) to Pentium (= 3). The processor's speed was denoted as  $SPEED_t$ . The amount of memory included was characterized by the ram and harddrive capacity ( $RAM_t, HARDDRIVE_t$ ). I ranked the presence of a communications device in  $INTERNET_t$  (0 for no device, 1 for modem, 2 for other). Dummies were created for whether a monitor, cd/dvd drive, and floppy drive was included or not ( $MONITOR_t, CD_t, FLOPPY_t$ ). If the auction description did not provide any information about a characteristic, the value was coded as 0.

## D Analytical derivation of $E[p]$

The bid function in Equation 1 can be written explicitly as

$$(7) \quad b(x_j) = \frac{\int_{\underline{v}}^{\bar{v}} v f_{X|V}^2(x_j|v) F_{X|V}^{n-2}(x_j|v) f_V(v) dv}{\int_{\underline{v}}^{\bar{v}} f_{X|V}^2(x_j|v) F_{X|V}^{n-2}(x_j|v) f_V(v) dv}, \quad (\text{Milgrom \& Weber, 1982})$$

where  $F_x(x_i|v)$  is the cumulative distribution of  $x$ . To derive the expected value of the 2nd highest bid, one would have to solve for

$$\Pr[b(x_j) \leq v] = \Pr[x_j \leq b^{-1}(v)] = F_{X|V}(b^{-1}(v))$$

with associated density

$$f_{X|V}(b^{-1}(v)) \frac{1}{b'(v)},$$

where

$$b'(v) = \frac{\partial b(v)}{\partial v},$$

and solve for the 2nd order distribution of

$$f_{X|V}^{(n-1)}(b^{-1}(v)) \frac{1}{b'(v)} = n(n-1) F_{X|V}(b^{-1}(v))^{n-2} f_{X|V}(b^{-1}(v)) \frac{1}{b'(v)} [1 - F_{X|V}(b^{-1}(v))],$$

and then integrate to get

$$\int_{-\infty}^{\infty} x_i (n-1) F_{X|V}(b^{-1}(v))^{n-2} f_{X|V}(b^{-1}(v)) \frac{1}{b'(v)} dx.$$

I numerically approximate this expression in order to generate Nash CV prices.

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