USING SURVEYS TO MEASURE INFORMATION IN AUCTIONS: EVIDENCE FOR RATIONAL BEHAVIOR, INFORMATIVE PRICES, AND THE IMPORTANCE OF CREDIBILITY IN EBAY COMPUTER AUCTIONS

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FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

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Abstract

This thesis examines the role of information in online auctions, with specific application to eBay auctions for computers. Market data is augmented by a survey-based measure of unobservable item values and information dispersion in the auctions. These measures are an important source of external information for hypothesis testing. They permit joint identification of the information structure (common or private values) and bidding behavior (Nash or naïve strategies) in these auctions. They also permit separate identification of the effects of reputation, information, and their interaction (credibility of information) on price. This information can also be used to determine whether prices on eBay converge to the common value.

My estimates indicate that eBay auctions for computers are best described as common value auctions where prices reflect Nash equilibrium bidding behavior. Sellers with good reputations have powerful incentives to reduce uncertainty and promote efficient trade due to the importance of credibility of information. The ability of eBay bidders to account for the winner's curse in these auctions leads to prices that partially aggregate information about the common value as the number of bidders increases.

The success of the survey-based measure described in this thesis contributes to the tools available to empirical researchers. The quantitative results regarding the role of information in auctions yields a better understanding of the importance of information in online auctions. These results are unattainable without employing theory, econometric modeling, and external survey data.

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Chapter 1

Introduction

This thesis examines the role of information in online auctions, with specific application to eBay auctions for computers. In all auctions, private information signals about the value of the item being sold are dispersed among the bidders. This private information is not directly observable. Chapter 2 explains how I employ a survey to measure the mean and dispersion of the information signals in eBay auctions for computers. The information from the survey differs significantly from information that could have been estimated using hedonic regression.

I find that the survey is able to successfully generate a measure of information dispersion and the value of the item. Auctions that my survey respondents designated to be of equal value contained equivalent hardware specifications. The auction description that provided more details (i.e., revealed more information to all auction participants) had a lower standard deviation of survey respondent's valuations. The price attained in that auction was higher than that attained for the item with a less informative auction description. This finding is consistent with the auction theory prediction that prices decline with more information dispersion in CV settings.

I collected background data on the survey respondents during the survey to determine which respondents were experienced with eBay computer auctions (and thus similar to the auction participants) and which respondents were not. I exploit the mixture of experienced and inexperienced respondents to correct for any bias between the mean and standard deviation of the survey responses and the true common value

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and dispersion of information facing the auction participants. The use of inexperienced respondents permits the survey to be implemented quickly and with a larger number of respondents. The use of experienced respondents allows me to correct for potential bias from using more noisy inexperienced responses.

These measures are an important source of external information for hypothesis testing. Chapter 3 derives testable implications of auction theory using results from Milgrom & Weber (1982) that were not previously clarified with respect to information dispersion. The measure of information dispersion from the survey allows me to test whether a model of Nash equilibrium behavior in a CV information structure characterizes eBay online computer auctions. Specifically, these comparative statics can distinguish between Nash behavior in a common values setting (Nash CV) and the alternatives of naïve bidding in a common values setting (naïve CV), Nash bidding in a private values settings (PV), and risk aversion in a PV setting. My survey data provides me with information about the distribution of signals independent of the bidding data. This allows me to 1) distinguish between common and private value settings without imposing fully rational bidding behavior, 2) distinguish between Nash and naïve bidding behavior without assuming a private or common values setting, 3) employ only price data from the auctions as opposed to all bids, and 4) estimate any potential bias between my measures of dispersion and the common value and the true values. My estimates indicate that eBay auctions for computers are best described as common value auctions where prices reflect Nash equilibrium bidding behavior.

By employing parametric estimation, I am able to estimate the extent of the winner's curse in these markets and determine the effect of information dispersion, reputation, and credibility (the interaction of information and reputation) on prices. I find that eBay winners do not suffer from the winner's curse. I also find that reputation complements information dispersion: a good reputation lends credibility to the information provided by the seller. Sellers with good reputations have powerful incentives to reduce uncertainty and promote efficient trade due to the importance of credibility of information.

Auction theory predicts that prices will converge to the common value as the number of bidders goes to infinity. This convergence is referred to as "information

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aggregation," since dispersed private information signals are aggregated into the price. In Chapter 4, I empirically test for information aggregation in eBay personal computer auctions. I derive observable implications of information aggregation on the path of convergence in commercial auctions with heterogeneous products. Using estimates for the mean and dispersion of common values from the previous chapter, I also generate predictions of information aggregation behavior away from the limit. The ability of eBay bidders to account for the winner's curse in these auctions leads to prices that partially aggregate information about the common value as the number of bidders increases.

The success of the survey-based measure described in this thesis contributes to the tools available to empirical researchers. The quantitative results regarding the role of information in auctions yields a better understanding of the importance of information in online auctions. These results are unattainable without employing theory, econometric modeling, and external survey data.

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Chapter 2

A Survey-Based Procedure for Measuring Unobservable Information

Traditionally, surveys have been used to elicit unobservable information about people's valuations of goods when markets and prices for those goods are absent. They can also be a valuable source of information when markets exist. This chapter shows how surveys can be used to exploit the ability of people who are outside of a market to assess information in order to generate a measure of the amount of information within that market. Specifically, in markets where participants possess different signals about an item's value due to noise and/or due to different costs and preferences, the survey can be used to estimate the characteristics (mean, variance) of the distribution of those signals.

The particular application used here is for eBay online auctions for personal computers (PCs). In all auctions, private information signals about the value of the item being sold is dispersed among the auction participants. This private information is not directly observable to the econometrician. This paper explains how I employed a survey to measure the mean and dispersion of the information signals in computer auctions.

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In a common values (CV) auction setting, each auction participant's private signal contains information that is relevant to the other participants' assessments of the value of the item. In this setting, the average of these survey responses measures the common value of the item being auctioned. The standard deviation of responses measures the dispersion of information in the auction. An auction where more information is publicly available to all the bidders will be reflected by less dispersed signals.

In a private values (PV) setting, the private signals only inform the recipient of the signal about her value for the item. In this case, the survey measures the average private value and dispersion of private values among bidders. One can use these averages and standard deviations to test between PV and CV settings while also testing for rational bidding behavior (see next chapter).

Analysis of the survey results confirms that the survey is able to successfully generate estimates of information dispersion and average item values. Auctions which my survey respondents designated to be of equal value contained equivalent hardware specifications. The auction description that provided more details (i.e., revealed more information to all auction participants) had a lower standard deviation of survey respondent's valuations. The price attained in that auction was higher than that attained for the item with a less informative auction description. This finding is consistent with the auction theory prediction that prices decline with more information dispersion in CV settings.

I collect background data on the survey respondents during the survey to determine which respondents are experienced with eBay computer auctions (and thus similar to the auction participants) and which respondents are inexperienced. I exploit the mixture of experienced and inexperienced respondents to correct for any bias between the mean and standard deviation of the survey responses and the true common value and dispersion of information facing the auction participants. The use of inexperienced respondents permits the survey to be implemented quickly and with a larger number of respondents. The use of experienced respondents allows me to correct for potential bias from using more noisy inexperienced responses.

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Section 2.1 reviews the motivation for a survey based measure of information dispersion in auctions. Section 2.2 presents the auction data employed and the survey design. Section 2.3 analyzes the success of the survey as a correlated measure. Section 2.4 presents the background data collected in the survey, and its implications for correcting for survey bias. Section 2.5 presents the bias correction procedure. Section 2.6 examines the difference between results from the survey-based measures and alternative hedonic regression methods. The Section 2.7 concludes this chapter.

2.1 Motivation for Survey Data

There are several reasons why a researcher might want to collect survey data to augment data from commercial markets, particularly in auctions. A researcher must often control for the value of the item when determining the effect of other regressors on price. Empirical work in general has employed hedonic regression of price on product characteristics to control for the value of the item. A large number of hedonic characteristics will demand a large number of observations for identification. A survey allows respondents to flexibly assess the value of a large number of characteristics even in a small sample of items. Alternatively, empirical work has restricted itself to examining identical items to control for item values. Identical items may lead to a restricted sample of items that is either too small or exhibits little variation in the regressors of interest. The ability of survey respondents to handle differences in item characteristics permits the researcher to more heterogenous items in order to ensure a sufficiently large sample and sufficient variation in the regressors of interest. The survey measure of value can be constructed to be independent of the price, as long as survey respondents are not shown price information. Thus, the survey data provides exogenous regressor that controls for the value of the item.

The surveys measure can be designed to be independent of other regressors as well. For example, in my survey design, details about the seller, the bidders, and the bids in the auction are omitted. This creates several advantages for using survey data over methods that recover the signals from the observed distribution of bids. My survey responses are functions of the product description only. Reserve prices and opening

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bids that appear in many online auctions would truncate the observed distribution of bids. My survey responses are not influenced by the number of bidders in the auction nor by the reputation of the seller. Thus, my survey estimates are also independent of bidding behavior, whereas observed bids may or may not reflect rational bidding behavior (e.g., adjustments for the winner's curse). The independence between my survey and the auction data allows me to test between different types of bidding behavior and separately identify the effect of reputation from other determinants of price.

Empirical work has also proxied for the common value using blue book values. However, blue book values and hedonic methods cannot take into account any anomalies in the products. For example, a computer that was being sold on eBay was described as working but locked: the password had been lost, so there was no way to logon to the computer. Hedonic estimation or the use of a blue book value would treat this anomaly as unobservable to the econometrician. Such anomalies may be important determinants of the price of the auctioned item. They might drive the number of bidders that enter the auction. The number of bidders is often included in the price model as a regressor. This presents an endogeneity problem for estimation, since the number of bidders is now correlated with the error term. In contrast, the human readers' estimates do reflect values that are more closely tied to the semantics of the product description than any hedonics-based measure or book value. By having people read the auction descriptions and respond with their value for the item, I am able to capture idiosyncrasies of each item in addition to the hedonic characteristics.

Variation in the survey responses also generates information that does not exist in one-dimensional measures from hedonic analysis or book values. The standard deviations over the responses in each auction serve as a measures of the dispersion of private information signals in the auctions. They provide a measure of the survey respondents' certainty about their valuations.

This extra information about the unobservable private signals is useful in testing auction theory. Often, the only information available from auctions is the number of bidders, observed bids, and product characteristics. In a limited number of cases, ex post values of the auctioned item are available. The literature on nonparametric

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identification has shown that given this observable data, the distribution of private signals is just identified assuming a private values setting, and underidentified in a common values setting without further parametric assumptions.[1] As a result, tests of information structure in an auction (whether auctions are private value or common value) and bidding behavior (whether bidders play Nash equilibrium strategies) are rarely conducted jointly. By measuring dispersion, identifying power is not expended on recovering the underlying distribution of information signals. As a result, a joint test of an auction's information structure and bidding behavior is possible.

The ability to design the independence of survey data from other regressors, the ability to exploit human assessment of information, and information provided by the second moment of survey data make it an appealing source of information to complement market data, in particular for auctions.

2.2 Survey Design

Over 5000 new and used computers are listed daily in the eBay PC desktop category by both individuals and businesses. Auction participants may perceive these computers as a mixture of common and private values. To obtain an estimate of the mean and dispersion of private signals received by the auction participants, I created a web-based survey. The survey encouraged survey respondents to focus on the CV component, since other evidence in this market suggested that the CV component dominates the PV component (see next chapter).

The content for the survey came from the auction descriptions for 222 eBay PC auctions held between June 24 and July 12, 2002. eBay works as follows. A seller posts an item on for auction. She creates a product description through text and pictures and any other media that can be displayed on the eBay website. Before choosing to submit a bid, auction participants can observe the auction description along with other information about the seller, the current price, and the number of bids submitted up to that point in the auction.

[1]Laffont and Vuong 1996; Li, Perrigne, and Voung 2000; Guerre Perrigne, and Vuong 2000; Athey and Haile 2002; Li Perrigne and Vuong 2003.

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Anyone could respond to my survey, except for the actual bidders in my sample of auctions. The survey was distributed to acquaintances by word of mouth. I asked people to read computer auction descriptions 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. I also collected background data on survey respondents, asking them about their experience working with computers, purchasing computers, and purchasing computers in online auctions.

I proposed incentives so that the survey respondents would make some effort to think about the computer values and in order encourage them to consider the CV component of the computers. Respondents viewing the "prize details" webpage were told that they would receive an extra $60 for being closest to all the other valuations, or an extra $60 for being closest to a panel of computer experts. I expected respondents with more familiarity with computers to think about the CV component they shared with other experts, while those unfamiliar with computer values would think about some combination of resale and retail values, drawing on general information that they believed the rest of the non-expert computer population possessed. The advantage to these incentives is that they focus participant attention on the CV component, rather than idiosyncratic private tastes. They also provide some incentive to discourage respondents from merely typing in random numbers. The disadvantage to these incentives is that they may introduce some bias that would be correlated with value of the item. However, I will propose a correction method for this bias in Section 2.5. Only a small percentage (6%) of respondents actually looked at a webpage on "prize details," so these issues only affected a small number of my respondents.

The survey was designed to employ as wide a pool of respondents as possible. This made implementation of the survey easier and faster. However, one must account for the potential bias from using survey data to estimate information possessed by the auction participants. Fortunately, one can collect background data on the respondents during the survey. This information can then been exploited in order to identify the

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types of adjustments that need to be made to correct for that bias.

2.2.1 Issues in Survey Methodology

The literature on the contingent valuation survey method, where people are asked to state their willingness-to-pay for a good, most closely relates to my survey method. Several critiques have been made about the validity of this method for estimating valuations (c.f. Hausman 1993), as well as the entire field of survey data. However, in several ways my survey either escapes those critiques, or employs suggested methods in the literature of responding to those critiques.

One problem with contingent valuation surveys is that respondents must often estimate the value of a vaguely defined item for which they have no previous market or pricing experience (e.g., "How much do you value clean water?"). In my case, since I am asking respondents for their value of an item for which they have references in a retail market, this criticism is not as relevant. The presence of an alternative retail market helps to create realistic bounds for valuations in the survey responses. Empirical studies comparing contingent valuation surveys to actual revealed preference data show that the estimates correspond very closely to the market prices. (Bjornstad & Kahn 1996) In addition, my survey respondents see everything that the bidder sees in that particular auction, so my survey reflects the appropriate informational context. The literature often refers to the differential effects that starting points can make in valuations. (Aadland & Caplan 1999; Bateman & Willis 1999) However, the auction participants would be influenced by the same types of anchor prices appearing in auction descriptions or in the retail market as my respondents..

Another criticism of survey data is the lack of realistic incentives. Since respondents were not dealing with their own money, their valuations may be inflated because they suffer no incentive to be conservative, or their valuations may be deflated since they have no incentive to think carefully about their true maximum willingness-to-pay. As a result, respondents may have different dispersion of valuations than the bidders. I suggest a procedure for correcting for such potential differences between bidders and respondents in Section 2.5.

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Table 2.1: Summary statistics for survey on 222 auctions

Variable (831 respondents)	**mean**	**st. dev.**	**min**	**max**
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

Survey data that is used to augment market data will tend to share the same advantages of my auction measure: by referring to a market that already exists, framing problems are less severe. In addition, since I will correct for differences between respondents and bidders, incentive issues are also less problematic.

2.3 Survey Performance

On average, I collected 46 responses per auction. For each respondent i and for each auction t, I denote the respondent's valuation of the item by $X_{i,t}$. I denote the average of the responses in each auction by V_t. I denote the standard deviation of responses in each auction by SD_t. Summary statistics are presented in Table 2.1.

In Figure 2.1, auctions are ordered along the horizontal axis by increasing eBay price, P_t. The corresponding averages of survey responses, V_t, are plotted for each auction as well. The plot shows that V_t is highly correlated with P_t. If prices are correlated with the value of the item, then this plot suggests that V_t is likely to be correlated with the value of the item. The correlation between P_t and V_t suggests that survey data can be used to measure unobservable item values.

Provision of more or better information should lead auction participants to be more certain about the value of the item and thus make the standard deviation in their signals lower. I examine items with similar V_t to see what my survey respondents considered to be high and low dispersion items. Figures 2.2 and 2.3 show the complete auction description from an item with $V_{highsd} = \$313.81$ and the auction description excluding picture for an item with a similar V_t of $V_{lowsd} = \$290.23$. The technical

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specifications (speed of processor, RAM, CD-ROM, and hard drive capacity) of these computers are approximately the same, indicating that the respondents valuations seem to account for hedonic characteristics. The first item had $SD_{highsd} = 505.23$, while the second item had $SD_{lowsd} = 304.74$ (the coefficients of variation are 1.61 and 1.05, respectively).

The survey seems to correctly distinguish between the informative and less informative product descriptions. Note that the high dispersion item lacks the level of detail in the low dispersion item. Both of the descriptions show pictures, but the high dispersion picture is of a similar computer, not of the computer itself. The low dispersion description actually includes a picture of the computer for sale. Presumably the high dispersion computer does not include monitor, keyboard, mouse, etc., but what is meant by "System" is not explicitly mentioned. The low-dispersion seller notes exactly what is still required.

The information that is dispersed with respect to the high dispersion computer may take the form of different knowledge among auction participants about the similarity between the computer for sale and the picture in the ad, or the quality of reclaimed computers generally. The low dispersion seller describes exactly how the computer does *not* work. Although this flaw may lower the auction participants' estimates of the value of the computer, participants are more certain about that valuation. If the seller merely said "This computer does not work," or didn't mention the flaw at all, information would be dispersed between those who were familiar with the types of failures encountered with Hewlett-Packard computers and those who were not. By revealing exactly what type of problem the computer possesses, the seller was able to lower the dispersion of that information.

In a CV setting, rational bidders respond to information dispersion when constructing their bids. Based on evidence in the next chapter that shows that eBay PC auctions are CV and exhibit rational bidding behavior, we would expect P_{highsd} to be lower than P_{lowsd}. Indeed, the high dispersion item was sold for \$55.00; the low dispersion item sold for \$96.50.

Both V_t and the SD_t generate results that are consistent with what we would expect from the relation between item values, information dispersion in the auctions,

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and prices in a CV setting. Surveys seem to be a successful source for measures of unobservable information. The next section describes the data used to correct for potential bias in these survey measures.

2.4 Participant Background

The survey asked about background characteristics of the respondents. Their responses are summarized in Table 2.4. The first set of responses in the table shows the number of yes and no responses for each auction in my sample, so those who responded to multiple auctions were counted multiple times. Responses seemed evenly split between those who were familiar with computers, those who had been shopping for computers, and those who had looked at an online computer auction before. Of those that had recently bought a computer, most had bought their computer via a retail outlet. The next set of responses in the table show the number of people who recently bought 0, 1, or 2 or more computers, respectively. The survey respondents were then asked how many online auctions they had entered (0, 1, 2 through 5, and 6 or more were the respondents' possible choices). Those who had entered auctions were then asked whether all, none, or some of those auctions were on eBay, and whether they had won all, some, or none of those auctions. The majority of respondents had not bought a computer in the last six months. Most people had not entered an online auction, including most of those who had looked at online auctions. Those who had entered auctions tended to have done so more than once, favored eBay auctions, and won some of those auctions.

I ran a least squares regression of individual responses $X_{i,t}$ on the background characteristics to determine how valuations differed between different types of respondents. The results are summarized in Table 2.4. The largest differences in valuations were due to differences in the respondents' familiarity with computers, recent purchases, and their familiarity with eBay auctions. More unexperienced respondents on these dimensions tended to value items more highly. Although a number of the coefficients are statistically significant, their magnitude relative to the average of V_t is low, and the overall explantory power reflected in the R-squared statistic is low.

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Table 2.2: Summary statistics of survey respondents' backgrounds

Background questions (10,350 observations)	**Responses**			
	no	**yes**		
familiar w/computers	5140	5202	-	-
shopped for computer in last 6 months	4923	5427	-	-
bought computer via auction	-	403	-	-
bought computer via retail	-	2988	-	-
bought computer via wholesale	-	967	-	-
looked at online computer auction	5762	4588	-	-
looked at eBay computer auction	6449	3881	-	-
	0	**1**	**2+**	-
# computers bought last 6 months	6836	2471	1033	-
v	**0**	**1**	**2-5**	**6+**
# online computer auctions entered	7428	750	1271	828
	none	**some**	**all**	-
... on eBay	4751	960	1509	-
... won on eBay	5338	1558	324	-

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Averaging over the responses of different types of respondents will probably not result in large differences from adjusting the mean for the different types, but we will allow for this possibility in the bias correction process in Section 2.5.

2.5 Bias Correction

V_t and SD_t may be biased measures of the true CV (or average PV), denoted v_t, and the dispersion of information facing auction participants, denoted $\sigma_{x|v,t}$. This section proposes a bias correction method that exploits the background data collected on survey respondents.

On average, 20% of the responses for each auction in my sample came from respondents who had won all or some of the eBay online computer auctions in which they had entered. I designate their responses as "experienced" responses (subscripted by e), and designate the rest of the responses as "inexperienced" responses (subscripted by a).

I model and estimate this potential bias as follows. I treat the valuations $X_{i,t}$ from my survey respondents as potentially biased draws of signals $x_{i,t}$ that the auction participants draw about v_t. Thus, $X_{i,t}$ are drawn from a potentially different distribution than the one that the auction participants face. I model the responses from my inexperienced respondents, denoted $X_{a,i,t}$, as draws from a distribution whose mean may differ from v_t by a shift factor γ_0 and a scale factor γ_1 and whose variance may be different as well: $X_{a,i,t} \backsim (\gamma_0 + \gamma_1 v_t, \sigma^2_{x|v,a,t})$. 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 θ_0 and whose variance may be different: $X_{e,i,t} \backsim (\theta_0 + v_t, \sigma^2_{x|v,e,t})$. An unbiased estimate of v_t can then be written as

$$\hat{v}_t = \frac{J_{e,t}}{J_t}(V_{e,t} - \theta_0) + \frac{J_{a,t}}{J_t}\left(\frac{V_{a,t} - \gamma_0}{\gamma_1}\right), \tag{2.1}$$

where $J_{e,t}$ is the number of experienced survey responses in each auction, $J_{a,t}$ is the number of inexperienced survey responses in each auction, and J_t is the total number

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Table 2.3: Effects of respondent's background on survey results

Variable	Coefficient
CONSTANT	\$736.78‡
	(10.6199)
Familiarity w/computers	-\$74.37‡
	(13.2572)
Recently shopped	\$23.76
	(15.4142)
No. bought	-\$42.74‡
	(11.4023)
Venue of purchase	-\$2.01
	(4.1568)
Looked @ auctions	\$18.17
	(22.6089)
Looked on eBay	-\$62.30‡
	(22.3294)
No. auctions entered	-\$26.78‡
	(9.2624)
On eBay	\$1.21
	(11.8184)
eBay auctions won	\$26.60†
	(14.2579)

‡significant at 5%, †significant at 10%, $R^2 = 0.01$

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of survey responses to each auction. The average of the survey responses $X_{e,t,i}$ and $X_{a,t,i}$ are denoted $V_{e,t}$ and $V_{a,t}$, respectively. The parameters to be estimated are θ_0, γ_0, and γ_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 $\sigma^2_{x|v,e,t} = \eta_0 + \sigma^2_{x|v,t}$, whereas my inexperienced respondents draw from a distribution with variance $\sigma^2_{x|v,a,t} = \delta_0 + \delta_1 \sigma^2_{x|v,t}$. The resulting unbiased estimate of the information dispersion faced by the auction participants is as follows:

$$\hat{\sigma}_{x|v,t} = \sqrt{\frac{J_{e,t}}{J_t}(SD^2_{e,t} - \eta_0) + \frac{J_{a,t}}{J_t}\left(\frac{SD^2_{a,t} - \delta_0}{\delta_1}\right)}. \tag{2.2}$$

The variance of the signals $X_{e,t,i}$ and $X_{a,t,i}$ are denoted $SD^2_{e,t}$ and $SD^2_{a,t}$, respectively. The parameters to be estimated are η_0, δ_0, and δ_1. They capture the amount of bias in the dispersion of responses.

I can use a moment condition to identify θ_0, γ_0, and γ_1. I set the standard deviation of the experienced survey responses equal to the definition of the sample standard deviation, replacing $V_{e,t}$ 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:

$$SD_{e,t} = \sqrt{\frac{\sum^{J_{e,t}}(X_{e,i,t} - (\hat{v}_t + \theta_0))^2}{J_{e,t} - 1}}. \tag{2.3}$$

Results from estimation of a price equation in the next chapter will show that the measurement bias in the common value is not severe relative to the average V_t of \$666.43: $\gamma_0 = \$83.61$, $\gamma_1 = 1.03$, and $\theta_0 = \$27.04$. So both the experienced and inexperienced respondents underestimate the average value of the items, although the experienced respondents underestimate by less. The inexperienced respondents capture the scale of v_t almost perfectly.

The bias on dispersion for the experienced respondents is $\eta_0 = -60222.6$, whereas $\delta_0 = 76381.0$ and $\delta_1 = 1.83$ for the inexperienced respondents. To place these parameter estimates approximately in the context of standard deviations, the experienced

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responses underestimate $\sigma_{x|v,t}$ by 245.40 ($=\sqrt{60222.6}$). The inexperienced responses are approximately 1.35 ($=\sqrt{1.83}$) times larger than $\sigma_{x|v,t}$ and overestimate $\sigma_{x|v,t}$ by 276.37 ($=\sqrt{76381.0}$). The measurement bias in dispersion is relatively large compared to an average SD_t of 472.38. The bias is consistent with the expectation one might have that information is more dispersed among my survey respondents compared to the auction respondents, even after viewing the same auction description. This difference could be due to different interpretation of the information by the two groups or differing initial levels of information dispersion between these groups prior to viewing the auction description.

The bias correction could be avoided by simply restricting the survey respondents to the experienced types. However, the rapid depreciation in values of the computer necessitated quick execution of the entire survey. By broadening the participant pool, I could achieve more responses per auction per day. Bias would be incurred whether I used a more restricted respondent pool or adjusted for depreciation for a more lengthy survey window; the use of a larger respondent pool had the advantage of avoiding the time and costs of a screening process for survey respondents.

Survey measures are prone to bias. However, the use of survey data also allows collection of covariates on the survey respondents. This information can be exploited to correct for potential bias. The ability to conduct such a correction makes implementation of the survey much easier and faster: a researcher need only find a small sample of survey respondents who are just like the target population. The rest of the respondents can be drawn from the general population and generate information with noise, as long as that information is correlated with the true values.

2.6 Performance of Hedonic Regression Alternative

The convenience of using hedonic regression to control for the item value or for the dispersion of information signals may outweigh the benefits of using a survey if the difference between estimates of v_t and $\sigma_{x|v,t}$ from both methods are not substantial.

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Table 2.4: Summary statistics for information dispersion covariates

Variable (222 auctions)	**mean**	**st. dev.**	**min**	**max**
memory not indicated RAMNI_t	0.03	-	0	1
OS not indicated OSNI_t	0.45	-	0	1
Floppy drive not indicated FLOPPYNI_t	0.33	-	0	1
Keyboard not indicated KEYBDNI_t	0.38	-	0	1
CD/DVD drive not indicated CDNI_t	0.16	-	0	1
Mouse not indicated MOUSENI_t	0.28	-	0	1
No. words in description WORDS_t	449.4	460.8	23	2727
No. pictures in description PICS_t	4.05	5.02	0	25

To examine the difference between estimates from the survey method versus estimates from hedonic regression, I first generate the bias-corrected estimates of v_t and $\sigma_{x|v,t}$ from my survey. I plug the estimated survey bias parameters 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 regress these variables on observable covariates from the auctions which one might employ in a hedonic regression. The difference between the fitted and dependent variables from these regressions will reveal the extent to which hedonic characteristics can explain the variation in information captured by my survey procedure.

The characteristics chosen to model the common value in each auction are presented in Table C.1 of Appendix C. The characteristics chosen to model the dispersion of information in each auction are presented in Table 4.4. These characteristics included dummies for whether the seller neglected to include information on various computer components (ram memory $RAMNI_t$, operating system $OSNI_t$, floppydrive $FLOPPYNI_t$, keyboard $KEYBDNI_t$, cd/dvd drive $CDNI_t$, mouse $MOUSENI_t$) and the number of pictures and words included in the auction description ($PICS_t$, $WORDS_t$). I also included $BRAND_t$ and $PROCESSOR_t$ regressors described in Appendix C, since they may reflect differences in popular knowledge of the performance and quality of different types of computers and processors.

The ordinary least squares results are reported in Tables 2.6 and 2.5. Table 2.6

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presents the regression of $\tilde{v}_t$ on covariates describing the item's value, and Table 2.5 presents the regression of $\tilde{\sigma}_{x|v,t}$ on covariates describing the information dispersion in the auction. The R^2 statistics are 0.71 for the common value and 0.27, respectively. The hedonic measures are unable to explain a third of the variation in common value and two-thirds of the variation in information dispersion that is captured by survey methods. These results suggest that employing my survey procedure can provide significantly different information from hedonic regression.

This regression of bias-corrected survey measures on hedonic characteristics suggests a possible means of extending the survey results to a different sample. The coefficients estimated in Tables 2.6 and 2.5 can be used to generate a prediction of v_t and $\sigma_{x|v,t}$ for auctions outside of my current sample if repeating the survey procedure is too costly. Thus, if the difference between the fitted values and dependent variable are acceptable, a researcher could employ survey methods for a small sample, and then extend the survey results to a larger sample by using the survey results to determine the relationship between hedonic characteristics and the survey measures.

2.7 Conclusion

This chapter has presented several reasons why the use of survey data to augment auction data is valuable and feasible. The survey method could be beneficial in other research involving dispersed private information accompanying market data. Survey based measures that are used to augment market data will avoid problems associated with traditional surveys about non-market valuations: by referring to a market that already exists, framing problems are less severe. In addition, background data on survey participants can be collected and used to correct for biases between the survey and the information in the actual market.

The survey is used in this chapter to generate a measure of average values and the dispersion of private information in eBay personal computer auctions. This method has several advantages over the traditional method of estimating private information from auction observables alone. The richer measure of the common value avoids problems of endogeneity with the number of bidders in modeling price. The use of a

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Table 2.5: OLS regression of $\tilde{v}_t$ on hedonic characteristics

Variable	Coefficient
CONSTANT	260.912‡
	(39.333)
PRICE	0.707‡
	(0.032)
BRAND	-15.864
	(27.664)
PROCESSOR	-2.949
	(11.061)
SPEED	0.049†
	(0.029)
RAM	0.123
	(0.102)
HARDDRIVE	-1.180E-03
	(0.001)
MODEM	-8.787
	(15.032)
MONITOR	32.545
	(31.450)
MOUSE	80.421†
	(49.750)
KEYBOARD	-94.556†
	(49.910)
ZIP	-14.737
	(57.688)
FLOPPY	38.305
	(26.002)
APPLICATION	-36.003
	(32.900)
OS	52.949†
	(26.968)

‡significant at 5%, †significant at 10%, $R^2 = 0.71$

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Table 2.6: OLS regression of $\tilde{\sigma}_{x|v,t}$ on hedonic characteristics

Variable	Coefficient
CONSTANT	309.508‡
	(31.793)
PRICE	0.161‡
	(0.022)
WORDS	-0.011
	(0.022)
PICS	-0.772
	(1.973)
SPEEDNI	11.452
	(79.522)
RAMNI	-41.403
	(73.793)
HDNI	-41.584
	(82.167)
MODEMNI	-14.826
	(44.100)
MONTITORNI	4.853
	(17.987)
MOUSENI	40.627
	(25.859)
FLOPPYNI	-2.052
	(17.051)
KEYBOARDNI	-56.329
	(24.402)
APPNI	-4.76949‡
	(20.322)
OSNI	20.867
	(17.233)
BRAND	-17.308
	(18.531)
PROCESSOR	-13.735†
	(7.362)

‡significant at 5%, †significant at 10%, $R^2 = 0.27$

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survey method also generates a second moment that can be interpreted as a measure of information dispersion. This external information permits hypothesis testing that cannot be conducted otherwise. Even if the setting is private values, the survey data can be interpreted as the average and dispersion of private values.

An analysis of my survey results suggests that it is successful at accounting for technical characteristics that would determine the value of the computer, as well as the semantics of the auction description that would determine the dispersion of information. Estimates of the actual bias and scale differences between bidders and my survey respondents were either small or in the expected direction. Estimates of the difference between information gathered via the survey process described here and alternative hedonic measures are large, indicating that the survey method does capture significantly more information.

This method has applications in any setting where hedonic estimation may ignore important idiosyncratic differences. Models which include expectations over privately held information may find surveys to be a useful way of simulating the distribution of that information. Since the researcher can exploit background characteristics of the survey respondents to correct for bias, the convenience and speed of implementing the survey is improved through the use of the general population in part as survey respondents. Even if a survey can only be conducted for a part of the sample, the survey results can be combined with hedonic regression to extend the survey results to the rest of the sample. The advantages to the extra information gathered combined with the tools available to correct for errors reduce the relative cost of administering a survey.

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Figure 2.1: eBay Prices P_t vs. Average of Survey Responses V_t

Auctions are ordered along the horizontal axis by increasing eBay price, P_t. The corresponding averages of survey responses, V_t, are plotted for each auction as well. The correlation between P_t and V_t suggests that survey data can be used to measure unobservable values of items.

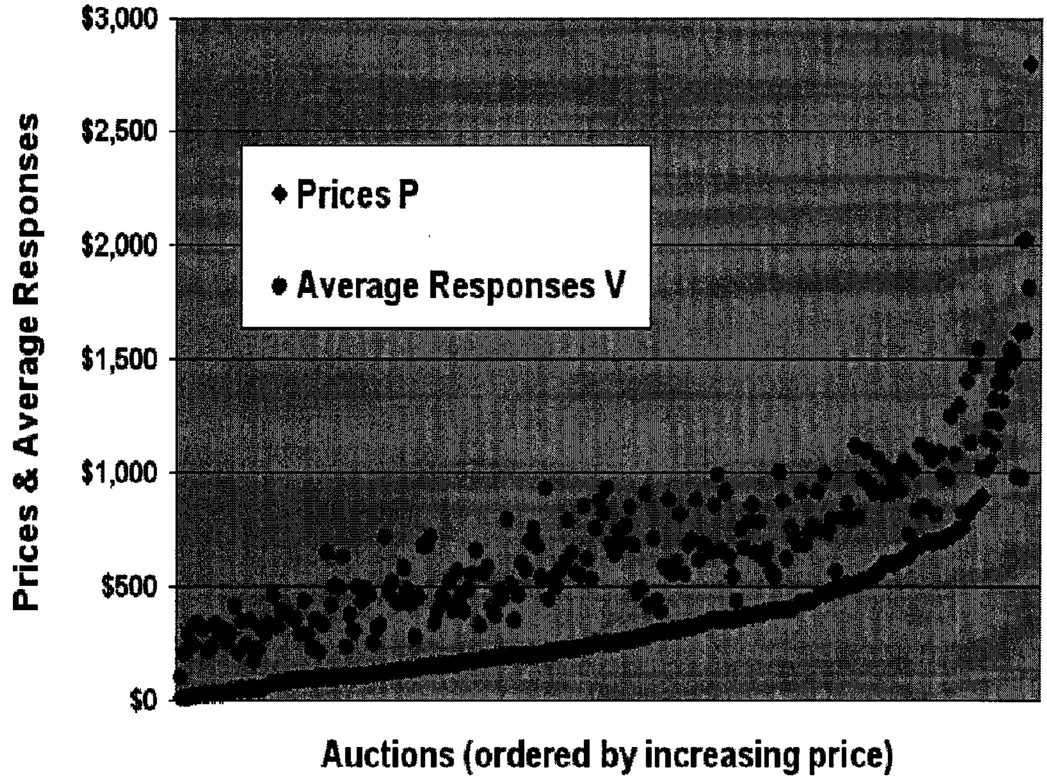

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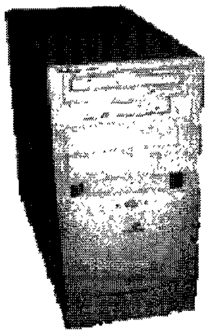
Figure 2.2: High dispersion item description ($V_{highsd} = \$318.81$)

Whaam! Lot #12923

Whaam!
Guaranteed Forever!
www.whaam.biz

Worldwide Leader in Tech Reclamation™



Gateway E-4200 Pentium II-300 Desktop Computer System

Pentium II-300 CPU
32Megs RAM
6.4Gig Hard Drive
CD-ROM
Zip 100 Drive
Network Interface

This Gateway E-4200 Pentium II-300 Computer with 32Megs of RAM (similar in style, but not identical to the unit pictured above) has been cleaned and tested and is covered by the Whaam! Forever Guarantee. Manuals, disks, drivers and external cables are not included.

Handling, Clean-Up, Packaging and Delivery by UPS Ground Service to the continental US is $59. Add $15 for locations in the Mountain or Pacific Time Zones and Florida. Local pick-up is not available.

Illinois Sales Tax applies to in-state shipments. Whaam! accepts VISA/MC, checks, money orders, I-checks and Paypal. Whaam! reserves the right to re-auction any lot remaining unpaid after seven days. No unlicensed software is included. Questions should be sent to greatstuff@whaam.biz.

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Figure 2.3: Low dispersion item description (V_{low} = \$290.23)

Hewlett-Packard Pavilion 6330 Computer

Includes:
Tower
Keyboard
Mouse
Power cord
Phone cord
Mousepad
Norton Utilities
America Online 7.0 installation disk
Prodigy installation disk
Mindspring installation disk
CompuServe Wow! installation disk
HP Pavilion recovery disk
Corresponding owner's manuals and documents
Extra parallel port(installed in tower)

Requires:
Monitor
Printer
Speakers

Hewlett-Packard Pavilion 6330 Specs:
Windows 98 Operating System
AMD-K6 - 2/300 processor with 3DNow! technology
Ultra expandable and upgradable with 6 bays and 5 slots(1 taken
_____by extra parallel port)
48 MB SDRAM shared memory architecture – up to 4 MB video
_____memory
Spacious 4GB hard drive
24x max CD-ROM drive
High velocity V.90.K56flex Data/fax modem
One-touch keyboard
2 USB ports for easy plug and play
Year 2000 compliant

This computer works fine when hooked up only to a monitor, printer,
and speakers with no other additional hardware options. Whenever

I connect my Iomega Zip Drive and scanner however, this
computer starts to have problems. As long as you don't connect
any unnecessary external hardware devices other than the printer
and speaker you should be alright.

Winning bidder to pay shipping & handling.
I reserve the right to refuse bidders with negative feedback.
I accept EBay online payments.
Please be prompt in your post-auction correspondence
Reserve price: $50.00.

The eBay Way to Pay - Enjoy Full Purchase Protection!

eb Payments VISA

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Chapter 3

Information Dispersion and Auction Prices

Are prices in eBay auctions for computers consistent with auction theory? This paper tests whether bidders behave rationally in Internet auctions by examining price responses to changes in information in the auctions. Information about the seller (reputation) is treated as distinct from information about the item being sold, allowing this paper to estimate how the interaction between these two types of information affect prices.

In markets where the value of a good is uncertain, private information, or "signals," about the value of the good may be dispersed among the participants. If participants could observe the private signals of others, then they would all would assess that information in the same way and arrive at a common value for the good. Economic theory says that an auction can elicit a price equal to the common value of the good even when information is dispersed. However, bidders are required to play sophisticated Nash equilibrium strategies. Each bidder needs to take into account the dispersion of information and number of bidders in constructing her bid. Failure to do so results in the "winner's curse," where the highest bidder wins the auction, but at a price greater than the common value of the item.

I employ a sample of eBay online auctions for computers to test theory. Different bidders may have private information about the reliability of a particular model of

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computer or its components. This is the source of privately dispersed information in this market. Auction descriptions 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 me to identify the effect of changes in information dispersion on price.

A feedback mechanism exists on eBay to address information asymmetry between the buyer and seller by creating reputations. While the body of empirical eBay research has focused on a price premium for good reputation[1], it has not focused on the effect of reputation on a bidders' perception of the credibility of information provided by the seller. This paper explicitly models the different effects of information dispersion, reputation, and the interaction between reputation and dispersion to determine their relative importance with respect to price.

In Section 3.1, I derive testable implications of auction theory with respect to information dispersion using results from Milgrom & Weber (1982, henceforth referred to as MW). I distinguish Nash behavior in a common values setting (Nash CV) from the alternatives of naïve bidding in a common values setting (naïve CV), Nash bidding in a private values settings (PV), and risk aversion in a PV setting. I include the private4 value alternatives beceuase they share certain behavioral features with naïve CV. My tests distinguish both the information structure of the auction (CV versus PV) and the rationality of bidder behavior (Nash versus naïve).

In order to apply these comparative statics to auction data, I need a measure of information dispersion that does not rely on any assumptions of rational bidding or common value auctions. I construct an "external" measure of the dispersion of private information signals. I conduct a survey among non-bidders using product descriptions from a sample of eBay computer auctions, described in Section 3.2. The survey asks people to report what they think is the most the item is worth. On average, 46 people

[1] In general, this work has found the price effect of reputation to be small. (Reiley, Bryan, Prasad and Reeves 2000), (Hauser and Wooders 2000), (Melnik and Alm 2002), (Resnick, Zeckhauser, Swanson and Lockwood 2002)(McDonald and Slawson Jr. 2002), (Livingston 2002), (Eaton 2002), (Jin and Kato 2003). A summary of the empirical work appears in Resnick, Zeckhauser, Swanson and Lockwood 2002.

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responded to each auction description. I use the standard deviation of responses for each auction description to estimate the dispersion of information in each auction.

Section 3.3 presents the empirical results. I find that eBay prices are consistent with Nash CV. I correct for any potential measurement bias in my survey. I then conduct simulations to estimate the winner's curse in these markets and the importance of reputation in Section 3.4. I find that eBay winners do not suffer from the winner's curse. I also find that reputation complements information dispersion: 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.

Some experimental literature has tested equilibrium bidding behavior by directly controlling the primitives. Kagel, Levin & Harstad (1994) 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.[2] Although bidders may be attempting to play Nash equilibrium strategies, they may not get the magnitudes right. However, contrary to Nash CV, increasing the number of bidders does not change the bids.[3] 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.[4]

Studies of commercial auctions have not yet been able to directly test implications of information dispersion. Part of the literature has been devoted to testing for Nash

[2]In experimental auctions with 4-5 and 6-7 bidders, Kagel, Levin & Harstad (1994) 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.

[3]Bidders also fail to account for the winner's curse in ascending oral auctions. (Kagel & Levin 1992) Other experimental tests (Kagel & Levin 1991, Lind & Plott 1991, Cox & Smith 1992) 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.

[4]A particularly relevant experimental exercise would be to leave the range of signals the same, but change the density of the distribution to reflect a lower variance of signals around the mean. It would also be useful to then conduct experiments with higher and lower variance for different numbers of bidders to observe any interaction effect between variance and number of bidders. 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.

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equilibrium behavior. Assuming a common values setting, authors have related ex post values to ex ante bids to draw inferences about strategic bidding.[5] In only a few cases have ex post values been available, and these values are typically measured with error compared to the true value.[6] Another part of the literature focuses on testing between common value and private value settings.[7] Assuming Nash equilibrium behavior, authors have explored how variation in the number of bidders can be used to test between private and common value settings, since the winner's curse is more severe with more bidders.[8] (Paarsch 1992; Haile, Hong & Shum 2000, Athey & Haile 2002). The challenge to these approaches (and potentially 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 1999, Bajari & Hortaçsu 2002a) The paper most closely related to my work is Hendricks, Pinkse & Porter (2001). Under the assumption of a common values setting, they test whether bids are consistent with Nash equilibrium in a first-price sealed-bid setting. They then exploit ex post information on values to test the common values assumption without imposing rational bidding behavior. Even with these assumptions and ex post information on values, the underlying parameters are just identified.[9]

[5]McAfee, Takacs & Vincent (1999) use ex post values to test the information aggregation properties of auction prices.(McAfee, Takacs and 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.

[6]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.)

[7]This empirical literature has been predicated on an extensive theoretical literature identifying empirically testable conditions for private value and common value settings, e.g. Elyakime, Laffont, Loisel & Vuong (1994); Laffont, Ossard & Vuong (1995); Donald & Paarsch (1996); Pinske & Tan (2000);

[8]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.

[9]Li, Perrigne & Vuong (2000) 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

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I avoid having to recover the distribution of the information signals. My survey data provides me with information about the distribution of signals independent of the bidding data. This allows me to 1) distinguish between common and private value settings without imposing fully rational bidding behavior, 2) distinguish between Nash and naïve bidding behavior without assuming a private or common values setting, 3) employ only price data from the auctions as opposed to all bids, and 4) estimate any potential bias between my measures of dispersion and the common value and the true values.

3.1 Theory and Empirical Implications

This section presents the theoretical model of Nash CV prices from second-price sealed-bid auctions. It then presents comparative static implications that distinguish between the Nash CV model and the PV model, naïve CV model, and the PV and naïve CV models with risk aversion.

A single, indivisible item is put up for auction. The item has the same, unknown value v to all n bidders, indexed by i. Bidders know the density of v, $f_v(v)$. Each bidder also observes a private signal x_i from a distribution around v. I assume the form of the mineral rights model, where x_i is independently and identically drawn from a distribution centered around v such that the signals x_i are affiliated with the values v. This distribution has commonly known density $f_{x|v}(x_i|v)$.

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 $b(x_i)$ for symmetric bidders in a sealed-bid auction is

$$b(x_i) = E[v|x_i, \max X_{j\neq i} = x_i], \tag{3.1}$$

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

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.

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The expected winning price is the expected value of the second order statistic of Equation ??. Let $x^{n-1:n}$ denote the 2nd highest signal from a set of n signals. We 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, we denote the standard deviations of $f_{x|v}(x|v)$ and $f_v(v)$ by $\sigma_{x|v}$,and σ_v, respectively, and the means of $f_{x|v}(x|v)$ and $f_v(v)$ by v and μ_v, respectively.

$$E[b(x^{n-1:n})] \approx p(n, v, \sigma_{x|v}, \mu_v, \sigma_v). \tag{3.2}$$

I use the function p to establish comparative static results from auction theory in the rest of this section.

I chose the second-price sealed-bid model for eBay auctions for several reasons. During the eBay auctions, bidders can see the current second-highest bid plus one increment. They 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.[10] To the extent that insufficient time exists to view all the information contained in those bids before the close of the auction, the auction tends to operate like the second-price sealed-bid model.

3.1.1 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.[11] Public revelation is equivalent to a seller providing more information in the auction description. The effect of publicly revealing

[10]Bajari & Hortaçsu (2002b) review empirical findings in online auction settings.

[11]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)

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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 $n > 2$, increasing the standard deviation of the distribution of a signal generates two effects: 1) the expected distance between the highest and second-highest signal increases, and 2) both of these signals increase on average. If bidders merely bid their signals, or shade their bid downward by some fixed percentage of their signal or absolute amount, then the second effect dominates, and both bids will rise. Prices fall in Nash equilibrium, where bidders account for the less narrow distribution of signals around the common value by shading more, causing the first effect dominate.

1a. $\frac{\partial p}{\partial \sigma_{x|v}} < 0$. The Nash CV price decreases if the dispersion of information signals increases.[12]

For distributions where the density of signals is symmetric about 0, the distance between the first and second order statistics is monotonically decreasing at a decreasing rate with $\sigma_{x|v}$. This property does not hold for asymmetric distributions, such as the lognormal.

2a. $\frac{\partial^2 p}{\partial \sigma^2_{x|v}} > 0$. Under symmetric distributions (e.g. normal, uniform), the Nash CV price decreases at a decreasing rate with the dispersion of signals.[13]

Although prices converge to the common value as $n \longrightarrow \infty$, prices may be decreasing or increasing in n away from the limit. (Wilson 1977, Milgrom 1979) As n

[12]This result is translation of Theorems 8 and 12 of MW. McMillan & Kazumori (2002) prove this result for distributions satistfying affiliation. Rothkopf (1968) 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.

[13]Result derived from analysis of order statistics. (Mood, Graybill & Boes 1974; Balakrishnan & Chen 1999)

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increases, the value of the highest signal drawn increases. Under Nash CV, bidders should shade more to account for this increase. Whether the draws from the higher distribution 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. The interaction effect between n and $\sigma_{x|v}$ will also depend on the values of n and $\sigma_{x|v}$.

3.1.2 Implications of PV and naïve CV auctions

In second-price auctions, prices equal the second highest signal under PV. 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 irrational versus rational 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 rational bidder behavior to involve errors in magnitude.

I derived the following comparative static implications from analysis of expected values of order statistics under uniform, normal, and lognormal distributions. I denote by $\underline{n}$ the minimum number of bidders necessary for an implication to hold, which may be a function of $\sigma_{x|v}$.

1b $\dfrac{\partial p}{\partial \sigma_{x|v}} > 0$. PV and naïve CV prices increase with the dispersion of signals for $n > \underline{n}(\sigma_{x|v})$.

2b. $\dfrac{\partial^2 p}{\partial \sigma^2_{x|v}} < 0$. PV and naïve CV prices increase at a decreasing rate with the dispersion of signals for $n > \underline{n}(\sigma_{x|v})$.

3b. $\dfrac{\partial p}{\partial n} > 0$.[14] PV and naïve CV prices increase with the number of bidders.[15]

[14]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: bidders and the econometrician must estimate n, and so they may not be constrained to integers.

[15]Thanks for John Morgan for his notes on order statistics.

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4b. $\dfrac{\partial^2 p}{\partial n \partial \sigma_{x|v}} > 0$. PV and naïve CV prices increase with dispersion at an increasing rate with the number of bidders for $n > \underline{n}(\sigma_{x|v})$.

For implications 1b, 2b, and 4b, $\underline{n} = 2$ for all $\sigma_{x|v}$ under symmetric distributions. Under lognormal distributions, $\underline{n} \geq 2$ and increasing in $\sigma_{x|v}$. Below $\underline{n}$, prices are first increasing, then decreasing, as $\sigma_{x|v}$ increases.

3.1.3 Implications of PV and naïve CV auctions with risk aversion

Assume that a risk averse bidder perceives higher $\sigma_{x|v}$ and lower n as more risky. Then risk-averse bidders under PV and naïve CV should lower their bids as $\sigma_{x|v}$ rises and raise their bids as n rises. Since the highest two signals also rise as $\sigma_{x|v}$ rises, prices may be increasing or decreasing with $\sigma_{x|v}$ depending on the bidder's response to risk aversion. Risk aversion will cause prices to rise even more than they normally would under PV and naïve CV as n rises.

1c. $\dfrac{\partial p}{\partial n} > 0$. Under risk aversion, PV and naïve CV prices increase with the number of bidders.

3.1.4 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 2 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). I hypothesize that more credible sellers' descriptions both raise bidders signals on average and increase the price effect of information dispersion.

Work by Akerlof(1970), Klein & Leffler (1981) and Shapiro (1983) suggest that prices should rise with better reputation, denoted r, under non-auction conditions.

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A seller with a reputation for good transactions may be signaling that she auctions better products.

5. $\frac{\partial p}{\partial r} > 0$. The expected common value 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 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. Consequently, I hypothesize that CV Nash prices will fall with dispersion at a faster rate with better reputations.

6. In Nash CV auctions, the perceived level of information dispersion is increasing in the level of information dispersion provided by the seller at an increasing (decreasing) rate with the seller's (bad) reputation. $\left(\frac{\partial^2 p}{\partial \sigma_{x|v} \partial r} < 0\right)$

3.1.5 Summary of Predictions

Table 3.1.5 summarizes the comparative statics predictions which would permit us to empirically distinguish the auction model generating the data. 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. Starred results indicate that the result holds

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Table 3.1: Comparative statics from auction theory

Model	$\frac{\partial p}{\partial \sigma_{x\|v}}$	$\frac{\partial^2 p}{\partial \sigma^2_{x\|v}}$	$\frac{\partial p}{\partial n}$	$\frac{\partial^2 p}{\partial n \partial \sigma_{x\|v}}$
PV/naïve CV	+*	−*	+	+*
Nash CV	−	+*	−/+	−/+
PV/naïve CV risk aversion	−/+	−/+	+	−/+

*Result holds for symmetrically distributed signals. For asymmetrically distributed signals, PV/naïve CV results hold if n is large enough.

for symmetrically distributed signals. Starred results for the PV/naïve CV results hold for n large enough if signals are asymmetrically distributed.

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, then the PV/naïve CV under risk neutrality or risk aversion applies.

If we can estimate all four comparative statics, it may also be possible to determine whether the distribution of signals is symmetric or not. Under Nash CV, if $\frac{\partial^2 p}{\partial \sigma^2_{x|v}} < 0$, then signals are asymmetrically distributed; otherwise, the distribution is unknown. Under PV/naïve CV, signals are asymmetrically distributed if we observe prices decreasing in dispersion at a decreasing rate or if we observe a negative cross partial with respect to the number of bidders and dispersion.

I will not be able to distinguish any of these models from a mix of pure and private values, but anecdotal evidence from eBay computer auctions suggest that the common value component is a dominant component to these products. A flurry of bidding occurs at the end of the auction, and some bidders update their bids. This behavior is theoretically inconsistent with private values auctions, where bidders should not be influenced by other people's bids and therefore should not be updating their bids and gain no advantage from bidding at the last second.

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3.2 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 222 eBay PC auctions held between June 24 and July 12, 2002. The auction descriptions were used to create a survey. This section defines the regressors that were drawn directly from the auction data and those generated by the survey.

3.2.1 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 auctions for which she received positive feedback minus the number where 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. They may also observe who has already bid in the auction and how many times, but not the amount of the bid.

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.

The summary statistics of data collected from my sample of auctions are presented

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Table 3.2: Summary statistics for 222 eBay computer auctions

Variable	mean	median	st. dev.	min	max
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

in Table 3.2. 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 negative feedback for the seller 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.

I selected auctions to ensure variation in the sellers' overall feedback score. I excluded auctions with less than two bidders and auctions for multiple units of computers. I also excluded auctions which were terminated 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 limited in order to gather more survey responses per auction and reduce depreciation issues by minimizing the time between which all auctions were held.

3.2.2 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 acquantainces by word of mouth. I asked people to read computer auction descriptions 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,

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Table 3.3: Summary statistics for survey on 222 auctions

Variable (831 respondents)	**mean**	**st. dev.**	**min**	**max**
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: $V_{e,t}$	\$603.76	351.43	\$46.11	\$1923.08
... inexperienced: $V_{a,t}$	\$682.48	317.59	\$95.97	\$1782.50
st. dev. experienced: $SD_{e,t}$	317.25	171.17	0	1429.78
... inexperienced: $SD_{a,t}$	492.03	168.31	138.94	1074.15

number of bidders, and the seller's identity and reputation were removed.

I also collected background data on survey respondents, asking them about their experience working with computers, purchasing computers, and purchasing computers in online auctions (see Chapter 2 for more details). I refer to respondents who have had experience with eBay online auctions for computers as "experienced." Approximately 20% 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 is a measure of v_t. The absolute value of the standard deviation of the responses in each auction, denoted SD_t, is a measure of $\sigma_{x|v,t}$. (See Chapter 2 for analysis of V_t and SD_t as measures of v_t.and $\sigma_{x|v,t}$). I also define $V_{e,t}$ and $V_{a,t}$ and $SD_{e,t}$ and $SD_{a,t}$ as the average and standard deviation of responses from the experienced and inexperienced respondents, respectively. Summary statistics from the survey are presented in Table 3.3.

Figure ?? 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,

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a pattern MW predict for Nash CV auctions. In the next section, I control for 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.

3.3 Estimation

I employ four estimation procedures to examine the robustness of my results. In each case, I estimate the price equation, Equation 3.2. The first case is OLS estimation of the price equation. Results are presented in Column 1 of Table 3.4.

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.[16] 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 $\sigma_{x|v,t}$. I also include $SCORE_t$, $SCORE_t^2$, and NEG_t as measures of reputation. Their interaction with $\sigma_{x|v,t}$ will capture the effect of credibility of information dispersion on price. I assume that *a priori* beliefs about the distribution of computer values are the same for all computers in my sample. As a result, I do not include any measures for μ_v and σ_v (I relax this assumption for μ_v later).

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 at a decreasing rate. Prices also fall as N_t increases, which is inconsistent with PV and naïve CV settings, as well as risk aversion under PV settings. The positive interaction

[16] I examined the robustness of various orders of polynomials and found no significant improvements from adding higher order terms, including interaction terms.

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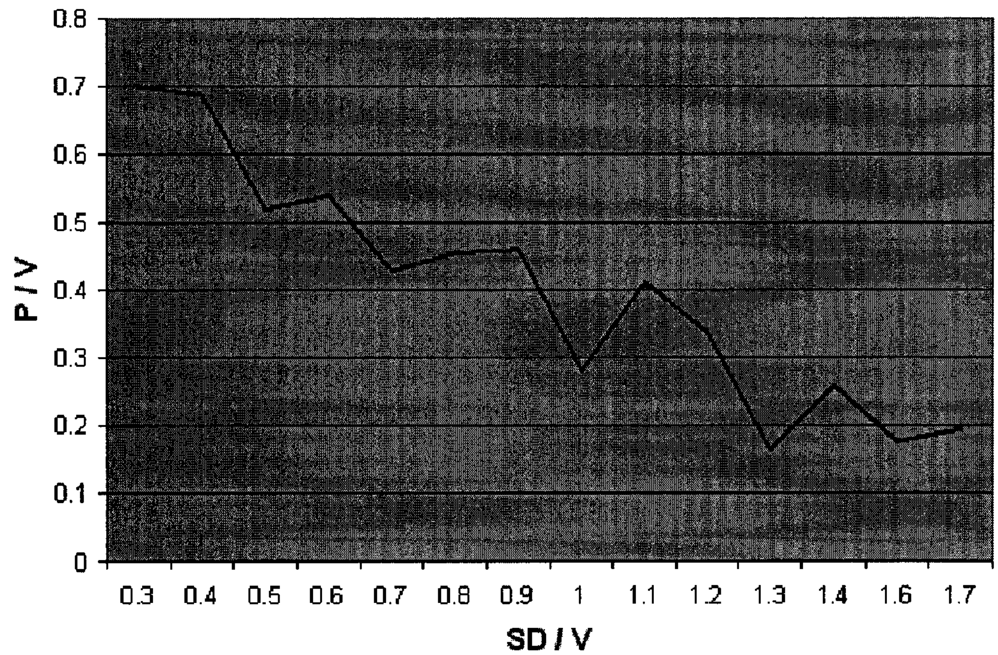
Figure 3.1: Normalized eBay prices P_t vs. normalized information dispersion SD_t

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.



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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 feedback in this case, we 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, within my sample worse reputations decrease price, but a worse reputation also diminishes the effect of dispersion on price.

We would expect prices to be directly proportional to changes in the value of the item. 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. Recall that the survey respondents could not view prices when submitting their valuations.

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 Chapter 2 suggests that V_t and SD_t are correlated with v_t and $\sigma_{x|v,t}$.

3.3.1 Correcting for potential bias in V_t and SD_t

V_t and SD_t are potentially biased measures of v_t and $\sigma_{x|v,t}$.I model and estimate the potential bias as follows. I treat the responses $X_{i,t}$ from my survey respondents as potentially biased draws of signals $x_{i,t}$ that the auction participants draw about v_t. Thus, $X_{i,t}$ are drawn from a potentially different distribution than the one that the auction participants face. I model the responses from my inexperienced respondents,

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denoted $X_{a,i,t}$, as draws from a distribution whose mean may differ from v_t by a shift factor γ_0 and a scale factor γ_1 and whose variance may be different as well: $X_{a,i,t} \backsim (\gamma_0 + \gamma_1 v_t, \sigma^2_{x|v,a,t})$. 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 θ_0 and whose variance may be different: $X_{e,i,t} \backsim (\theta_0 + v_t, \sigma^2_{x|v,e,t})$. An unbiased estimate of v_t can then be written as

$$\hat{v}_t = \frac{J_{e,t}}{J_t}(V_{e,t} - \theta_0) + \frac{J_{a,t}}{J_t}\left(\frac{V_{a,t} - \gamma_0}{\gamma_1}\right), \tag{3.3}$$

where $J_{e,t}$ is the number of experienced survey responses in each auction, $J_{a,t}$ is the number of inexperienced survey responses in each auction, and J_t is the total number of survey responses to each auction. The parameters to be estimated are θ_0, γ_0, and γ_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 $\sigma^2_{x|v,e,t} = \eta_0 + \sigma^2_{x|v,t}$, whereas my inexperienced respondents draw from a distribution with variance $\sigma^2_{x|v,a,t} = \delta_0 + \delta_1 \sigma^2_{x|v,t}$. The resulting unbiased estimate of the information dispersion faced by the auction participants is as follows:

$$\hat{\sigma}_{x|v,t} = \sqrt{\frac{J_{e,t}}{J_t}(SD^2_{e,t} - \eta_0) + \frac{J_{a,t}}{J_t}\left(\frac{SD^2_{a,t} - \delta_0}{\delta_1}\right)}. \tag{3.4}$$

The parameters to be estimated are η_0, δ_0, and δ_1. They capture the amount of bias in the dispersion of responses.

I can use a moment condition to identify θ_0, γ_0, and γ_1. I set the standard deviation of the experienced survey responses equal to the definition of the sample standard deviation, replacing $V_{e,t}$ 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:

$$SD_{e,t} = \sqrt{\frac{\sum^{J_{e,t}}(X_{e,i,t} - (\hat{v}_t + \theta_0))^2}{J_{e,t} - 1}}. \tag{3.5}$$

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Column 2 presents the results of simultaneously estimating the price equation and the moment condition in Equation 3.5. I remove the constant from the price equation since θ_0 and γ_0 now serve to estimate the intercept. I now estimate v_t and $\sigma_{x|v,t}$ in the price equation by $\hat{v}_t$ and $\hat{\sigma}_{x|v,t}$, respectively.

Overall, we 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 $V_{a,t}$ and $SD^2_{a,t}$ 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 significant. Since the coefficient on V_t in Column 1 was already equal to 1, this seems to merely indicate that there was not much need for bias correction of the survey measure. Indeed, the estimate of the scale bias in $V_{a,t}$ 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 $\sigma^2_{x|v,t}$. Translating this into standard deviation terms, $SD_{a,t}$ is approximately 1.35 ($= \sqrt{1.83}$) times larger than $\sigma_{x|v,t}$ and overestimates $\sigma_{x|v,t}$ by 276.37 ($= \sqrt{76381.0}$). Since inexperienced respondents might not understand all the details of the auction description, we 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 $\sigma_{x|v,t}$ by 245.40 ($= \sqrt{60222.6}$). This is consistent with the concept that those who have participated in eBay auctions have learned how to better interpret auction descriptions 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

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coefficients on $\hat{\sigma}_{x|v,t}$, $\hat{\sigma}^2_{x|v,t}$, and $\hat{\sigma}_{x|v,t} \times N_t$ 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.

3.3.2 Instrumental Variables Estimation

I present an alternative empirical specification in Column 3 of Table 3.4 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 employing 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 we 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. We 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.[17] 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

[17]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.

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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 simulataneously 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 B.1.

The weakness of the instruments is reflected in numerous insignificant coefficients in Column 3. Nevertheless, we 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 parameters (η_0, δ_0, and θ_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.

3.3.3 Modeling $\mu_{v,t}$

In my specifications thus far, I assumed that all bidders faced a common μ_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 μ_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

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just using $\hat{v}_t$ alone. Results are presented in Column 4 of Table 3.4.

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 μ_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 approximately the same as in Columns 1 and 2, except for some of the survey bias parameters (γ_0, γ_1, and η_0) and the coefficient on $\hat{v}_t$. However, the estimate of γ_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. We 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 employing $\mu_{v,t}$ 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, we should divide its coefficient in half (= 0.98). The resulting effect on price from v_t is thus equivalent across all columns. Likewise, we should then divide the parameter γ_1 in half to get the effect of $V_{a,t}$ 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.

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Table 3.4: Simultaneous equation estimates of price equation

Parameter	Column 1	Column 2	Column 3	Column 4
θ_0		27.039‡	1.772	289.748‡
		(0.407)	(156.267)	(0.544)
γ_0		83.611‡	60.405	-76.906‡
		(0.397)	(162.560)	(1.289)
γ_1		1.033‡	1.029‡	2.392‡
		(2.72E-04)	(0.050)	(1.015E-03)
η_0		-60222.6‡	-9259.78	78034.3‡
		(803.752)	(302009)	(997.537)
δ_0		76381.0‡	58047.6	5247.51‡
		(268.241)	(1557071)	(397.027)
δ_1		1.83103‡	2.488	1.396‡
		(7.64E-03)	(1.760)	(7.57E-03)
Variable				
CONSTANT	69.301			
	(120.627)			
$\hat{\mathbf{v}}_t$	1.046‡	1.086‡	1.172‡	1.960‡
	(0.059)	(3.85E-04)	(0.104)	(7.63E-04)
$\hat{\sigma}_{x\|v,t}$	-1.483‡	-1.48479‡	-1.448‡	-1.446‡
	(0.450)	(3.45E-03)	(0.692)	(5.50E-03)
$\hat{\sigma}^2_{x\|v,t}$	1.20E-03‡	1.73E-03‡	1.79E-03	0.16E-02‡
	(4.26E-04)	(7.07E-06)	(1.20E-03)	(-8.85E-06)
$\mathbf{N}_t$	-11.811	-9.120‡	-21.819	-8.423‡
	(11.145)	(0.047)	(23.900)	(0.053)
$\mathbf{N}_t \times \hat{\sigma}_{x\|v,t}$	0.021	0.024‡	0.012	0.018‡
	(0.022)	(1.35E-04)	(0.059)	(1.31E-04)
$\mathbf{SCORE}_t \times \hat{\sigma}_{x\|v,t}$	-1.16E-04†	-1.38E-04‡	-7.05E-05	-1.29E-04
	(6.68E-05)	(4.78E-07)	(4.82E-04)	(4.97E-07)
$\mathbf{NEG}_t \times \hat{\sigma}_{x\|v,t}$	1.39E-03	1.52E-03‡	-6.56E-04	1.41E-03‡
	(1.73E-03)	(1.05E-05)	(0.015)	(1.08E-05)
$\mathbf{SCORE}_t$	0.091‡	0.079‡	0.079	0.086‡
	(0.038)	(1.66E-04)	(0.125)	(1.96E-04)
$\mathbf{NEG}_t$	-0.901	-0.731‡	-0.281	-0.780‡
	(0.816)	(3.39E-03)	(4.202)	(4.08E-03)
$\mathbf{SCORE}_t^2$	-1.12E-06	-1.10E-06	-2.13E-06	-1.24E-06
	(1.15E-06)	(5.76E-09)	(3.03E-06)	(5.79E-9)
$\boldsymbol{\mu}_{v,t}$				0.114‡
				(1.69E-03)
$\mathbf{R}^2$	0.72	0.72	0.69	0.71

‡significant at 5%, †significant at 10%.

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3.4 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 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 3.4 for my analysis.

3.4.1 Differences between Nash CV & eBay prices

The price equation estimated in Section 3.3 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 3.4 are free of any assumptions about bidder behavior or CV vs. 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 μ_v and σ_v over all t auctions. I tried several measures for n_t, including the first stage fitted value from instrumental variables and $N_t \pm 20\%$, $\pm 50\%$, and $+100\%$. 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 $\tilde{\sigma}_{x|v,t}$.[18] I generated the Nash CV price

[18] 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

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for each auction using these values and a numerical approximation to the theoretical Nash CV price (see Appendix D).[19] 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 3.4. Simulated naïve CV prices were generated by taking the average over the draws of the second highest signal and then adjusting for reputation effects.

Figure 3.2 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 crosses, while the associated eBay price is plotted as diamonds.

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%. Figure 3.2 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 (2004) establish that as $n \to \infty$, 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. Away from the limit, this behavior might result in prices that are consistently lower than simulated Nash CV prices.

observed distribution of survey responses.

[19]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.

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Figure 3.2: 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.

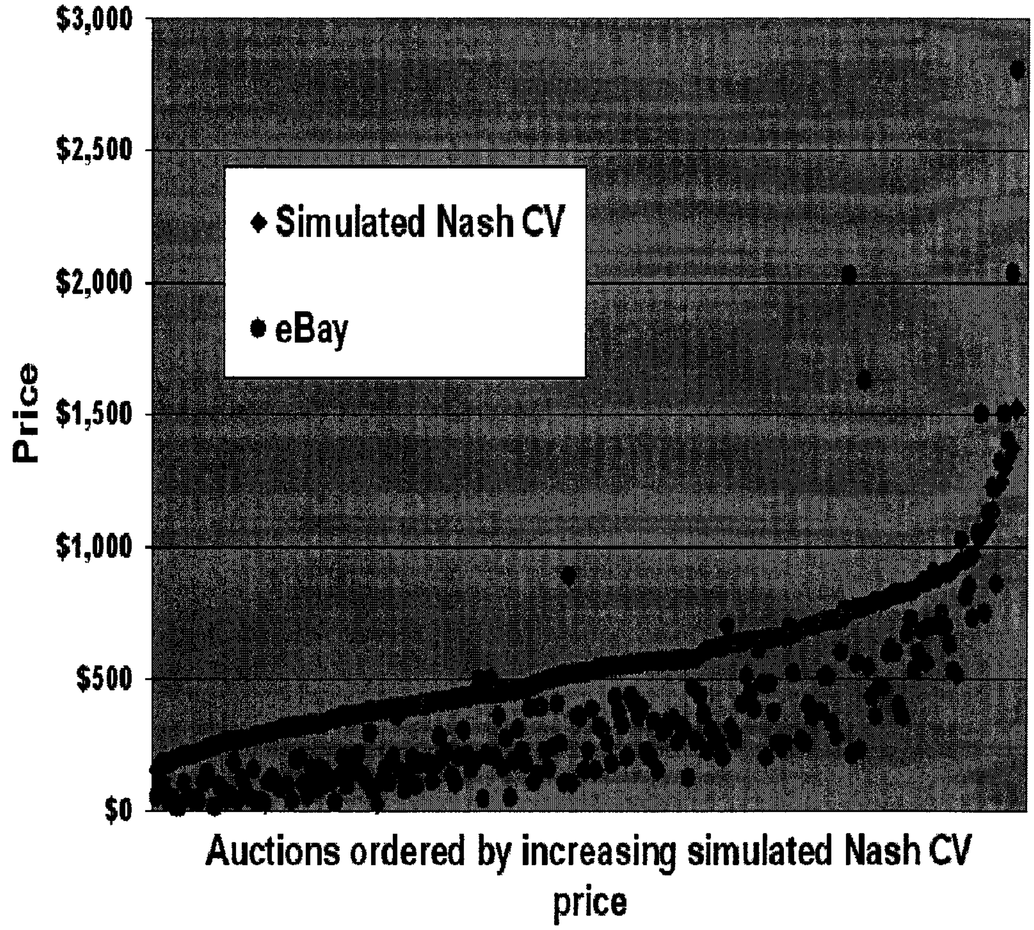

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Table 3.5: Potential winner's curse

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

3.4.2 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? We can answer this question by considering the prices the winning bidder would have paid if auction participants had employed naïve CV bidding behavior. We 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 3.5 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% 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.[20] 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.

[20] eBay winners paid more than $\tilde{v}_t$ in less than 5% 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.

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Table 3.6: Price effects of naïve behavior

Behavior	**Price change from**		
	incr. $\sigma_{x\|v,t}$ **by 1**	**incr.** n_t **by 1**	**both**
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

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 3 scenarios: an increase in information dispersion by 1 unit, an increase in the number of auction participants by 1 person, and both changes. The columns of Table 3.6 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 3.4. 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 3.4 to 0, respectively. The results for each of those models of bidding behavior are presented in the remaining rows of Table 3.6.

Comparing the first two rows in Column 1, we 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

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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 overpayed 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.

3.4.3 Information Dispersion, Reputation, and Credibility

What do these estimates mean for seller strategies on eBay? Table 3.7 examines how prices will change with dispersion and reputation.

A seller who invests in acquiring and publishing more information in the auction

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Table 3.7: 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
Total effect	\$0.34	\$0.04	\$0.38

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

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 another \$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.

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. 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

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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.

3.5 Conclusion

The results in this chapter are unattainable without employing theory, econometric modeling, and external survey data. From auction theory, I derive implications of different auction models when information dispersion is observable with error. These implications permit joint identification of the information structure (common or private values) 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. My estimates indicate that eBay auctions for computers are best described as common value auctions where prices reflect Nash equilibrium bidding behavior.

Treatment of information about the item being sold as distinct from information about the seller allows me to 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 sellers with a good feedback score have an incentive to provide precise descriptions, since they benefit from the interaction between reputation and information dispersion.

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, paying 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.

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Chapter 4

Empirical Tests of Information Aggregation

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

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

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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 derives 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 to the common value, then we would expect actual prices to converge as well under information aggregation.

Section 4.1 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 examine two types of convergence: 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 4.2 reviews the auction and survey data employed. I employ data from a sample of eBay auctions for computers. The previous chapter 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 4.3, I estimate the relevant comparative statics in my sample of eBay computer auctions. I also employ the predicted Nash CV prices from the previous chapter 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

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information fully in the limit. The last section concludes.

4.1 Conditions for Information Aggregation

This section reviews the necessary and sufficient conditions for information aggregation from auction theory. It then derives 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 $n \to \infty$.

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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

[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.

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increases for large enough n.

3. $\frac{\partial^2 |\mu_v - \overline{p_n}|}{\partial n \partial \sigma_{x|v}} > 0$ 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.

4. $\frac{\partial |sd[p_n] - \sigma_v|}{\partial n \partial \sigma_{x|v}} > 0$ 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.

4.2 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 (see previous chapter Section 3.1). 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

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Table 4.1: 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

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. More details on the eBay auction mechanism and the eBay reputation mechanism can be found in Section 3.2.1.

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 chapter, denoted $\tilde{\sigma}_{x|v,t}$ and $\tilde{v}_t$, are the result of work done in the previous chapter. The previous chapter established that I can treat the common values from all the eBay personal computer auctions as 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. The simulation and choice of the lognormal distribution are described in Section 3.4.1. Summary statistics for these auction characteristics are reported in Table 4.1.

In order to empirically examine the comparative statics with respect to n from

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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 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 4.2.

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. As developed in the previous chapter, N_t itself is an approximation to the number of participants in the auction (see Section 3.3.2). 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.

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Table 4.2: 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 $\bar{\tilde{v}}_{\overline{N}}$	\$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 $\bar{\tilde{\sigma}}_{x\lvert v,\overline{N}}$	319.34	31.17	240.77	382.23
s.d. dispersion $sd[\tilde{\sigma}_{x\lvert v,\overline{N}}]$	126.23	19.32	75.49	174.54
avg. credible $\overline{\tilde{\sigma}_{x\lvert v,\overline{N}} \times SCORE_{\overline{N}}}$	294264	266478	26056	864903
avg. discount $\overline{\tilde{\sigma}_{x\lvert v,\overline{N}} \times NEG_{\overline{N}}}$	8730.94	8176.39	386.39	23626
s.d. credible $sd[\tilde{\sigma}_{x\lvert v,\overline{N}} \times SCORE_{\overline{N}}]$	855522	952900	62788	3.1E06
s.d. discount $sd[\tilde{\sigma}_{x\lvert v,\overline{N}} \times NEG_{\overline{N}}]$	30322	31893	637.68	94789
avg. dispersion² $\overline{\tilde{\sigma}^2_{x\lvert v,\overline{N}}}$	126.23	19.32	75.49	174.54
avg. score² $\overline{SCORE^2_{\overline{N}}}$	7.8E06	9.3E06	28501	2.9E07

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4.3 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 4.3. 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 4.1. 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 4.1). 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.

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 4.4 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 4.3, 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.

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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 4.1, the simulated Nash prices are on average \$196.16 higher than the eBay prices. In Column 3 of Table 4.3, 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 the previous chapter: 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.

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.

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Table 4.3: 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)
$\overline{\tilde{\sigma}_{x\mid v,\overline{N}}}$	1.693	4.170	-3.219
	(1.547)	(3.798)	(2.556)
$sd[\tilde{\sigma}_{x\mid v,\overline{N}}]$	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)
$\overline{\tilde{\sigma}_{x\mid v,\overline{N}} \times N_{\overline{N}}}$	-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)
$\overline{\tilde{\sigma}_{x\mid v,\overline{N}} \times SCORE_{\overline{N}}}$	-.45E-03†	0.12E-02†	0.24E-02‡
	(0.27E-03)	(0.67E-03)	(.45E-03)
$\overline{\tilde{\sigma}_{x\mid v,\overline{N}} \times NEG_{\overline{N}}}$	0.017	-0.040	-0.101
	(0.012)	(0.030)	(0.020)
$sd[\tilde{\sigma}_{x\mid v,\overline{N}} \times SCORE_{\overline{N}}]$	0.13E-03‡	-0.38E-03‡	-0.56E-03
	(0.59E-04)	(0.15E-03)	(0.98E-04)
$sd[\tilde{\sigma}_{x\mid v,\overline{N}} \times NEG_{\overline{N}}]$	-0.34E-02	0.93E-02	0.023‡
	(0.27E-02)	(0.66E-02)	(0.44E-02)
$\overline{\tilde{\sigma}^2_{x\mid v,\overline{N}}}$	-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 $R^2 = 0.76$.

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Table 4.4: Convergence of simulated Nash prices

Variable	Column 1	Column 2
CONSTANT	1680.43‡	-149.877
	(198.202)	(102.831)
$\bar{\tilde{\sigma}}_{x\|v,\overline{N}}$	-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)
$\bar{\tilde{\sigma}}_{x\|v,\overline{N}} \times \overline{N}_{\overline{N}}$	0.274‡	0.547‡
	(0.039)	(0.020)
$\bar{\tilde{v}}_{\overline{N}}$	0.360‡	-0.100‡
	(0.060)	(0.031)
$sd[\tilde{v}_{\overline{N}}]$	-0.070*	-0.659‡
	(0.041)	(0.021)
$\bar{\tilde{\sigma}}_{x\|v,\overline{N}} \times \overline{SCORE}_{\overline{N}}$	0.16E-02‡	0.16E-03
	(0.25E-03)	(0.13E-03)
$\tilde{\sigma}_{x\|v,\overline{N}} \times \overline{NEG}_{\overline{N}}$	-0.055	0.14E-03
	(0.011)	(0.58E-02)
$sd[\tilde{\sigma}_{x\|v,\overline{N}} \times SCORE_{\overline{N}}]$	-0.45E-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-02‡	0.55E-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 $R^2 = 0.97$.

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4.4 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 chapter 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 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. Using estimates from the previous chapter, 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 indicates an efficiency gain over one-to-one trade

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of used goods with uncertain common values.

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Chapter 5

Conclusions

This thesis contributes to both methodology in empirical work and findings that help us understand the role of information in auctions. This research allows us to identify the forces that drive prices and efficient transactions in these markets.

The use of survey data to augment auction data is valuable and feasible. Survey based measures can provide an important source of external information for hypothesis testing. In the case of eBay online auctions for personal computers, this external information permits identification of both bidding behavior and the information setting. Furthermore, this external measure allows the price effects of the reputation mechanism, number of bidders, information dispersion, and interactions of those regressors to be separately estimated.

The survey method could be beneficial in other research involving dispersed private information accompanying market data. Survey based measures that are used to augment market data will tend to share the same advantages of my auction measure: by referring to a market that already exists, framing problems are less severe. In addition, since all that is necessary for estimation is a correlated measure, incentive issues are also less severe. This method has applications in any setting where hedonic estimation may ignore important idiosyncratic differences between observations. For models which include expectations over privately held information, the surveys allow the researcher to reconstruct the distribution of private information signals. The researcher can exploit background characteristics of the survey respondents to

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correct for survey errors. The convenience and speed of implementing the survey is improved through the use of the general population in part as survey respondents. The advantages to the extra information gathered through surveys combined with the tools available to correct for errors render the cost of administering a survey less prohibitive.

The quantitative results in this thesis yield a better understanding of the importance of various mechanisms to efficient transactions in online auctions. eBay prices are consistent with a common values model of Nash equilibrium bidding and lognormally distributed information. As predicted by MW and auction theory, prices fall with increased dispersion of information, and the rate of decline depends on the level of information dispersion, the number of bidders, and the seller's credibility. I am able to identify two different effects of reputation: the premium that reputation adds to the expected common value, and the credibility reputation lends to information provided in an auction. There is a strong interaction effect between reputation and information, providing incentives for the seller to both increase their reputation score and provide more information in the auction. Bidders on eBay seem to do quite well at accounting for a potentially large winner's curse: they pay less than the common value on average, and overpay in less than 5% of the auctions. Prices in eBay online computer auctions reflect Nash equilibrium common value price behavior in reaction to changes in the dispersion of signals. Even in the pedestrian market of online computer auctions, prices exhibit the equilibrium behavior predicted by sophisticated conditioning behavior by strategic bidders.

Auctions seem to be a feasible and effective means of setting prices for uncertain goods. Although tests for the convergence of prices to their common values fail, I do find evidence that eBay prices partially aggregate information about the common value: eBay prices converge to a value below the expected common value as the number of bidders increases. This may explain why eBay has succeeded as a marketplace for used goods when many other online markets have failed.

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Appendix 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 Yin, http://www.stanford.edu/~pyin, 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. 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 pyin@stanford.edu if you can't make the deadline but still want to participate.

"Thanks very much! Email pyin@stanford.edu if you have questions. Privacy will

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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 email address. This will be used only to contact you if you win. Please use the same email if you participate more than once.

   Did someone refer you to this survey? Please enter his/her email 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)?

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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 email to pyin@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 buying 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."

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Appendix 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.

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.

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Table B.1: Summary statistics for bidder instruments

Variable (222 auctions)	**mean**	**s.d.**	**min**	**max**
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

$OTHERN_t$ 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.

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Appendix 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 satisfying 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 C.1.

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.

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Table C.1: Summary statistics for regressors for a priori value

Variable (222 auctions)	**mean**	**s.d.**	**min**	**max**
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

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Appendix D

Analytical derivation of $E[p]$

The bid function in Equation 3.1 can be written explicitly as

$$b(x_i) = \frac{\int_{\underline{v}}^{\overline{v}} v f_x^2(x_i|v) F_x^{n-2}(x_i|v) f_v(v) dv}{\int_{\underline{v}}^{\overline{v}} f_x^2(x_i|v) F_x^{n-2}(x_i|v) f_v(v) dv}, \text{ (Milgrom,1981)} \tag{D.1}$$

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

$$\Pr[b(x_i) \leq v] = \Pr[x_i \leq b^{-1}(v)] = F_x(b^{-1}(v))$$

with associated density

$$f_x(b^{-1}(v))\frac{1}{b'(v)},$$

where

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

and solve for the 2nd order distribution of

$$f_x^{(n-1)}(b^{-1}(v))\frac{1}{b'(v)} = n(n-1)F_x(b^{-1}(v))^{n-2} f_x(b^{-1}(v))\frac{1}{b'(v)}[1 - F_x(b^{-1}(v))],$$

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and then integrate to get

$$\int_{-\infty}^{\infty} x_i(n-1)F_x(b^{-1}(v))^{n-2}f_x(b^{-1}(v))\frac{1}{b'(v)}dx.$$

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

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