SELLER PRICING BEHAVIOR IN AUCTION AND POSTED-PRICE MARKETS

By

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To Abby and Annalise.

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CHAPTER I

Comparing Revenue from Auctions and Posted Prices

I analyze the market for compact discs using an original data set of items listed for sale online. Over 5,000 listings of both new and used compact discs were collected from eBay (which provides sellers a choice between two mechanisms: auction or posted price) and its subsidiary, Half.com (which features only posted prices). Despite the often cited revenue-dominance property of auctions, many sellers choose to post a fixed price. To explain this anomaly, I examine empirically the determinants of the revenue earned by sellers in this market. I find that posted-price goods sell for higher prices, while auctioned goods sell with a higher probability. Further results suggest that the size of a seller's inventory is the key factor in the choice between selling in an auction and posting a fixed price. In particular, sellers with large inventories are more likely to use the posted-price mechanism.

Introduction

Browsing through online marketplaces such as eBay, potential buyers encounter numerous goods, some of which are being auctioned, others selling at a posted price. This coexistence of auctions and other selling mechanisms presents a puzzle to economists. Namely, if auctions raise more revenue than other selling mechanisms, why aren't more goods being auctioned? I approach this question using data from eBay, and its subsidiary, Half.com. On a given day, nearly 500,000 compact discs are available for purchase on eBay. Though it is commonly thought of as an auction website, eBay sellers may also sell their goods at a posted price. Unlike eBay, Half.com allows its users to sell only at a posted price and only certain types of goods: CDs, books, movies, and video games. Drawing from a sample of 49 albums, I collected over 5,000 listings of both new and used compact discs from the two sites. Approximately 60% of the data are posted-price goods, confirming that coexistence is present in this market. Using this original data set, I estimate the effect of a seller's mechanism choice on the outcomes of interest: a good's revenue, selling price, and probability of sale.

One of the central results in auction theory is the revenue dominance of auctions, given a monopolistic market in which symmetric buyers have private values and independent signals (Myerson 1981). Auctions are not always optimal however. Once buyer symmetry (Myerson 1981) or the independence of the information structure (Crémer and McLean 1985) is relaxed, auctions fail to maximize revenue but they still revenue dominate posted-price selling. Relaxing the assumption of private values, Campbell and Levin (2006) show that posted-price selling can revenue dominate auctioning when buyers' values are sufficiently interdependent. Wang shows that posted-price selling can revenue dominate auctioning when there is a fixed cost for holding an auction and buyers' values are not too dispersed.[1]

The empirical regularities of these data suggest that a simple revenue-dominance story masks the fact that auctions have advantages and disadvantages relative to posted-price selling. While I find revenue equivalence between the auction and posted-price mechanisms, there are interesting differences when analyzing the two components of revenues separately. Specifically, the posted-price mechanism earns 11% higher prices than the auction mechanism. Further, I find some evidence that auctioneers are compensated for a lower selling price with a higher probability of sale, but the effect is only economically and statistically meaningful in the sample of only eBay items.

I then turn to an examination of the mechanism choices of the sellers in the online compact-disc market. To explain why the auction and posted-price mechanisms coexist, I focus on sellers' inventories. The importance of inventories is illustrated by two papers from the literature. Harris and Raviv (1981) find that if the number of goods in a monopolist's inventory exceeds potential demand, a posted price is optimal. If the inventory is smaller

[1] Another set of related papers deal with Buy-It-Now auctions, a hybrid mechanism combining elements of an auction and posted-price selling. See Anderson *et al* (2004); Wang *et al* (2004); and Reynolds and Wooders (2009).

than potential demand on the other hand, selling in an auction is optimal. The rationale for this result is that an auction can only profitably exploit the scarcity of a seller's inventory when it is scarce.

Zeithammer and Liu (2006) study a monopolist with either one or two units, where goods are of one of two types. They find that a monopolist with a heterogeneous inventory prefers the auction mechanism, while a homogeneous inventory favors posted-price selling. The degree of heterogeneity is important because, in their model, offering a posted price imposes a fixed cost on the seller that is incurred only once per type of item, while auctioning imposes a cost that must be paid once for each auction that the seller offers. Having more types of items (i.e., a more heterogeneous inventory) favors the auction mechanism.

I use these two characteristics of a seller's inventory to explain the results of this paper. I find that sellers differ in the size and the heterogeneity of their inventories but that inventory size is the key determinant of whether a seller chooses to sell in an auction or at a posted price. Consistent with the arguments of Harris and Raviv, sellers with large inventories choose to post a fixed price. I do not find support for the inventory-heterogeneity hypothesis of Zeithammer and Liu and conclude that the size of a seller's inventory is the most important factor in the mechanism choices of eBay compact-disc sellers. I now describe the data.

Data

Summary statistics are in Table 1 and detailed descriptions of all variables are in Appendix I.8. The sample contains 5,009 items over 49 albums listed for sale between August 1 and October 5, 2005. For the week of August 14-20, 2005, 10 albums were randomly selected from each of the following lists: the Billboard 100, Amazon's Top 100, and Amazon's Top 100 Indie.[2] The Amazon lists are based solely on sales at Amazon.com, while Billboard ranks sales in both brick-and-mortar stores and online retailers. The remaining 30 albums were selected from an unrestricted population of all albums ever produced (excluding classical music), randomly selected from the *All Music Guide* (Bogdanov *et al* 2002). From these 60 albums, 9 were never released on compact disc and 2 albums were never listed for sale on either site during the sample period, leaving data for 49 albums.

Institutional Features of eBay and Half.com

The most common way for sellers to list their items on eBay is in an ascending-bid, second-price (English) auction with a fixed end time. The auction length is set by the seller and can be 1, 3, 5, 7, or 10 days. If an item has received multiple bids when its end time is reached, it is sold to the highest bidder at the second highest bid (plus one bid increment). If the item has received only one bid, it is sold to the lone bidder at the reserve price. Finally, if the item has not received any bids, it does not sell and is retained by the seller.

Potential buyers who search for a particular item on eBay are shown all open listings matching the search criteria. They observe the standing bid (the second highest of the bids already placed), shipping cost, number of bids already placed, and end time. The shipping cost is set by the seller and ranges from free shipping to upwards of five dollars in these data. A potential buyer observes the (public) reserve price, which is also set by the seller. The standing bid is equal to the reserve price until a bid is placed and bids below the reserve price are not accepted.[3]

[2] An album is considered "indie" (independent) if it is published by a company that is not a member of the Recording Industry Association of America (the trade group that represents the U.S. recording industry).

[3] eBay auctioneers may also employ a secret reserve price. Potential bidders observe the public reserve and may bid any amount above it. If the auction ends with the highest bid below the secret reserve price,

Table 1. Summary Statistics

	All	Half.com	eBay Posted Price	eBay Auction
Dependent Variables:				
Selling Price	\$10.74	\$9.78	\$12.42	\$10.34
	(3.921)	(3.470)	(3.878)	(3.885)
Pr(Sale)	63.8%	32.9%	87.6%	87.7%
	(0.481)	(0.470)	(0.330)	(0.329)
Seller Characteristics:				
Score	15,771.00	17,760.14	18,305.31	12,269.51
	(43,233.096)	(36,751.293)	(47,074.812)	(47,724.425)
Rating	98.7%	98.1%	99.2%	99.2%
	(0.030)	(0.031)	(0.033)	(0.026)
Inventory Size	14.29	18.98	16.98	7.62
	(21.484)	(27.095)	(14.580)	(14.028)
Inventory Homogeneity	0.638	0.504	0.658	0.780
	(0.391)	(0.437)	(0.310)	(0.310)
Buyer Characteristics:				
Score	230.08		262.58	214.66
	(576.535)		(706.190)	(501.439)
Rating	98.9%		99.0%	98.8%
	(0.063)		(0.054)	(0.067)
Item Characteristics:				
New CD	57.4%	55.3%	81.0%	48.5%
	(0.494)	(0.497)	(0.393)	(0.500)
Scratched CD	1.9%	2.3%	0.2%	2.3%
	(0.137)	(0.151)	(0.047)	(0.149)
No Description	7.8%	11.4%	2.4%	6.4%
	(0.269)	(0.317)	(0.153)	(0.245)
Promotional CD	5.5%	5.1%	2.9%	7.1%
	(0.227)	(0.220)	(0.169)	(0.257)
Case Damaged	0.9%	1.0%	0.8%	0.9%
	(0.096)	(0.100)	(0.087)	(0.097)
Case Missing	1.1%	1.3%	0.4%	1.1%
	(0.102)	(0.113)	(0.066)	(0.104)
Recently-Released Album	58.7%	51.1%	65.7%	64.0%
	(0.492)	(0.500)	(0.475)	(0.480)
Observations	5,009	2,183	920	1,906

Notes: Standard deviations are in parentheses. For all analyses, the selling price is equal to the price at which the item sold plus shipping minus all fees paid by the seller. Buyer characteristics are only observed on eBay. See Appendix I.8 for a discussion of each variable. The following items were excluded from all analyses: items listed on Half.com during the last 7 days of the sample period (54 items) and unsold items listed on eBay as auctions with a Buy-It-Now price (323 items).

Instead of selling in an auction, an eBay seller may post a fixed price. A buyer who searches for a certain album is shown all copies available for purchase and it is made clear which mechanism is being used for each item. As with auctions, there is a fixed end time for posted-price items. But unlike auctions, the buyer can win a posted-price item immediately by choosing to pay the seller's specified price. As mentioned in footnote 1, eBay also offers a hybrid of the two mechanisms studied here, known as a Buy-It-Now auction. My focus is on a comparison between pure auctions and pure posted-price sales, as these are common mechanisms found in a wide range of on and offline settings. As a result, I ignore Buy-It-Now auctions in my analysis and exclude unsold Buy-It-Now items (323 items) from all summary statistics and regression analyses.

Half.com allows sellers to list only at a posted price. Buyers can search for any item as they would on eBay.[4] After entering their search terms, Half.com buyers view all copies of the album available for purchase on Half.com. Shipping is fixed at \$2.49. An important distinction between eBay and Half.com is the interpretation of an unsold item. For eBay, these items were listed for a fixed period of time (typically seven days) during which they were available to buyers. For the unsold eBay items in the data set, their window closed without attracting a buyer. For Half.com on the other hand, items are available until they sell, meaning that an unsold item has simply not sold *yet*. I take this difference into account by excluding from all analyses those Half.com items listed within seven days from the close of the sample period.[5]

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the item does not sell. Secret reserves are rarely used in these data (7 listings; $< 1\%$ of all auctions) and are therefore ignored.

[4]Given the popularity of the "Music→CD" category, most albums are available for purchase on both sites at all times. Only 2 of the 51 albums randomly selected for this study were unavailable from either site and only 1 album was available from one site but not the other; Bing Crosby "Swingin' with Bing" was listed on Half.com only.

[5]Seven days was used because it is the modal length of an eBay listing.

eBay and Half.com profit from their role as intermediaries by charging fees to sellers; buyers pay nothing to eBay/Half.com to join or use either site. eBay has three types of seller fees: insertion fees, final value fees, and fees for optional features. Insertion fees are paid by the seller for listing an item whether or not the item sells. The fees are as follows: $0.20 for items with a reserve price between $0.01-$0.99, $0.40 for $1.00-$9.99, $0.60 for $10.00-$24.99, and $1.20 for $25.00-$49.99. Final values fees are paid as a percentage of the selling price (excluding shipping) for sold items. The fees are 5.25% of the selling price for all prices below $25.00, plus 3.25% of any amount above $25.00. eBay sellers pay a $0.05 to $0.25 fee for introducing a posted-price option, depending on the price posted. Half.com sellers incur fees only at the time of sale, with fees of 15% for items that sell for a price (excluding shipping) below $50.00 and 12.50% for prices above $50.00. I construct a dependent variable equal to the log of the selling price plus shipping minus fees.[6]

Overview of the Outcomes

First note in Table 1 the prices at which goods sell, where eBay posted-prices items outperform eBay auctions but both outperform Half.com items. The probability of sale statistics show a clear tendency for items on eBay to sell with a higher frequency but the effect of the mechanism is ambiguous. Concerning new versus used items, Table 2 suggests that the dominance of eBay posted prices over eBay auctions is much larger for brand-new items. Further, t-tests indicate that the price differences across eBay posted-price items and eBay auctions is significant only for brand-new items (t statistic of 7.73 for new items versus 1.34 for used). For the probability of sale, Table 2 again indicates that eBay items

[6]The regression analysis is robust to using price as the dependent variable with shipping and fees as controls.

Table 2. Dependent Variables by New/Used Items

	All	Half.com	eBay Posted Price	eBay Auction
New Items:				
Selling Price	\$12.07	\$11.12	\$13.12	\$11.56
	(3.837)	(3.220)	(3.736)	(3.924)
Pr(Sale)	59.8%	22.6%	86.6%	86.7%
	(0.490)	(0.419)	(0.341)	(0.340)
Observations	2,877	1,207	745	925
Used Items:				
Selling Price	\$9.20	\$8.96	\$9.60	\$9.24
	(3.419)	(3.364)	(3.087)	(3.500)
Pr(Sale)	69.2%	45.7%	92.0%	88.6%
	(0.462)	(0.498)	(0.272)	(0.318)
Observations	2,132	976	175	981

sell with a higher frequency than Half.com items. Though new items are less likely to sell than used items in all categories, the differences in the likelihoods of sale across mechanism seem to be independent of whether the item is new or used.

Rationales for in which mechanism an item is listed fall into three categories: seller-specific, buyer-specific, or item-specific explanations. First, one might wonder if there exist discernible differences between auctioneers and sellers who post fixed prices. The seller panel of Table 1 suggests that posted-price sellers have higher scores than auctioneers and eBay sellers have higher ratings than Half.com sellers (with both differences statistically significant). Inventories are also meaningfully different across the three outlets: posted-price sellers have larger and more heterogeneous inventories.

Buyer-specific explanations can only be explored using eBay data because Half.com does not provide any information about buyers. From the buyer panel of Table 1, auction buyers look reasonably similar to posted-price buyers; neither the difference in scores nor in ratings is significant at the 5% level. Finally, the most striking feature in the item panel of

Table 1 is that posted-price items on eBay are significantly more likely to be brand new, a fact that does not appear attributable to mechanism (does not hold for Half.com) or website (does not hold for eBay auctions). This leads to a meaningfully smaller fraction of items with negative attributes sold at a posted price on eBay.

Though it makes little sense to draw definitive conclusions from summary statistics, the set of hypotheses concerning seller-specific heterogeneity seems most powerful in explaining the choice of mechanism in these data. The econometric analysis exploits this fact and is discussed now.

Estimation Strategy

The outcomes of interest are the revenue, selling price, and sale dummy (equal to one for sold items) for each of the 5,009 items in the data set.

Selling Price of Unsold Items

A good's selling price is a latent variable because all items have a price (possibly negative) at which they would sell but that price is unobserved for unsold items. This empirical problem can be accounted for in one of two ways. First, I could assume that an unsold item has a true selling price strictly below its reserve price (or posted price for non-auction items); this assumption generates a censored-regression model. Second, I could assume that the true selling price is *completely* unobserved when an item does not sell and therefore use a sample-selection model of the selling price. Either assumption may be valid under alternative market environments, leading me to use the Vuong (1989) likelihood-ratio test for non-nested models to find the model that is closer to the truth. The results indicate that the sample-selection model is more appropriate (z=-64.46, p-value=1.00). As a result, I treat the selling price of unsold items as completely unobserved and use a Heckman (1979) selection model.[7]

Endogeneity of Mechanism/Website

The next econometric issue to address is the endogeneity of the seller's mechanism choice problem. There are two arguments for why the mechanism and website may be endogenous. First, sellers should form expectations of the revenue from each mechanism when deciding auction versus posted price and likewise, eBay versus Half.com. If factors that are unobserved (by the econometrician) influence the way in which sellers form these expectations, then the mechanism and website are endogenous. Second, if covariates that are unobserved by the econometrician affect the mechanism choice as well as the outcomes of interest, then endogeneity is present.

To address this problem, I use seller-specific covariates as instruments, specifically focusing on sellers' inventories. Harris and Raviv (1981) highlight the crucial role that the size of a seller's inventory plays in the choice between auctioning and posted-price selling. They show that a seller prefers to post a fixed price only when her inventory is larger than potential demand. Based on this result, the first instrument used here is inventory size, measured by the number of goods that the seller lists for sale during the sample period for those albums in the sample. The second instrument is the heterogeneity of a seller's inventory. Zeithammer and Liu (2006) show that a seller with a heterogeneous inventory prefers the auction mechanism. I measure inventory heterogeneity with a Herfindahl-type index, defined as the sum of the squares of the share of each CD in the seller's inventory. A completely homogeneous inventory would take an index value of 1, while an inventory with

[7] In addition to the econometric argument I offer, see Livingston (2005) for a theoretical argument for the appropriateness of the sample-selection model to handle the selling price of unsold items.

equal numbers of each of the 49 CDs in the sample would take an index value of 0.204.

From the theoretical insights of these two papers, we should expect inventory size and heterogeneity to be sufficiently correlated with a seller' mechanism choice. Further, Table 1 provides evidence that these two measures are systematically related to mechanism and site. The next step in establishing the appropriateness of these two instruments is to argue that they have no direct impact on the outcomes of interest. Importantly, the characteristics of a seller's inventory are not observed by buyers. Also, inventory characteristics are unlikely to be correlated with other seller characteristics that are observed and valued by buyers.

Regression Procedures

Before presenting the results, I detail the estimation technique for each outcome of interest. Each model is estimated by maximum simulated likelihood because each system of equations has two (potentially) endogenous binary regressors. Roodman (2007) details the use of the Geweke-Hajivassiliou-Keane simulator to evaluate the multivariate normal integrals in the simulated likelihood functions.

1. Revenue is a corner-solution outcome variable equal to the selling price plus shipping minus fees for sold items and the (negative of) the listing fee for unsold items. I use a censored-regression model with idiosyncratic censoring because fees (the censoring point) vary across observations.

2. The selling price plus shipping minus fees is a continuous outcome variable; I take the log because it takes only non-negative values. Section I.5.1 described the sample-selection model that deals with unsold items.

3. The probability of sale is a binary outcome variable. Cappellari and Jenkins (2003) discuss implementation of a probit maximum simulated likelihood model in Stata and document the advantages of simulation methods in similar cases.

Results

Revenue

First, I compare the expected revenue of each mechanism in Table 3. I address the potential endogeneity of the mechanism and site using instrumental variables in columns (2) and (4). Diagnostic tests lead me to reject the null of exogeneity (F=127.72; p-value=0.00).[8] The results suggest that auctioned goods earn lower revenue but the magnitudes of the differences are small. Taking column (2) as the more appropriate specification, I cannot reject revenue equivalence. Rerunning the analysis with only eBay items provides similar results. Instead of dissecting these results and those from the remaining regressors, I analyze separately the two components of revenue: selling price and probability of sale. Analyzing price and sale probability individually has several advantages over revenue alone. First, unsold items can be relisted and sold in a future period but the present formulation of revenue is static in nature. Second, the risk preferences of sellers are unobserved and setting revenue equal to price times the probability of sale arbitrarily assumes risk neutrality. The remainder of this section analyzes each component of revenue separately.

[8] The Kleibergen-Paap (2006) rank statistic rejects the null of an underidentified model (χ^2=4.53, p-value=0.03), providing some evidence that the instruments are sufficiently correlated with the endogenous variables.

Table 3. Regression Results for Revenue

	(1)	(2)	(3)	(4)
	All Items		eBay Items Only	
Control for Endogeneity?	No	Yes	No	Yes
Auction Dummy	-0.443	-0.623	-0.371	-0.270
	(0.119)**	(0.501)	(0.119)**	(0.283)
eBay Dummy	0.431	2.919		
	(0.165)**	(0.680)**		
New CD	1.473	0.815	1.320	1.354
	(0.124)**	(0.183)**	(0.138)**	(0.139)**
Log(Seller's Score)	0.226	0.180	0.231	0.236
	(0.022)**	(0.035)**	(0.026)**	(0.031)**
Seller's Rating	7.373	9.897	9.876	9.893
	(2.054)**	(2.944)**	(2.779)**	(2.759)**
Scratched CD	-1.026	-1.032	-0.922	-0.924
	(0.301)**	(0.371)**	(0.392)*	(0.397)*
No Description	-0.250	-0.449	-0.337	-0.333
	(0.158)	(0.220)*	(0.217)	(0.218)
Promotional CD	-0.681	-0.138	-0.612	-0.630
	(0.184)**	(0.203)	(0.215)**	(0.224)**
Case Damaged	-0.505	0.207	-0.801	-0.810
	(0.343)	(0.441)	(0.432)	(0.431)
Case Missing	-1.541	-1.460	-0.934	-0.928
	(0.331)**	(0.389)**	(0.396)*	(0.395)*
Observations	5,009	5,009	2,826	2,826

Notes: The dependent variable is equal to the selling price plus shipping minus fees for sold items and the (negative of) the listing fee for unsold items. Robust standard errors are in parentheses. * and ** denote significance at the 5% and 1% level, respectively. Fixed effects for each album are including in all regressions; their coefficients, along with the constant term, are suppressed.

Selling Price

Results for the selling price estimation are in Tables 4 and 5. The notes to Table 5 detail the calculation of the marginal effects. As discussed in Section I.5.1, I use a sample-selection model to correct for the bias from observing the prices of only sold items. As with revenue, diagnostic tests for endogeneity suggest that columns (2) and (4) are more appropriate (χ^2=16.91; p-value=0.00). Posted-price items sell at higher prices (conditional on selling) irrespective of controlling for endogeneity or excluding Half.com items. From column (2), auctioned items sell for prices that are, on average, $1.11 lower than posted-price items. Given a mean selling price (plus shipping minus fees) of $10.74, this translates to approximately 11% lower prices for auctioned items. Considering only eBay items, posted-price selling still outperforms the auction mechanism with an estimated price differential of $0.82, or 7% (relative to a mean price on eBay of $11.02).

Other findings indicate that eBay items fare better than those on Half.com. Intuitively, brand-new items fetch higher prices than used items. The reputation of the seller matters; both the quantity (score) and quality (rating) have the predicted relationship with a good's selling price. Certain negative item attributes result in lower prices: scratches on the surface of the disc and no description of the item's condition. Finally, CDs without a jewel case sell for lower prices but those with a damaged case do not.

Probability of Sale

Tables 6 and 7 show the regression results and marginal effects for a probit estimation of the probability of sale. Again, I reject the null of exogeneity (χ^2=169.57; p-value=0.00) but present both the exogenous and endogenous results. In columns (2) and (4), the treatment effect of auctioning on the probability of sale is positive. The effect is

Table 4. Regression Results for Selling Price

	(1)	(2)	(3)	(4)
	All Items		eBay Items Only	
Control for Endogeneity?	No	Yes	No	Yes
Auction Dummy	-0.042	-0.086	-0.032	-0.062
	(0.011)**	(0.026)**	(0.011)**	(0.010)**
eBay Dummy	0.145	0.067		
	(0.014)**	(0.024)**		
New CD	0.134	0.135	0.136	0.129
	(0.011)**	(0.011)**	(0.012)**	(0.012)**
Log(Seller's Score)	0.020	0.017	0.024	0.022
	(0.002)**	(0.002)**	(0.002)**	(0.002)**
Seller's Rating	0.786	1.107	0.895	0.885
	(0.220)**	(0.244)**	(0.290)**	(0.296)**
Scratched CD	-0.151	-0.155	-0.155	-0.139
	(0.041)**	(0.041)**	(0.051)**	(0.050)**
No Description	-0.052	-0.072	-0.043	-0.043
	(0.020)**	(0.021)**	(0.027)	(0.027)
Promotional CD	-0.011	-0.008	-0.032	-0.028
	(0.018)	(0.019)	(0.020)	(0.020)
Case Damaged	-0.021	-0.028	-0.062	-0.057
	(0.040)	(0.039)	(0.047)	(0.045)
Case Missing	-0.201	-0.211	-0.106	-0.109
	(0.046)**	(0.049)**	(0.055)	(0.054)*
Observations	5,009	5,009	2,826	2,826

Notes: The dependent variable is equal to the log of the price at which the item sold plus shipping minus all fees paid by the seller.

Table 5. Marginal Effects for Selling Price

	(1)	(2)	(3)	(4)
	All Items		eBay Items Only	
Control for Endogeneity?	No	Yes	No	Yes
Auction Dummy	-0.542	-1.105	-0.423	-0.817
	(0.141)**	(0.336)**	(0.138)**	(0.138)**
eBay Dummy	1.774	0.866		
	(0.167)**	(0.304)**		
New CD	1.654	1.700	1.679	1.647
	(0.131)**	(0.136)**	(0.149)**	(0.151)**

Notes: For all marginal effects, continuous variables (seller's score and rating) are evaluated at their sample means, discrete variables at their sample modes. This implies that the reference CD is a brand-new copy of Celtic Woman's self-titled album sold by an eBay posted-price seller with a score of 15,727.05 and a rating of 98.69%.

Table 6. Regression Results for Sale Probability

	(1)	(2)	(3)	(4)
	All Items		eBay Items Only	
Control for Endogeneity?	No	Yes	No	Yes
Auction Dummy	-0.064	0.102	0.054	1.373
	(0.070)	(0.098)	(0.072)	(0.146)**
eBay Dummy	1.513	1.628		
	(0.067)**	(0.087)**		
New CD	-0.564	-0.545	-0.419	-0.141
	(0.056)**	(0.054)**	(0.079)**	(0.080)
Log(Seller's Score)	-0.027	-0.019	0.028	0.073
	(0.010)**	(0.010)	(0.015)	(0.015)**
Seller's Rating	2.074	1.438	-0.956	-1.214
	(0.670)**	(0.741)	(1.459)	(1.332)
Scratched CD	0.007	0.019	-0.159	-0.178
	(0.162)	(0.155)	(0.252)	(0.240)
No Description	-0.103	-0.060	-0.050	-0.019
	(0.086)	(0.085)	(0.159)	(0.144)
Promotional CD	0.284	0.267	0.073	-0.088
	(0.106)**	(0.100)**	(0.138)	(0.132)
Case Damaged	0.527	0.534	0.400	0.390
	(0.263)*	(0.239)*	(0.507)	(0.446)
Case Missing	0.121	0.144	0.056	0.166
	(0.223)	(0.217)	(0.312)	(0.357)
Observations	5,009	5,009	2,826	2,826

Notes: The dependent variable is a dummy variable equal to one if the item sold.

3.5% in the entire sample and 48.5% using only eBay items. These results suggest that, while auctioned goods sell for lower prices, auctioneers are compensated with a higher probability of sale. By breaking revenue into a separate analysis of the selling price and probability of sale, I am able to understand more fully why the two mechanisms earn similar revenues.

Turning to other regressors, eBay items and used items sell with a higher probability, both of which were apparent in the aggregate statistics. The relationship between the probability of sale and the seller's reputation is less clear than with the selling price estimation. The quantity of reputation has a negative effect in the entire sample but a pos-

Table 7. Marginal Effects for Sale Probability

	(1)	(2)	(3)	(4)
	All Items		eBay Items Only	
Control for Endogeneity?	No	Yes	No	Yes
Auction Dummy	-0.023	0.035	0.009	0.485
	(0.025)	(0.034)	(0.012)	(0.051)**
eBay Dummy	0.515	0.562		
	(0.020)**	(0.029)**		
New CD	-0.192	-0.160	-0.068	-0.054
	(0.018)**	(0.018)**	(0.012)**	(0.031)

itive effect when considering only eBay items. Investigating this issue further, unreported results point toward the following relationship. Sellers yet to establish a reputation sell less often. Presumably, the initial returns to reputation are a premium for establishing a history of delivering goods of the promised condition, thereby alleviating some of the uncertainty in seller quality. Once a seller has established a reputation however, the returns to more positive feedback are severely decreasing. In the case of Half.com items, these returns are actually negative. Finally, for item-specific covariates, promotional items and items with damaged cases sell more frequently but these results are likely due to the fact that these items being offered with lower reserve/posted prices.

Explanations and Future Directions

In these data, posted-price goods sell for higher prices than auctioned goods, yet auctioned goods are more likely to sell. Taken together, the revenues of the two mechanisms cannot be statistically distinguished from one another. To understand these results, it is necessary to understand what factors lead a seller to choose an auction versus the posted-price mechanism. In this section, I test between three hypotheses concerning sellers' mechanism choices: (1) the size of a seller's inventory, (2) the heterogeneity of a seller's inventory, and (3) buyer impatience.

The importance of a seller's inventory is shown by Harris and Raviv (1981) and Zeithammer and Liu (2006). To see why buyer impatience may be related to the posted-price premium, recall that a listing ends immediately when a willing buyer purchases a posted-price good, while a bidder must wait for an auctioned good to end, no matter how high the bid. Given this, one might expect that some buyers are willing to pay a premium for a posted-price good in order to receive the good more quickly. I proxy for buyer impatience with the release year of the album, arguing that buyers of recently-released albums should exhibit more impatience than buyers of older albums.

I test between these hypotheses by estimating a probit model with a dependent variable equal to one if the seller listed their item in an auction, zero if the seller listed their item at a posted price. The results are in Table 8 and provide the most support for the inventory-size hypothesis. Specifically, sellers with large inventories are more likely to post a fixed price. In contrast to the inventory-heterogeneity hypothesis, I find that sellers with heterogeneous inventories are *less* likely to use the auction mechanism. Using the sample of only eBay items however, sellers with more heterogeneous inventories are no more or less likely to sell in an auction. In contrast to the buyer-impatience hypothesis, the regression suggests that recently-released albums are *more* likely to be auctioned in the entire sample. There is support for the claim that sellers facing impatient buyers are more likely to sell in an auction using only eBay items however.

These results suggest that the coexistence of the auction and posted-price markets that I find can be rationalized by the size of a seller's inventory. In particular, sellers with large inventories are more likely to post a fixed price. I do not find that sellers with

Table 8. Regression Results for Mechanism Choice

	(1) All Items	(2) eBay Items Only
Seller's Inventory Size	-0.008	-0.012
	(0.002)**	(0.003)**
Seller's Inventory Homogeneity	0.722	-0.035
	(0.077)**	(0.113)
Recently-Released Album	0.522	-0.517
	(0.113)**	(0.186)**
New CD	-0.167	-0.571
	(0.049)**	(0.069)**
Log(Seller's Score)	0.001	-0.094
	(0.011)	(0.015)**
Seller's Rating	3.410	0.682
	(0.838)**	(0.969)
Scratched CD	-0.047	0.540
	(0.140)	(0.333)
No Description	-0.387	-0.048
	(0.078)**	(0.138)
Promotional CD	0.122	0.418
	(0.087)	(0.130)**
Case Damaged	-0.210	0.035
	(0.202)	(0.302)
Case Missing	-0.154	-0.207
	(0.192)	(0.341)
Observations	5,009	2,826

Notes: The dependent variable is a dummy variable equal to one if the item was listed for sale in an auction.

heterogeneous inventories are more likely to sell in an auction. I also do not find consistent evidence that recently-released albums are more likely to sell at a posted price but there is some support for the buyer-impatience hypothesis in the sample of only eBay items. These results confirm the insights of Harris and Raviv (1981) and suggest that sellers think carefully about their capacity constraints when selling goods in an environment, such as an online marketplace, that features both the auction and posted-price mechanisms.

Appendix - Regressors

Define the following four variables: Y_1^* = Selling Price (plus shipping minus fees), Y_2 = Sale Dummy (equal to one if the item sold), Y_3 = Auction Dummy (equal to one for auctioned items), and finally Y_4 = eBay Dummy (equal to one if the item was listed at eBay). X_1 and X_2 are vectors of covariates believed to influence the selling price and probability of sale, respectively. Consider the following specification:

$$Y_1^* = X_1\beta_1 + \gamma_1 Y_3 + \gamma_2 Y_4 + \varepsilon_1$$

$$Y_1 = Y_1^* \quad if \; Y_2 = 1$$

$$Y_2 = 1(X_2\beta_2 + \gamma_3 Y_3 + \gamma_4 Y_4 + \varepsilon_2 > 0)$$

$$Y_3 = 1(X\beta_3 + \varepsilon_3 > 0)$$

$$Y_4 = 1(X\beta_4 + \varepsilon_4 > 0)$$

where $1(\cdot)$ is the indicator function. The key parameters of interest measure the treatment effect of auctioning on the selling price (γ_1) and probability of sale (γ_3). The regressors in X_1 and X_2 control for seller-specific and item-specific heterogeneity.

X_1: **Seller Reputation:**

eBay and Half.com share a common feedback system, which serves as a reputation mechanism. Following completion of a transaction, both the buyer and the seller have the opportunity to leave a feedback report the other party (with reports being positive, neutral, or negative). A user receiving feedback for a transaction on one site has it combined with her total feedback, which includes all transactions from both sites. I measure reputation with the following two variables:

- *Log(Seller's Score)* - the log of the seller's feedback score plus one. The score is defined by eBay as the number of positive feedback reports minus the number of negative reports.

- *Seller's Rating* - the number of positive reports divided by the total number of reports.

X_1: **Item-Specific Characteristics:**

- *New Item* - item is still sealed in the original packaging.

- *Scratched* - the surface of the CD is scratched, scuffed, or marked in some way.

- *No Description* - item listed without description of its condition.

- *Promotional* - item is not a retail version of the album. Promotional copies are sent to media outlets by the record label for review purposes prior to the released of the album.

- *Case Damaged* - jewel case is cracked or otherwise damaged.

- *Case Missing* - jewel case is missing (only the disc is being offered for sale).

- *Compact Disc* - fixed effects for each album in the sample.

X_2 includes all of the covariates in X_1 in addition to the following:

- *Start Price* - the minimum bid (for auctions) or the posted price at which unsold items did not sell (for posted-price goods). This is included in the Heckman selection equation (as an exclusive restriction to identify the selection bias) but not in the sale probability estimation.

X includes all of the covariates in X_1 in addition to the following:

- *Seller's Inventory Size* - number of albums in the sample that the seller lists for sale during the sample period. The sample is split at its median into large inventories (greater than or equal to three goods) and small inventories (less than three goods).

- *Seller's Inventory Homogeneity* - fraction of a seller's inventory that is a different album than the album of the current item. Inventories are categorizes as homogeneous (all goods are for the same album) or heterogeneous (more than one album is represented).

Additional Variable

- *Album Release Year* - calendar year in which the album was released. Albums are categorized as recently released when released since 2005 but the results are checked with the alternative definition of released since 2004.

CHAPTER II

A Structural Model of Competing Sellers: Auctions and Posted Prices

In an original data set of goods listed for sale online, I observe that multiple selling mechanisms are popular with buyers and sellers in the compact-disc market. I construct a model to explain how heterogeneous sellers choose between selling in an auction and posting a fixed price. An important contribution of this work is that I model competing sellers instead of a monopolist. In doing so, I show that accounting for the competitive structure of the marketplace is vital in explaining the coexistence of mechanisms. In the model, the value of each seller's outside option is identified using an optimality condition from the seller's pricing problem. The main result of the paper is that sellers with more valuable outside options choose to post a fixed price. On the demand side, my approach for estimating the unobserved number of potential buyers compares favorably to an approach that assumes there are infinitely many buyers. The findings are consistent with a highly competitive market that is more closely approximated by perfect competition than monopoly.

Introduction

Why do we observe goods offered for sale simultaneously using different selling mechanisms? In an original data set of online compact disc sales, I observe some sellers auctioning their goods and other sellers choosing to post a fixed price. Numerous papers in the mechanism-design literature show that a seller earns higher expected revenue when selling in an auction. In fact, one can more easily list the papers that do not find the auction to be optimal; I review several such papers in the next section. Given the wealth of theoretical evidence in favor of the auction mechanism, it is puzzling why any seller with the option to sell in an auction would post a fixed price.

I approach the apparent puzzle of mechanism coexistence in the context of a structural model of competing sellers and find that seller heterogeneity explains the structure of this market. Specifically, sellers with more valuable outside options choose to post a fixed price. This result contrasts with explanations of mechanism coexistence that are based on differences across buyers. Two such explanations do not hold in these data: (1) the posted-price mechanism does not attract more buyers than the auction mechanism and (2) posted-price buyers do not have higher values.

An alternative approach in explaining coexistence is to show that, within the context of a particular model, a monopolist prefers an auction under certain conditions and the posted-price mechanism under other conditions. The conclusion one might draw is that the coexistence of mechanisms in a competitive environment can be explained by some sellers meeting the conditions that make auctions optimal and other sellers meeting the conditions that make posted-price selling optimal. While such an exercise is useful in pointing out the relative merits of each mechanism, it is not always clear how the insights from monopoly models extend to a competitive environment.

Given that I consider competing sellers, it is increasingly difficult to answer the question of coexistence without first developing a theoretical framework. Accordingly, I develop a new structural model where sellers enter either the auction or posted-price mechanism. The structural approach has become increasingly common in the empirical analysis of auction data, beginning with Paarsch (1992) and first used in the context of online auctions by Bajari and Hortasu (2003). In my setting, a structural model is especially useful in isolating the determinants of coexistence because of the increased strategic interactions that are present when considering multiple sellers.

Several features of the online music compact-disc (CD) market motivate the theoretical model. First, this market is likely to be competitive, if only due to the fact that these goods are available at a number of retail outlets, such as Wal-Mart or Circuit City. Second, the ratio of potential buyers to sellers is lower than in many other markets on eBay. If the number of potential buyers per seller is large, it may be appropriate to ignore the strategic interactions between sellers. However, when sellers compete for a relatively small pool of buyers, it is essential to account for the competitive structure of the marketplace. Third, it is likely that the demand for CDs is driven by idiosyncratic tastes and preferences, consistent with an independent-private-values model in which buyers' values are i.i.d. random variables. I introduce the model after discussing related papers from the literature.

Monopoly Comparisons Between Mechanisms

In a number of different settings, a seller maximizes her expected revenue by offering an auction. Under different assumptions however, an auction is no longer optimal and can be inferior to other common mechanisms such as posted-price selling. In particular, posting a fixed price is optimal if the monopolist's capacity exceeds potential demand (Harris and Raviv 1981), while the posted price mechanism revenue dominates auctions (but is not itself optimal) when buyers' values are highly interdependent (Campbell and Levin 2006). Wang (1993) argues that a monopolist prefers posted-price selling when buyers' values are not too dispersed. In his model, an auction costs the seller a marginal cost (for storage) and a fixed cost incurred once per auction, while the posted-price mechanism costs the seller only a marginal cost (for displaying). Building on Wang's model, Zeithammer and Liu (2006) show that a monopolist with a homogeneous inventory is more likely to post a fixed price.

Competing Mechanism Designers

While the monopoly assumption is common in the study of mechanism design, several papers consider multiple sellers who compete for a fixed pool of buyers. The literature on competing mechanism designers shows that, as was seen in the context of a monopolist, the auction mechanism revenue dominates the posted-price mechanism in many settings. McAfee (1993) finds that when sellers can offer any direct mechanism (see Myerson (1981) for a definition), auctions are optimal. Peters (1997) extends this result to sellers with heterogeneous values. Like McAfee (1993) and Peters (1997), I assume that a buyer knows his value when choosing between sellers. In contrast, other papers assume that a buyer does not know his value when choosing between sellers. Of these, Damianov (2008) finds that equilibrium mechanisms are payoff equivalent to second-price auctions, while Peters (1994) finds that the posted-price mechanism is optimal in a model where sellers communicate with buyers sequentially.

Coexistence

Ellison et al. (2004) address the issue of coexistence in the context of competing auction houses instead of competing auctioneers. The authors show that, while two auction houses can coexist, a monopolistic auction house is always an equilibrium. Another set of related papers consider directed search, where all buyers are homogeneous and all sellers are homogeneous. In Coles and Eeckhout (2003), there exists a continuum of equilibria that do not uniquely tie down the payoffs to buyers and sellers. The all posted-price equilibrium and the all auction equilibrium both exist, though sellers prefer the latter. In a model with two buyers and two sellers, Julien et al. (2001) find that whether coexistence is an equilibrium depends on the model's timing assumptions. Specifically, when sellers choose mechanisms first and prices second, only the auction-auction equilibrium is subgame perfect. Coexistence is an equilibrium when mechanisms and prices are chosen simultaneously.

The Timing of Moves

Buyers are subscripted by $i \in [1, ..., N]$, sellers by $j \in [1, ..., M]$, and mechanisms by $k \in \{A, P\}$.[1] Let $N = N_A + N_P$ and $M = M_A + M_P$. The timing is as follows:

Stage 0 Sellers observe their costs for each mechanism and the value of their outside option.

Stage 1 Buyers and sellers simultaneously enter either the auction or posted-price market.

Stage 2 Sellers simultaneously set prices.

Stage 3 All players observe the number of buyers and sellers who entered each mechanism as well as the prices and characteristics of all sellers. Buyers observe their values.

Stage 4 Buyers simultaneously choose between the sellers in their chosen mechanism and all players observe the number of buyers who chose each seller.

Stage 5 Buyers choose an action and each mechanism proceeds according to its rules.

I assume that all market participants are risk neutral. All decisions (choice of mechanism, choice of seller, etc.) are irreversible and I consider a one-shot game where unfulfilled demand remains unfulfilled and all sellers who do not sell retain their good.

Sellers

M sellers are endowed with a single, indivisible unit of a good that can be sold in an auction or at a posted price. I focus on a second-price auction, where the buyer submitting

[1] I use the terminology buyers and sellers though some buyers may not purchase a good and some sellers' goods may not sell. In the auction literature, my notion of buyers corresponds to potential bidders.

the highest bid obtains the good at a price equal to the maximum of the (public) reserve price and the second-highest bid. In the initial discussion, I abstract from several details of an eBay-style auction; these are discussed in Section II.3. If the seller posts a fixed price, the good is sold to a willing buyer at the posted price. Buyers in the posted-price mechanism indicate their willingness to purchase at the posted price simultaneously. If multiple buyers indicate a willingness to buy a posted-price seller's good, I assume that the seller chooses each with an equal probability.

I use a random-utility-maximization model to analyze the sellers' mechanism-choice problem. In these models, agents have heterogeneous preferences over a discrete set of choices. Preferences consist of a systematic component and a random component, both of which are observed by the agent. An outside observer, however, never observes the random component, implying that utility is random from the perspective of the econometrician (McFadden 1974; Manski 1977). In my setting, sellers choose between the auction and posted-price mechanisms by comparing their expected profit from each, where the profit of seller j in mechanism k is π_{jk}. The systematic component of π_{jk} is the expected revenue from each mechanism, $E(Rev_{jk})$, which includes v^0_{jk}, their payoff from an unsold good. I refer to v^0_{jk} as the value of the seller's outside option. It could be her personal consumption value or the value of selling in another market. Under risk neutrality, $E(Rev_{jk}) = \Pr(Sale_{jk}) \cdot E(Price_{jk}) + (1 - \Pr(Sale_{jk})) \cdot v^0_{jk}$.

The random component of profits takes the form of an additive, mechanism-specific shock, ω_{jk}. The shocks are each seller's private information and are unobserved by the econometrician. There are numerous reasons why a seller may have idiosyncratic preferences for a mechanism outside of its price or probability of sale. The introduction outlined a number of papers that provide conditions under which an auction revenue dominates the posted-price mechanism. Papers that compare mechanisms in a monopoly framework indicate that, if sellers are heterogeneous along one of several dimensions, different sellers may prefer different mechanisms. Sellers may have heterogeneous inventories (Harris and Raviv 1981; Zeithammer and Liu 2006); degrees of impatience (Ziegler and Lazear 2003); or degrees of risk aversion (Mathews and Katzman 2006).

To fix ideas, I focus on a single explanation (outside of expected revenue concerns) for why sellers have idiosyncratic preferences over mechanisms. Namely, I assume that the auction and posted-price mechanisms entail different costs for different sellers.[2] If I define ω_{jk} as seller j's cost of selling in mechanism k, the seller's expected profit from each mechanism is: $\pi_{jk} = E(Rev_{jk}) - \omega_{jk}$. Using this, define π_j as the seller's net expected profit from offering an auction and assume the ω_{jk}'s are i.i.d. draws from a distribution with cdf $G_k(\cdot)$: $\pi_j = E(Rev_{jA}) - E(Rev_{jP}) - \omega_j$, where $\omega_j = \omega_{jA} - \omega_{jP}$. Under my interpretation of the random component of sellers' profits, ω_j is how much more costly it is for seller j to sell in an auction rather than at a posted price. The ω_{jk} terms could then be the cost of finding the optimal price for a given mechanism. Because setting a reserve price is quite different from setting a posted price, it seems reasonable that these costs are heterogeneous across sellers. Within this structure, I can generate any outcome in the sellers' mechanism-choice subgame including all sellers auctioning, all sellers posting a fixed price, and most importantly, the coexistence of mechanisms.

If the factors mentioned above play a role in the mechanism-choice problem, they can be captured by the ω_{jk} terms as well. In the case of risk aversion, the cost terms can be interpreted as a risk premium. In the case of impatience, they can be interpreted as the cost of waiting for an auction to end (since posted-price listings end immediately upon purchase).

[2] It is useful to highlight the distinction between a seller's outside option and her cost. The value of a seller's outside option is her payoff if the item does not sell, while a seller's cost is the amount incurred upon entering a particular mechanism, irrespective of whether the good sells.

If either was the sole reason why different sellers entered different mechanisms, then the correct approach would be to model sellers as heterogeneous in either their coefficients of risk aversion or their discount rates. The model could then be used to find the value of these parameters such that all seller more risk averse or more impatient than the cutoff value posted a fixed price. My view, however, is that the data available from eBay are not sufficient to distinguish between the numerous competing explanations. As a result, I model all factors outside of expected revenue concerns in an additive, mechanism-specific shock and refer to these shocks as costs.

Buyers

Buyers' Mechanism Choice

N buyers each demand at most one unit to be purchased in an auction or at a posted price.[3] Buyers who do not purchase receive a payoff that is normalized to zero. Buyers enter mechanisms before observing their values or the numbers of buyers and sellers who entered each mechanism. Define $F_k(\cdot)$ as the distribution of the values of buyers in mechanism k; $f_k(\cdot)$ its corresponding density; $\rho_B \in [0,1]$ and $\rho_S \in [0,1]$ as the share of buyers and sellers, respectively, who enter the auction mechanism; and $q_{jk} \in [0,1]$ as the share of buyers in mechanism k who choose seller j.[4]

Expected utility for a buyer who enters the auction mechanism is $E(U_A) =$

[3] In the data, 3.8% of goods were purchased by a buyer who I observe purchasing another unit. I ignore the possibility of multi-unit demand throughout because the assumption of unit demand seems appropriate for CDs. Buyers who demand multiple units can be thought of as drawing multiple, independent values.

[4] The word "share" implies that participants use pure strategies but buyers use a mixed strategy when entering a mechanism. Accordingly, ρ_B is the symmetric probability with which buyers enter the auction mechanism.

$\sum_{j=1}^{M_A} (q_{jA} \cdot E(U_{jA}))$. Expected utility from a given auctioneer j is:

$$E(U_{jA}) = \sum_{N_A=1}^{N} \binom{N}{N_A} \rho_B^{N_A} (1-\rho_B)^{N-N_A} \sum_{n_j-1=0}^{N_A-1} \binom{N_A-1}{n_j-1} q_{jA}^{n_j-1} (1-q_{jA})^{N_A-n_j}$$
$$\cdot \left(\int_{r_j}^{\infty} (1-F_A(v)) F_A(v)^{n_j-1} dv\right).$$

The summation over N_A governs the number of buyers who enter the auction mechanism, while the summation over $n_j - 1$ governs the number of buyers who choose auctioneer j (other than buyer i, from whose point of view the expected utility is taken). Similarly:

$$E(U_{jP}) = \sum_{N_P=1}^{N} \binom{N}{N_P} (1-\rho_B)^{N_P} \rho_B{}^{N-N_P} \sum_{n_j-1=0}^{N_P-1} \binom{N_P-1}{n_j-1} q_{jP}^{n_j-1} (1-q_{jP})^{N_P-n_j}$$
$$\cdot \frac{1}{n_j} \left(\int_{p_j}^{\infty} v f_P(v) dv - (1-F_P(p_j)) p_j\right).$$

Buyers' Choice Among Sellers

Having entered mechanism k, buyers observe the number of buyers and sellers in each mechanism along with the prices and characteristics of all sellers. Each buyer chooses the seller in mechanism k who offers him the highest utility, where utility has a systematic component and a random component. Prior to choosing between sellers, buyers observe both components of their utility function, while the econometrician never observes the random component. The utility function of buyer i who chooses seller j in mechanism k has the following components: the utility from seller j's good, v_{ijk}; the utility from a good with certain observable characteristics, X_j; and the disutility from the expected payment, τ_{jk}, to seller j. That is, $U_{ijk} = v_{ijk} + X_j \theta_k - \tau_{jk}$. The idiosyncratic value, v_{ijk}, is a match-specific scalar, drawn from $F_k(\cdot)$. X_j is of dimension $1 \times h$, while θ_k is an $h \times 1$

vector of parameters that governs how buyers value the observable covariates.

To complete the parameterization of the model, I need to handle the expected payment, τ_{jk}, which (under risk neutrality) is the product of the expected probability of receiving seller j's good and the expected price. Consider each mechanism in turn. For the posted-price mechanism, the story is similar to the typical discrete-choice framework (McFadden 1974) but there is an important difference. In my setting, a buyer who selects posted-price seller j may be one of several buyers who selected this seller. Since the seller has only one good, buyers who choose between sellers must not only consider the price but also the probability with which they expect to obtain the good. Instead of fully modeling how buyers form these expectations, I take a reduced-form approach and posit that buyers view the expected payment as a simple function of the posted price: $\tau_{jP} = p_j \alpha_P$. For the auction mechanism, I assume that buyers take the expected auction payment to be a simple function of its clearest available signal, the reserve price: $\tau_{jA} = r_j \alpha_A$.

As is common (e.g., Berry (1994)), buyers have an outside option, labeled seller 0, from whom they receive $U_{i0k} = v_{i0k}$.[5] Buyers draw a value for the outside seller from the same distribution that they draw values for the inside sellers. The remaining components of the utility that buyer i receives from seller 0 are normalized to zero, implying that the X_j and τ_{jk} components for the inside sellers should be viewed as differences between seller j and the outside seller.

Trade

After choosing a particular seller, buyers consider their consumption value from the good, V_{ijk}, when formulating a strategy. In particular, buyers choose an action (what

[5] Buying from the outside seller can be thought of as exiting the market after choosing a particular mechanism. This may occur when a buyer's value is below the lowest (reserve or posted) price.

to bid in an auction; whether or not to buy in the posted-price mechanism) based on the following specification: $V_{ijk} = v_{ijk} + Z_j\beta_k$. Before proceeding, I make two notational points. First, while observable characteristics enter the value specification as they entered the utility function, I use $Z_j\beta_k$ in the value specification to allow for the possibility that different characteristics influence a buyer's utility (i.e., his choice of seller) than influence a buyer's value (i.e., his bid/buy strategy). Second, I refer to V_{ijk} as a buyer's consumption value and v_{ijk} as a buyer's idiosyncratic value. Since sellers are endowed with one unit of a good with given characteristics, the seller cares about the distribution of V_{ijk} because this is the distribution that enters the expression for the expected revenue. In particular, in the auction case, a buyer who is said to bid truthfully (as buyers do in the equilibrium of second-price auctions) bids V_{ijA}.

Because the choices of mechanism and seller are irreversible, buyers formulated their strategies in the trade stage in a similar way to buyers who face a monopolist.[6] I discuss the remaining details regarding buyers' strategies after introducing the details of an eBay-style auction, as these rules determine the modeling and estimation approach that I use.

Compact Disc Sales on eBay

On eBay, sellers choose two prices: a (public) reserve price and a Buy-it-Now (BIN) price.[7] The reserve price is also known as the minimum bid; bids below this price are not accepted. The BIN price allows buyers the opportunity to circumvent the auction

[6] In contrast, Lee and Malmendier (2008) assume that losing bidders can purchase immediately at the posted price, implying an upper bound on rational bids. Their empirical results, however, indicate that buyers do bid above the prevailing posted price in what they deem "over-bidding."

[7] I ignore secret reserve price because they are rarely used by the sellers in this market.

process and win the good immediately. If the BIN price is set to infinity, the mechanism is said to be an auction. If the BIN price is set equal to the reserve price, the mechanism is said to be a posted price. Sellers may also set a finite BIN price that is above the reserve price, in what is known as a BIN auction. To maintain focus on common mechanisms that are available in a variety of on and offline settings, I ignore BIN auctions and consider only pure auctions and pure posted prices.[8] All prices are inclusive of shipping, which is set by the seller and ranges from \$0 to \$16 in these data.[9]

Buyers who search for a particular good can view all open listings in either mechanism. The number of days that items are listed is chosen by the seller to be either $1, 3, 5, 7$, or 10 days and buyers can place a bid or accept the posted price at any point before the listing closes. The rules of an eBay auction resemble those of a second-price, ascending (English) auction. The buyer placing the highest bid obtains the good at the price equal to the maximum of the reserve price and the second-highest bid. eBay uses proxy bidding, where the computer accepts a buyer's bid and incrementally raises the standing bid such that it is equal to the second-highest of the bids already placed. The buyer placing the highest of the bids already placed is listed as the current high bidder. If a seller chooses to sell at a posted price (i.e., sets the BIN price equal to the reserve price), the listing closes and the good is sold to the first buyer who selects the "Buy-It-Now" option. If a listing closes without attracting a buyer, the good is unsold and is retained by the seller.

The sample from the current paper contains 21 albums. These albums were drawn from a larger sample used in previous work. The albums in the older sample were randomly

[8]BIN auctions are analyzed in Ackerberg et al. (2006), Anderson et al. (2004), and Zeithammer and Liu (2006).

[9]The script that collected the data reported shipping as missing in 826 cases (12.6% of all auction observations and 9.7% of all posted-price observations). I impute shipping for these observations with the Stata package *ice*. Imputation is preferred to the alternatives such as mean-plugging or casewise deletion (Little and Rubin 2002). The imputation model is available upon request.

Table 9. Number of Goods

Condition	Auction Market	Posted-Price Market	All
New	3,788	1,703	5,491
Used	1,106	302	1,408
All	4,894	2,005	6,899

Notes: The number of goods listed for sale in each market is shown by condition of the good. I drop 163 observations that correspond to $\{CD, week, condition\}$ groups for which either the auction or posted-price market was inactive (i.e., $M_k = 0$).

selected, half of which were restricted to being recently released. The current sample uses only those albums listed more than 100 times in the older data set. I collected all listings for these 21 albums from February 5 to March 22, 2006. See Table 9 for a breakdown of the number of goods across mechanisms and condition of the good (new or used). For sellers, I model the eBay market as being generated from M sellers each offering one good for sale. In actuality, the data set contains $6,899$ goods sold by $1,859$ sellers. I ignore this distinction and assume that the observations of multiple-listing sellers are independent.[10]

For buyers, the biggest complication with the observed data is that the number of potential buyers who enter either mechanism is unobserved. In an eBay auction, the difficulty in observing the number of potential buyers is due to the truncation problem discussed in Song (2004). As she describes, the number of buyers who bid on a particular auction is only a lower bound on the number of buyers who chose that seller because only bids above the current standing bid are accepted. This implies a truncation of bidders whose bids would have been placed but were not because the standing bid was above their

[10] An important next step is to consider the intermediate case between the common approach of one seller with M goods and my approach of M sellers each with one good. Moldovanu et al. (2007) model competing sellers with endogenously-determined capacities but their sellers may only sell in an auction.

willingness-to-pay at the time they attempted to bid. For the posted-price mechanism, it is extremely common for the researcher not to observe the number of potential buyers because data from posted-price markets almost always shows in which mechanisms buyers are *purchasing,* not in which mechanisms buyers are *entering.* I discuss my approach for estimating N_A and N_P in Section II.4.2.1.

I group observations into $\{CD, week, condition, mechanism\}$ tuples. In doing so, I argue that a buyer makes his purchase decision by considering all sellers who have listed a given CD of a given condition in a given week. Any time frame chosen is somewhat arbitrary but the results are robust to alternative time frames and it seems reasonable that buyers may "shop around" for one week. Concerning the condition of the good, new or used, I argue that there are separate populations of buyers for new and used goods. It is more likely that some buyers of new goods may consider buying a used good and vice versa. Without knowing these preferences however, it is unclear what fraction of buyers would have been willing to purchase a good of the other condition. I now introduce the estimation strategy.

A Structural Model

Sellers

Sellers' Mechanism Choice

Define A_j as a dummy variable equal to one if seller j offers an auction and equal to zero if seller j posts a fixed price. The econometric specification is:

$$\Pr(A_j = 1) = \Pr(E(Rev_{jA}) - E(Rev_{jP}) - \omega_j > 0).$$

This is standard for the most part but my objective is different than the usual case. I am not interested in the effect of some vector of covariates on the outcome variable, A_j. Instead, since costs are unobserved by the econometrician, I use the above equation to infer sellers' costs from their mechanism choices. Specifically, I assume that, conditional on $E(Rev_A)$ and $E(Rev_P)$, ω_{jk} follows a Gumbel distribution, $G_k(\cdot)$.[11] I assume that the two cost distributions have the same scale, σ, but different location parameters, μ_k. As a result, $\omega_j = \omega_{jA} - \omega_{jP}$ follows a logistic distribution with parameters $\mu = \mu_A - \mu_P$ and σ:

$$\Pr(A_j = 1) = \Pr\left(\frac{\omega_j - \mu}{\sigma} < \frac{E(Rev_{jA}) - E(Rev_{jP}) - \mu}{\sigma}\right). \tag{II.1}$$

Using the formulations for the expected revenues (found in Appendix II.7), I construct a new variable equal to $E(Rev_{jA}) - E(Rev_{jP})$. I can then estimate the parameters μ and σ in a logit maximum-likelihood regression of A_j (the auction dummy for seller j) on $E(Rev_{jA}) - E(Rev_{jP})$, which is now data. The scale parameter for each cost distribution, $G_k(\cdot)$, is σ and the difference between the two location parameters is $\mu = \mu_A - \mu_P$. While

[11] A random variable x that follows a Gumbel distribution with parameters μ (location) and σ (scale) has cdf $F(x) = \exp(-\exp(-\frac{x-\mu}{\sigma}))$ and pdf $f(x) = \frac{1}{\sigma}\exp(-\frac{x-\mu}{\sigma})\exp(-\exp(-\frac{x-\mu}{\sigma}))$. The Gumbel distribution is also known as the extreme value type I distribution or the double exponential distribution.

the individual location parameters, μ_A and μ_P, are not identified, μ indicates how the centers of the two distributions differ.[12] The parameter μ is meaningful because the difference between ω_{jA} and ω_{jP} determines which mechanism a seller enters. The magnitude of the ω_{jk} terms only affects whether the seller enters one of the mechanisms or exits the market, and my data are limited to those sellers who entered a mechanism. Finally, it is worth pointing out the simplicity of this estimation approach as the structural parameters can be recovered in a simple, univariate logit regression.

Pricing

Based on my timing assumptions, sellers do not observe the number of buyers or other sellers in each mechanism before pricing but are aware of their costs and outside options. Given the nature of the costs in this paper, they are irrelevant (i.e., sunk) when sellers are selecting a price. The value of the seller's outside option, however, does matter. This highlights the distinction pointed out in footnote 2 between the two concepts. If sellers set the optimal price by maximizing the expected revenue of their chosen mechanism (equation (A1) or (A2) in Appendix II.7), I can infer each seller's outside option from her pricing decision. This implies that the distribution of outside options, $H\left(v^0\right)$, is identified without any assumption on its parametric form.

There are two ways to measure the intensity of price competition in this model: using the estimates of α_k or using prices. (Recall that α_k is the coefficient on the (reserve or posted) price in a buyer's utility function.) If $\alpha_k = 0$, then prices have no influence on the way in which buyers select sellers. Inferring competitiveness from the α_k terms is advantageous because it does not require strong assumptions on sellers' pricing behav-

[12] The mode of a Gumbel distribution is μ. The mean is $\mu + 0.57721\sigma$, where 0.57721 is the Euler constant.

ior. Alternatively, I can measure competitiveness directly from prices. For the auction, Appendix II.7 shows that seller j's price will lie in the interval $[v_{jA}^0, r_j^M]$, where r_j^M solves $r_j^M = v_{jA}^0 + \frac{1-F_A(r_j^M)}{f_A(r_j^M)}$ and is seller j's optimal reserve price when $\alpha_A = 0$. I construct a Lerner-type index equal to $\frac{r_j - v_{jA}^0}{r_j}$, interpreted as the mark-up that a seller charges above her outside option. For the posted-price mechanism, seller j will never post a price below v_{jP}^0 but there is no upper bound analogous to the auction case, as described in Appendix II.7. I measure the intensity of posted-price competition with $\frac{p_j - v_{jP}^0}{p_j}$.

Buyers

Buyers' Mechanism Choice

As described in Section II.3, the number of buyers who entered each mechanism is unobserved. Here I outline my approach for overcoming this problem in order to identify ρ_B, the rate at which buyers mix between mechanisms.[13] For the auction market, I set N_A equal to the number of buyers who placed any bid in any seller's auction. This approximation will be quite good when bidding costs are low (as they should be in an online setting) and some sellers set a low reserve price (which would allow a buyer with a low value to place a bid before the standing bid exceeds it). The grouping described in Section II.3 implies that I estimate N_A separately for each $\{CD, week, condition\}$.

Buyers enter the mechanism offering highest expected utility but do so before observing their values. As a result, the two mechanisms can coexist only when they offer buyers the same expected utility. This result is useful because it allows me to overcome the common problem of not observing the number of buyers in a posted-price market.[14] If

[13] In Appendix II.8.3, I estimate an alternative model with an infinite number of buyers in each mechanism. The results indicate that my approach for estimating N_k provides a better fit for these data.

[14] Other solutions to this problem seem less appropriate in my case. Berry et al. (1995), for example,

both mechanisms are active in equilibrium, the following equality must hold, where $F_k(\cdot)$ is the distribution of buyers' consumption values:

$$\sum_{n-1=0}^{N_A-1}\binom{N_A-1}{n-1}(\frac{1}{M_A})^{n-1}(1-\frac{1}{M_A})^{N_A-n}\cdot(\int_{\bar{r}}^{\infty}(1-F_A(v))F_A(v)^{n-1}dv)$$
$$=\sum_{n-1=0}^{N_P-1}\binom{N_P-1}{n-1}(\frac{1}{M_P})^{n-1}(1-\frac{1}{M_P})^{N_P-n}\cdot\frac{1}{n}(\int_{\bar{p}}^{\infty}vf_P(v)dv-(1-F_P(\bar{p}))\bar{p}). \tag{II.2}$$

Note that these differ from the expected utility terms outlined in Section II.2.2.1 in three ways. First, I use the realized number of buyers who entered each mechanism instead of the distributions of N_A and N_P. In essence, this is assuming that there is no aggregate uncertainty. This means that, although buyers mix between mechanisms simultaneously, buyers expect that the number of buyers in a mechanism will be equal to its average value (i.e., $N_A = \rho_B \cdot N$ and $N_P = (1-\rho_B)\cdot N$). Second, buyers assume they will pay the mean price in their chosen mechanism, $\bar{r}$ or $\bar{p}$, when they should take the expectation of the decision rule ($r(v^0)$ or $p(v^0)$) with respect to v^0. This is again assuming that there is no aggregate uncertainty. Third, I impose that, when buyers forecast their expected utility, they expect all buyers to choose each seller with an equal probability (i.e., $q_k = \frac{1}{M_k}$). This follows from the fact that each seller is expected to charge the mean price, $\bar{r}$ or $\bar{p}$. Under these restrictions, equation (II.2) uniquely identifies N_P.[15]

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assume that the number of buyers of automobiles is equal to the number of households in the United States.

[15]More precisely, equation (II.2) uniquely identifies N_P once the distribution $F_P(V)$ is known but N_P is needed to recover $F_P(V)$. I use priors for the distribution's parameters, γ_P and δ_P, to solve for $\hat{N}_P$, use this $\hat{N}_P$ to solve for $\hat{\gamma}_P$ and $\hat{\delta}_P$, and iterate the process until it converges.

Buyers' Choice Among Sellers

After entering a particular mechanism, buyer i observes all components of his utility function ($U_{ijk} = v_{ijk} + X_j\theta_k - \tau_{jk}$) and chooses the seller offering the highest utility. Buyers draw their idiosyncratic values, v_{ijk}, conditional on X_j and τ_{jk}, from $F_k^v(v)$, where I use $F_k^v(\cdot)$ instead of the more precise $F_k^v(\cdot|X,\tau)$. The distributional assumption for buyers' values plays a critical role in any parametric estimation of market data because it determines what fraction of the buyers have a willingness-to-pay at or below a particular price. Here though, the parametric form of $F_k^v(\cdot)$ plays a dual role in that it also determines the structure of the shares, q_{jk}.

Given that the v_{ijk}'s follow a Gumbel distribution, the share of buyers who choose seller j has a multinomial-logit form:

$$q_{jk} = \frac{\exp(X_j\theta_k - \tau_{jk})}{1 + \sum_{l=1}^{M_k} \exp(X_l\theta_k - \tau_{lk})}, \tag{II.3}$$

where $\tau_{jA} = r_j\alpha_A$ and $\tau_{jP} = p_j\alpha_P$. The outside seller's share is:

$$q_{0k} = \frac{1}{1 + \sum_{l=1}^{M_k} \exp(X_l\theta_k - \tau_{lk})}.$$

This makes it clear that the probabilities sum to one, $\sum_{j=0}^{M_k} q_{jk} = 1$.

The Gumbel distribution works particularly well because it provides a simple form for the q_{jk} terms. It also does not impose symmetry, which is convenient given that there is no a priori reason that values should follow a symmetric distribution. A major drawback of the Gumbel distributional assumption is the well-known Independence from Irrelevant Alternatives (IIA) property. IIA implies that, $\forall\, j,\ j' \in M_k$, the ratio $\frac{q_{jk}}{q_{j'k}}$ is unchanged under the addition or subtraction of any third seller. This could be violated, for example, if the buyers who chose the seller with the lowest price would deviate to the seller with the second-lowest price if the low-priced seller exited the market. I check for violations of the IIA property in Appendix II.8.2.

An important assumption necessary for my estimation approach is that the v_{ijk} terms are uncorrelated with not only X_j but also prices. In essence, I assume that there are no unobserved seller or product characteristics and that all relevant factors are captured by X_j. It is reasonable in my setting to ignore unobserved heterogeneity because, in an online setting, all of the information that is available to buyers is also available to the econometrician. Everything that buyers know about the seller and the good is viewable on the eBay listing page. If buyers have outside information, either from e-mail contact or previous purchase experience with the seller, then simultaneity may be a problem (Berry 1994). It is important to point out, however, that the common way to deal with unobserved heterogeneity allows only product-level unobservables and would not control for different buyers having different information. E-mail contact and previous purchase experience are captured in v_{ijk} as long as this information is i.i.d. across buyers.[16]

Trade

After buyers have chosen a seller, the game is modeled following the literature on incomplete auctions (Haile and Tamer 2003). To illustrate, first consider the auction mechanism. In an incomplete model, the exact way that buyers formulate their bidding strategies is left unspecified. Recall that buyers bid based on their consumption values: $V_{ijA} = v_{ijA} + Z_j\beta_A$. I follow Haile and Tamer and assume that buyers: (1) place a bid no larger than their consumption value, V_{ijA}, and (2) do not allow an opponent to win at

[16]The i.i.d. assumption imposes a private-values model, which I test in Appendix II.8.1.

a price below V_{ijA}. In an eBay-style auction, the proxy bidding system insures that these assumptions guarantee the two things needed for identification (Ackerberg et al. 2006; Canals-Cerd and Pearcy 2006): (1) the buyer with the highest value wins the auction and (2) the buyer with the second-highest value places a bid in the amount of his value. I take an incomplete approach because the structural parameters of interest can be identified without limiting the results to the context of a particular model of bidding.[17] Generality is important at this stage of the game because numerous bidding strategies are available to buyers. The disadvantage of the incomplete approach is that only one bid per auction that can be taken as truthful (since the highest bid is not observed in an English auction).

I place similar restrictions on the buyers in the posted-price mechanism: (1) do not buy at a posted price higher than their consumption value, V_{ijP}, and (2) do not allow a good to remain unsold at a price below V_{ijP}. In the posted-price setting however, these assumptions generate a clear strategy for posted-price buyers: indicate a willingness to buy if the posted price is less than or equal to V_{ijP} and refuse to buy otherwise. Despite being generated from assumptions that are analogous to those made in the auction case, the model for posted-price buyers is complete.

If the parameters of $F_k^v(v_{ijk})$ are γ_k (location) and δ_k (scale), then it follows that the parameters of $F_k(V_{ijk})$ are $\gamma_k + \bar{Z}_k\beta_k$ (location) and δ_k (scale). $\bar{Z}_k$ is a vector of the mean values for each covariate in Z_k and has a k subscript for mechanism because I take the mean for sellers in each mechanism separately. The remaining structural parameters are β_k, the parameter vector on the covariates Z in buyers' value specification, which can be recovered by OLS in a hedonic regression.

[17]Peters and Severinov (2006) detail a complete model that is well-suited for the eBay environment but it is difficult to extend their model to a structural setting because values are discrete (i.e., lie on a finite grid) and the bidding game has multiple equilibria, only some of which can be characterized.

Estimation of the Buyers' Side of the Marketplace

I express the probability that a good sells and use maximum likelihood to estimate the structural parameters for buyers. The likelihood function says that the probability of sale is the probability that at least one of the n_j buyers who chose seller j has a consumption value above her price, r_j or p_j, weighted by the probability distribution of n_j:

$$\begin{aligned}
\Pr(Sale_{jA}) = \sum_{n_j=1}^{N_A} \binom{N_A}{n_j} & \left(\frac{\exp(X_j\theta_A - r_j\alpha_A)}{1+\sum_{l=1}^{M_A}\exp(X_l\theta_A - r_l\alpha_A)}\right)^{n_j} \\
& \cdot \left(1 - \frac{\exp(X_j\theta_A - r_j\alpha_A)}{1+\sum_{l=1}^{M_A}\exp(X_l\theta_A - r_l\alpha_A)}\right)^{N_A-n_j} \\
& \cdot \left(1 - \left(\exp\left(-\exp\left(-\frac{r_j - \gamma_A - \bar{Z}_A\hat{\beta}_A}{\delta_A}\right)\right)\right)^{n_j}\right),
\end{aligned} \tag{II.4}$$

$$\begin{aligned}
\Pr(Sale_{jP}) = \sum_{n_j=1}^{N_P} \binom{N_P}{n_j} & \left(\frac{\exp(X_j\theta_P - p_j\alpha_P)}{1+\sum_{l=1}^{M_P}\exp(X_l\theta_P - p_l\alpha_P)}\right)^{n_j} \\
& \cdot \left(1 - \frac{\exp(X_j\theta_P - p_j\alpha_P)}{1+\sum_{l=1}^{M_P}\exp(X_l\theta_P - p_l\alpha_P)}\right)^{N_P-n_j} \\
& \cdot \left(1 - \left(\exp\left(-\exp\left(-\frac{p_j - \gamma_P - \bar{Z}_P\hat{\beta}_P}{\delta_P}\right)\right)\right)^{n_j}\right).
\end{aligned} \tag{II.5}$$

The structural parameters are θ_k, α_k , and the parameters of the value distribution, γ_k and δ_k.

There are several advantages of this approach. First, I am able to jointly estimate the seller-choice and trade stages of the game. Second, I avoid any potential selection bias by using all observations, while some approaches (in auction markets) use only auctions in which at least two bids were placed. Third, data from posted-price markets are less amenable to the estimation techniques typically used with auction data because many of these techniques are based on the selling price. It is difficult to make structural inference

Table 10. Potential Buyers and Sellers

Condition	N	M	$\frac{N}{M}$	$\frac{N_A}{M_A}$	$\frac{N_P}{M_P}$	ρ_B	ρ_S
New	61.58	43.96	1.593	1.482	1.942	49.76%	56.86%
	(6.838)	(5.517)	(0.069)	(0.084)	(0.123)	(0.021)	(0.019)
Used	27.62	12.87	2.625	2.672	2.507	76.74%	71.93%
	(1.526)	(0.825)	(0.188)	(0.125)	(0.374)	(0.017)	(0.014)
All	46.91	30.53	2.039	1.996	2.186	61.42%	63.37%
	(4.099)	(3.321)	(0.097)	(0.083)	(0.177)	(0.017)	(0.013)

Notes: For this and subsequent tables, standard errors are in parentheses. N and M are the total numbers of buyers and sellers, respectively. These figures are the mean values across all $\{CD, week, condition\}$ tuples. $\frac{N}{M}$ is the ratio of buyers to sellers. ρ_B and ρ_S are the share of buyers and sellers, respectively, who enter the auction mechanism.

on the buyers' side of the posted-price market based on the selling price, given that the price is not determined as an outcome of the trade stage as it is in the auction market.

Results

Sellers

Table 10 breaks down the allocation of buyers and sellers in the two markets for new and used goods separately. First note that there are more buyers and sellers of new goods. Further, the number of buyers per seller is low, as described in the introduction. The buyer to seller ratios for the two markets are roughly equal except when considering only new goods, where their equality can be rejected ($t = -3.07$, p-value $= 0.00$). As a result, some buyers (sellers) may have an incentive to deviate to the auction (posted-price) market. However, these summary statistics are only suggestive and do not take into account factors such as the mix of albums across markets. Finally, the share of both buyers and

Table 11. Sellers' Revenues and Earnings

				Ex Ante		Ex Post	
	v^0	Selling Price	Pr(Sale)	E(Rev)	E(Earnings)	E(Rev)	E(Earnings)
Auction	\$5.31	\$9.87	50.82%	\$10.07	\$8.18	\$8.02	\$5.01
	(0.032)	(0.081)	(0.007)	(0.080)	(0.106)	(0.054)	(0.082)
Posted Price	\$6.50	\$13.11	23.80%	\$7.42	\$2.94	\$7.84	\$3.12
	(0.111)	(0.197)	(0.009)	(0.113)	(0.061)	(0.113)	(0.129)
All	\$5.72	\$10.42	42.52%	\$9.17	\$6.40	\$7.97	\$4.43
	(0.044)	(0.079)	(0.006)	(0.069)	(0.084)	(0.051)	(0.070)

Notes: Selling price is the price for which the good sold if it sold, while Pr(Sale) is the share of goods that sold. Each seller's revenue is the selling price if the good sold and the seller's outside option otherwise. Each seller's earnings is the selling price if the good sold and zero otherwise. Ex ante quantities are expectations and ex post quantities are the realized outcomes.

sellers of used goods is larger in the auction market.[18]

A seller's primary concern is expected revenue, defined as the payoff from a sale times the probability of sale plus the payoff from the outside option times the probability of no sale. I also consider expected earnings, which are the payoff from selling the good times the probability of sale. Earnings are of interest because my formulation for earnings is more comparable with other papers that do not consider the value of the outside option. In Table 11, revenues and earnings are expressed in both ex ante and ex post terms. Ex ante quantities reflect expectations taken prior to the realization of n_j, the number of buyers by whom seller j is chosen. As argued in Section II.4.1.2, sellers set the price that maximizes their ex ante expected revenue. Ex post revenues and earnings consider the realized selling price of the good.

Table 11 suggests that posted-price goods earn higher prices but sell with a lower probability. Auction revenues are higher both ex ante and ex post but only ex ante expected revenues are meaningfully higher ($t_{ex\ ante} = 19.23$, $t_{ex\ post} = 1.42$). For earnings,

[18] In contrast, Anderson et al. (2004) find that used goods were more likely (than new goods) to be sold at a posted price in the market for Palm Vx handheld computers on eBay.

the auction market fares even better against the posted-price market. The difference in the results for revenues and earnings is explained by the fact that posted-price sellers have more valuable outside options than auctioneers.

The value of each seller's outside option can be inferred from her pricing decision, meaning that its distribution $H\left(v^0\right)$ is identified without any assumption on its parametric form. Figure 1 provides a histogram of the outside options overlaid with a kernel density plot separately for each market. While the means (shown in Table 11) provide evidence that sellers in the two markets have different outside options, the distributions tell much more. Outside options are concentrated around \$5 to \$7 dollars for auctioneers; 50% of the v^0's fall in this interval. On the other hand, posted-price sellers have outside options that are somewhat uniformly distributed between \$0 and \$10. A meaningful fraction (9%) exceeds \$12 in the posted-price market, while this is true for less than 1% of auctioneers. Further, 46% of posted-price sellers have outside options valued above \$7 compared to less than 8% of all auctioneers.

The final item of interest for sellers is the distribution of costs, $G(\omega)$. The results from a logit estimation of the auction dummy on the difference in expected revenues are in Table 12.[19] Intuitively, I find that sellers who expect a larger revenue advantage for the auction mechanism are more like to sell in an auction. The main purpose of Table 12, however, is in transforming the coefficients to recover the parameters of $G(\omega)$. These parameters, μ (location) and σ (scale), show how sellers view the cost of offering an auction in relation to the costs of posting a fixed price. The fact that μ is less than 0 says that the auction mechanism is less costly, on average.

Taken together, the findings for sellers' outside options and their costs imply that

[19]The unit of observation in this estimation is an individual seller. If a seller lists the same CD of the same condition in the same week, she is counted only once. This assumes that sellers choose between mechanisms separately for each CD and separately for new and used goods.

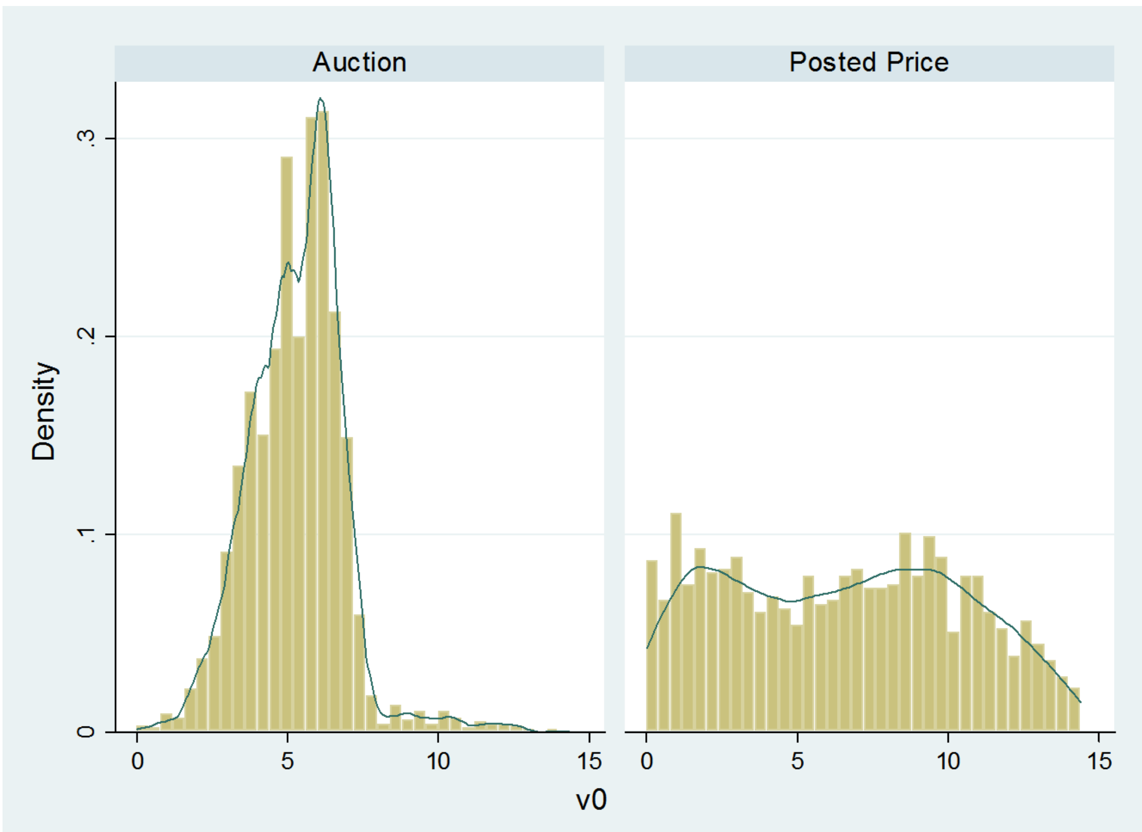


Figure 1. Densities of v^0 by Market

Table 12. Sellers' Cost Distribution

$G(\omega)$ location: μ	-3.704
	$(0.500)^{**}$
$G(\omega)$ scale: σ	7.933
	$(0.664)^{**}$
$E(Rev_A) - E(Rev_P)$	0.125
	$(0.010)^{**}$
Constant	0.463
	$(0.038)^{**}$
Observations	3653
Log-Likelihood Value	-2251.485
LR χ^2 Statistic	173.75
Pr $> \chi^2$	0.000

Notes: $*$ and $**$ denote significance at the 5% and 1% level, respectively. The unit of observation is an individual seller as described in footnote 19. The values for μ (location) and σ (scale) are the estimates of the parameters of the sellers' cost distribution, $G(\omega)$. The coefficient on $E(Rev_A) - E(Rev_P)$ and the constant term are the estimates from a logit maximum-likelihood estimation of the auction dummy. If B_0 is the constant term and B_1 is the coefficient, then $\mu = -\frac{B_0}{B1}$ and $\sigma = \frac{1}{B_1}$. See equation (II.1).

costs are not the entire story. Costs do not completely explain the coexistence of auctions and posted-price selling because costs, on average, favor the auction mechanism. An interpretation is that there are two types of posted-price sellers: (1) sellers with a valuable outside option and (2) sellers with a low-valued outside option but with a large ω_{jA} relative to ω_{jP}. The decision of type (1) sellers to enter the posted-price mechanism can be explained in the context of a monopolist. In the monopoly case, the revenue advantage of the auction over the posted-price mechanism is decreasing in v^0. When v^0 equals the upper bound of the buyers' value distribution, the two mechanisms generate the same expected revenue because the seller will set a price such that she never sells the good. In my model, the same factors are at work. Sellers with valuable outside options view the mechanisms more similarly than sellers with low-valued outside options. As a result, the coexistence of mechanisms is more likely to occur in the former case. In contrast, the decision of type

(2) sellers cannot be rationalized by their v^0. Here, the model predicts that these sellers must have a sufficiently large $\omega_{jA} - \omega_{jP}$. Factors such as risk aversion, impatience, and inventories are likely causes.

Buyers

Table 13 reports a hedonic regression of the good's selling price on the characteristics (Z) that should influence buyers' values. These characteristics are the log of the seller's feedback score, her feedback rating, a dummy variable for new goods, and CD and week fixed effects. The score proxies for the quantity of a seller's reputation and the rating proxies for quality.[20] The seller's reputation matters somewhat but the results reflect a weak relationship that has been found elsewhere (Ackerberg et al. 2006; Canals-Cerd and Pearcy 2006). Further, for the auction market, new goods sell for \$1.11 more than used goods; the difference is \$2.13 for posted-price goods.

The main results for buyers are in Table 14. This estimation includes the characteristics (X) believed to influence which seller a buyer chooses. For the auction market, X includes all of the characteristics in Z in addition to the length of the auction and the reserve price. Adams (2007) argues that the length of a listing should influence which seller a buyer chooses but not the buyer's value. For the posted-price market, I do not observe a listing's length, so X includes the characteristics in Z in addition to the posted price. The results for the coefficients on the reserve price, α_A, and the posted price, α_P, indicate that buyers respond in the expected way to higher prices; I discuss these results in detail in the next section.

[20]Both measures are calculated by eBay based on post-transaction reports submitted by buyers on the sellers from whom they purchase a good. The seller's score is the number of positive reports minus the number of negative reports, while her rating is the number of positive reports divided by the total number of reports. I add two to the feedback score so that all sellers have a positive value and take the log to account for nonlinearities.

Table 13. Buyers' Hedonic Regression

	Auction Market	Posted-Price Market
Ln(Seller's Score)	0.020	0.216
	(0.023)	(0.051)**
Seller's Rating	3.478	−4.253
	(1.724)*	(15.261)
New Good	1.108	2.131
	(0.125)**	(0.351)**
Constant	2.164	12.156
	(1.831)	(15.133)
Observations	2487	489
R^2	0.60	0.71

Notes: The dependent variable is the selling price of the good. Only sold goods are included. The coefficients for CD and week fixed effects are suppressed for both regressions.

Table 14. Buyers' Estimation Results

	Auction Market	Posted-Price Market
$F_k^v(v)$ location: γ_k	4.267	0.723
	(0.524)**	(3.006)
$F_k(V)$ location: $\gamma_k + \bar{Z}\beta_k$	12.129	10.934
	(0.524)**	(3.006)**
$F_k^v(v)$ & $F_k(v)$ scale: δ_k	5.687	12.227
	(0.534)**	(5.860)**
Price (Reserve or Posted)	−0.463	−0.321
	(0.057)**	(0.038)**
Ln(Seller's Score)	−1.480	0.053
	(0.182)**	(0.038)
Seller's Rating	10.815	9.558
	(5.361)*	(7.395)
Length of Listing	1.064	
	(0.119)**	
Constant	1.580	−8.695
	(5.347)	(7.406)
Observations	4894	2005
Log-Likelihood Value	−2336.082	−910.354
LR χ^2 Statistic	324.08	57.65
Pr $> \chi^2$	0.000	0.000

Notes: The results are from maximizing the likelihood functions shown in equations II.4 and II.5.

The distribution of values is the key primitive for buyers. While the model provides no formal prediction on the stochastic ordering of the two distributions, they should be similar across markets.[21] The results suggest that $F_A(V)$ is centered around \$12.13 and $F_P(V)$ around \$10.93. The difference between these central locations is not statistically significant ($t = 0.39$, p-value $= 0.70$) but \$1.20 is an economically meaningful amount given the inexpensive nature of CDs. If I remove the effects of observable characteristics (X) and look only at buyers' idiosyncratic values, the difference across the auction and posted-price markets is larger, yet still statistically insignificant ($t = 1.16$, p-value $= 0.25$). I also fail to reject that $\delta_A = \delta_P$ ($t = -1.11$, p-value $= 0.27$) but it should be noted that these two parameters are meaningfully different ($\delta_A = 5.69$, $\delta_P = 12.23$). The test fails to reject only because δ_P is estimated with a great deal of noise.

The remaining quantities in Table 14 show the effects of observable characteristics on which seller a buyers chooses. The quality of the seller's reputation (her rating) matters in the expected way but is estimated imprecisely. The quantity of her reputation hurts a seller in the auction market and does little to help in the posted-price market. Finally, I use estimates of the share of buyers that each seller receives, q_{jk}, to find the share of buyers who exit the market, q_{0k}. 23.8% of auction buyers and 69.2% of posted-price buyers exit and choose seller 0. That more posted-price buyers than auction buyers exit the market is consistent with buyers exiting when their value is too low given that the lowest posted price is above the lowest reserve price for all CDs in these data.

[21] Because buyers draw their values after entering a particular mechanism, the model does not require the distributions to be the same (hence $F_k(\cdot)$ has a k subscript). But, if the estimated distributions are not similar, then the assumption that buyers mix between mechanisms may be unreasonable.

Intensity of Price Competition

The key advantage of the structural approach is that the magnitudes of the estimates have a precise interpretation. As a result, I am able to use the structural parameters to measure the competitiveness of the market: first, by quantifying the intensity of price competition and second, by measuring consumer surplus. As argued in Section II.4.1.2, the estimates for α_A and α_P are useful measures of the competitiveness of the auction and posted-price markets. I calculate the elasticity of q_{jk} with respect to price, measured at the means for each market. The auction elasticity is -2.06, while the posted-price elasticity is -4.62. These elasticities suggest that buyers are highly responsive to changes in price. That buyers are more responsive to the posted price is intuitive given that the posted price is the price that a buyer actually pays, while the reserve price is only the starting point of the bidding process.

I also measure the intensity of price competition using Lerner-type indices equal to $\frac{r_j - v^0_{jA}}{r_j}$ and $\frac{p_j - v^0_{jP}}{p_j}$. The means for the auction and posted-price market are 0.155 and 0.508, respectively. The difference is even larger when comparing the medians, which are 0.001 (auction) and 0.544 (posted price). From the auction market, the reserve price mark-up is approximately zero for the majority of sellers but the distribution of the mark-ups is positively skewed. Comparing the two markets indicates that posted-price sellers charge prices that are meaningfully above the value of their outside options, to a larger extent than auctioneers.

Consumer Surplus

Another way to measure the competitiveness of the online compact-disc market is consumer surplus. First consider the auction market. The realized consumer surplus in an individual auction is the difference between the highest bidder's value and the winning bid. Because the highest-bidder's value is not observed, I follow the convention of estimating expected consumer surplus (Song 2004; Giray et al. 2006). Define b^w as the winning bid and let $V_A^{(n-1:n)}$ refer to the buyer with the second-highest out of n values:

$$E[CS_A|V_A^{(n-1:n)} = b^w] = \frac{\int_{b^w}^{\infty} V \cdot f_A(V)dV}{1 - F_A(b^w)} - b^w.$$

The formulation in the posted-price market is similar but the logic is different. As before, we want the expected value of the buyer who obtains the good minus the price he pays. However, the buyer who obtains the good in the posted-price market is chosen randomly from the set of buyers who chose the seller and have a value above her posted price. Expected consumer surplus is:

$$E[CS_P|V_{iP} > p] = \frac{\int_{p}^{\infty} V \cdot f_P(V)dV}{1 - F_P(p)} - p.$$

On average, the expected consumer surplus per good is \$7.91 and \$14.88 in the auction and posted-price markets, respectively.[22] After calculating producer surplus, I find the share of total surplus that is received by consumers: $E[\frac{CS_A}{TS_A}] = 64.5\%$ and $E[\frac{CS_P}{TS_P}] = 69.4\%$. Figures at the median are \$8.29 (73.0%) for the auction market and \$15.04 (72.0%) for the posted-price market. One explanation for posted-price buyers receiving a higher (absolute) surplus is the larger variance of $F_P(V)$ relative to $F_A(V)$, implying that the posted-price distribution has more weight in its right tail. Recall though that the scale parameter of $F_P(V)$ is estimated imprecisely.

[22] While it may not be intuitive, expected consumer surplus in both markets is independent of N or N_k. For the auction market, Giray et al. (2006) provide a simple proof. For the posted-price market, $E[CS_P]$ is independent of N_P because the winning buyer is chosen randomly among those with a value above the posted price.

Conclusion

I examine the competitive structure of a marketplace that features simultaneous auctions and posted-price selling. Several novel aspects of my estimation approach allow new insights into how sellers choose between selling in an auction and posting a fixed price. Most importantly, the value of each seller's outside option is identified using an optimality condition from the seller's pricing problem. As a result, I can recover the distribution of these outside options without any assumption on its parametric form. The distribution of sellers' costs can be estimated in a simple, univariate discrete-choice model. On the demand side, I am able to estimate the distribution of values under weak assumptions that hold in numerous models of bidding or posted-price buying. Finally, I use a new technique for identifying the unobserved number of potential buyers in the posted-price market. My results compare favorably to an approach that assumes there are infinitely many buyers.

I find that a seller chooses which mechanism to enter based on the value of her outside option. Since, the value of each seller's outside option is identified, I am able to quantify the degree to which sellers are pricing competitively. The findings suggest that buyers in the online compact-disc market are highly responsive to price. Higher prices have a large, negative effect on the share of buyers who choose a particular seller. In response, sellers price competitively and the majority of auctioneers set a price equal to the value of their outside option. These results reconcile the commonly-cited revenue-dominance property of the auction mechanism with the observation that many sellers choose to post a fixed price.

Appendix - Optimal Pricing

Seller j's expected revenue for each mechanism is:

$$E(Rev_{jA}) = \sum_{N_A=1}^{N} \{ \binom{N}{N_A} \rho_B^{N_A} (1-\rho_B)^{N-N_A} \sum_{n_j=0}^{N_A} \{ \binom{N_A}{n_j} q_{jA}^{n_j} (1-q_{jA})^{N_A-n_j}$$

$$\cdot (n_j \int_{r_j}^{\infty} (v f_A(v) + F_A(v) - 1) F_A(v)^{n_j-1} dv + F(r_j)^{n_j} \cdot v_{jA}^0) \} \}, \quad \text{(A1)}$$

$$E(Rev_{jP}) = \sum_{N_P=1}^{N} \{ \binom{N}{N_P} (1-\rho_B)^{N_P} {\rho_B}^{N-N_P} \sum_{n_j=0}^{N_P} \{ \binom{N_P}{n_j} {q_{jP}}^{n_j} (1-q_{jP})^{N_P-n_j}$$

$$\cdot ((1 - F_P(p_j)^{n_j}) p_j + F(p_j)^{n_j} \cdot v_{jP}^0) \} \}. \quad \text{(A2)}$$

$F_k(V)$ is the distribution of buyers' consumption values, V_{ijk}: $F_k(V) = \exp(-\exp(-\frac{V-\gamma_k}{\delta_k}))$, with density: $f_k(V) = \frac{1}{\delta_k} \exp(-\frac{V-\gamma_k}{\delta_k}) \exp(-\exp(-\frac{V-\gamma_k}{\delta_k}))$. Equation II.3 defines q_{jk}.

The parameters ρ_B, θ_k, and α_k, along with the parameters of $F_k(v)$ are common knowledge, implying that sellers can forecast the expected revenue in each mechanism. The expected revenue in the mechanism that the seller entered can be found by inserting these parameters along with the price charged (r_j or p_j) and v_{jk}^0. On the other hand, the expected revenue in the mechanism that the seller did not enter is more complicated. In theory, the seller could use the structural parameters along with v_{jk}^0 to calculate the optimal price in the other mechanism. I argue that it seems unlikely that sellers are able to engage in this level of optimization. Instead, I assume that sellers use a heuristic for the price that they would charge (counterfactually) in the mechanism that they did not enter. Specifically, I assume that sellers expect to charge a price in each mechanism that earns the same share of buyers and therefore expect the following equality to hold:

$$\frac{\exp(X_j\theta_A - r_j\alpha_A)}{1+\sum_{l=1}^{M_A}\exp(X_l\theta_A - r_l\alpha_A)} = \frac{\exp(X_j\theta_P - p_j\alpha_P)}{1+\sum_{l=1}^{M_P}\exp(X_l\theta_P - p_l\alpha_P)}.$$

Using this restriction, sellers can calculate the optimal price in one mechanism and use this equation to solve for the price in the other mechanism. Once a seller knows these two prices, she chooses the mechanism offering the highest profit, where $\pi_{jk} = E(Rev_{jk}) - \omega_{jk}$.

For comparison, consider two results from the auction literature. First, the optimal reserve price for a monopolist, r^M, solves the following equation (Myerson 1981):

$$r_j^M = v_{jA}^0 + \frac{1 - F_A(r_j^M)}{f_A(r_j^M)}.$$

Second, the literature on competing sellers (see Section II.1.2) shows that, under certain conditions, all sellers set a reserve price at the value of their outside option, $r_j^C = v_j^0$. Many of these results rely on limit concepts where the number of sellers goes to infinity (e.g., McAfee (1993)). In my model, the optimal reserve price, r_j^*, maximizes equation (A1). Differentiating this function shows that $r_j^* = r_j^M$ when $\alpha_A = 0$, while r_j^* approaches v_{jA}^0 from above when $\alpha_A \to \infty$. The latter could occur because the number of sellers is very large or because buyers are very sensitive to price. Monotonicity of $E(Rev_k)$ in price insures that r_j^* lies in the interval $[v_{jA}^0, r_j^M]$.

The optimal posted price cannot be bounded as easily because with $\alpha_P = 0$, the optimal posted price in my model depends n_j, while with $\alpha_A = 0$, the optimal reserve price does not. As a result, any comparison between a seller in my model when $\alpha_P = 0$ and a monopolist depends on the number of buyers that the monopolist faces. Consider a monopolist and define p_j^M as her optimal posted price when facing n_j buyers:

$$p_j^M = v_{jP}^0 + \frac{1 - F_P(p_j^M)^{n_j}}{n_j F_P(p_j^M)^{n_j - 1} f_P(p_j^M)}.$$

When $\alpha_P = 0$, one can show that the optimal posted price of seller j may exceed p_j^M when the expected number of buyers is the same in the two cases ($n_j = q_{jP} \cdot N_p$). For example, if $v_{jP}^0 = 0$, $N_p = 20$, $q_{jP} = \frac{1}{10}$, and $F_P(\cdot)$ is the Gumbel distribution recovered in Section II.5.2, then the optimal posted price of seller j is \$21.69 while the optimal posted price of a monopolist facing 2 buyers ($2 = q_{jP} \cdot N_p$) is \$20.33. This example illustrates that an upper bound analogous to r_j^M does not exist for the posted-price mechanism, even when $\alpha_P = 0$ and each seller can raise her price without influencing the number of buyers that she faces. There is a clear lower bound though because no seller should price below v_{jP}^0.

Appendix - Testable Assumptions

The key drawback of the structural approach is that stronger assumptions (relative to a reduced-form approach) are required for estimation. This appendix tests many of the key assumptions.

The Nature of Demand

The main restriction placed on the demand structure is that of a symmetric-independent-private-values (SIPV) framework. By using a SIPV model, I assume that all buyers draw their values from $F_k^v(v)$ and that these values are i.i.d. random variables. While the econometric literature has developed a number of ways to test the appropriateness of the SIPV assumptions using auction data, I know of no analogous approach using data from posted-price markets. As a result, I test the SIPV assumptions using only the auction data. In an auction setting, Athey and Haile (2002) show that the SIPV framework is testable if either: (1) more than one bid per auction is observed or (2) there is exogenous variation in the number of buyers. While multiple bids are observed in eBay data, the truncation of bidders discussed earlier implies that the interpretation of bids below the second highest is unclear. As a result, I am unable to use a testing approach that requires multiple bids (such as an approach based on equation (13) in Athey and Haile (2002)).[23]

On the other hand, there are reasons to believe that I can exploit exogenous variation in the number of buyers. Recall that I group observations into $\{CD, week, condition, mechanism\}$ tuples and estimate N_k separately for each group. Accordingly, N_k varies by CD, by week, by condition (new or used), and by mechanism. If the variation along one of these dimensions can be taken as plausibly exogenous, then I can estimate $F_A^v(\cdot)$ separately across this dimension and test for the appropriateness of the SIPV assumptions. I argue that time is the most likely dimension to generate exogenous variation in N_A. While the demand for CDs certainly changes over time, the sample period of 45 days is likely short enough to avoid depreciation in demand due to a CD losing popularity. Further, the argument that there may be additional differences between distributions for the early and late periods provides more evidence against the null, biasing the test against me. I divide the sample into two periods and test $F_A^{v,early}(\cdot) = F_A^{v,late}(\cdot)$. The results in Table 15 support the SIPV assumptions in that I fail to reject the equality of the two parameters.

[23]Using eBay data, Zeithammer and Adams (2007) reject that multiple bids per auction can be taken truthfully revealing the buyer's value.

Table 15. Testing Private-Values Assumption

	Auction Market		
	Obs	γ_A	δ_A
Early	2743	4.952	5.656
		(1.599)	(1.164)
Late	2151	4.629	5.915
		(0.631)	(0.724)
Difference		0.323	−0.259
		(1.719)	(1.370)
t-Statistic		0.188	−0.189
p-value		0.851	0.850

Notes: The test fails to reject the null of private values when the p-value is greater than 0.05.

Independence from Irrelevant Alternatives

The share of buyers that each seller receives, q_{jk}, is restricted by the IIA property of the Gumbel distribution. To check whether IIA is rejected in these data, I follow Hausman and McFadden (1984) and compare the results from the full model to a restricted model where buyers can choose from only a subset of the sellers. I choose the restricted set to include all sellers except the low-price seller, dropping one seller for each $\{CD, week, condition, mechanism\}$ group. By dropping the seller with the lowest price, I induce the largest possible shift in buyers. As a result, the test is more likely to reject IIA than tests with higher-priced sellers. I find that IIA is not rejected in these data, providing support for the Gumbel distributional assumption (for the auction market, $\chi^2 = 4.87$, p-value $= 0.30$; for the posted-price market, $\chi^2 = 5.91$, p-value $= 0.20$).

Multinomial Distribution

I have assumed that the number of buyers who choose each seller follows a multinomial distribution. An alternative approach is to assume that the number of potential buyers in each market is infinite and use a Poisson distribution for the number of buyers who choose each seller. Under this assumption, the mean number of arrivals, λ_{jk}, at each seller j is a function of X_j and τ_{jk} (recall that τ is the payment that a buyer expects to make). In my setting, λ_{jk} is interpreted as the mean number of buyers who arrive at seller j's listing before it closes. One downside to using a Poisson approach is that it is more difficult to motivate the empirical specification with an underlying theoretical framework, such as the random-utility-maximization model used in this paper.

I now outline an estimation strategy based on a Poisson specification to check which provides a better fit for the data. The reduced-form specification is: $\lambda_{jk} = X_j\theta_k - \tau_{jk}$, where $\tau_{jA} = r_j\alpha_A$ and $\tau_{jP} = p_j\alpha_P$ as before. The likelihood functions are:

$$\Pr(Sale_{jA}) = \sum_{n_j=1}^{\infty} \frac{(X_j\theta_A - r_j\alpha_A)^{n_j}\exp(-(X_j\theta_A - r_j\alpha_A))}{n_j!}(1 - F_A(r_j)^{n_j}), \tag{B1}$$

$$\Pr(Sale_{jP}) = \sum_{n_j=1}^{\infty} \frac{(X_j\theta_P - p_j\alpha_P)^{n_j}\exp(-(X_j\theta_P - p_j\alpha_P))}{n_j!}(1 - F_P(p_j)^{n_j}). \tag{B2}$$

Results are in Table 16; the differences with those in Table 14 are stark. The estimate of α is only significantly different from zero in the auction market. Further, the recovered distribution is shifted toward lower values in relation to the distribution recovered using a multinomial approach.[24]

Because the multinomial and Poisson models are non-nested, I compare them

[24]While the number of buyers is said to be infinite in the Poisson model, in practice it is necessary for the researcher to specify an upper bound for the summation. I find that the mean of the distribution varies depending on the upper bound because, in order to explain the number of goods that remain unsold in the data, the buyers' value distribution must shift to the left as the upper bound gets larger. I choose an upper bound based on the seller who is chosen by the largest number of buyers in the multinomial model ($\max(q_{jA} \cdot N_A) = 7$, $\max(q_{jP} \cdot N_P) = 4$).

Table 16. Buyers' Poisson Estimation Results

	Auction Market	Posted-Price Market
$F_k^v(v)$ location: γ_k	-7.093	-3.313
	$(0.942)^{**}$	$(0.884)^{**}$
$F_k(V)$ location: $\gamma_k + \bar{Z}\beta_k$	0.769	6.897
	(0.942)	$(0.884)^{**}$
$F_k^v(v)$ & $F_k(v)$ scale: δ_k	12.517	5.010
	$(1.547)^{**}$	$(0.600)^{**}$
Price, Reserve or Posted	-0.085	-0.043
	$(0.005)^{**}$	(0.036)
Ln(Seller's Score)	-0.394	0.059
	$(0.017)^{**}$	(0.052)
Seller's Rating	1.391	8.901
	$(0.660)^{*}$	$(2.548)^{**}$
Length of Listing	0.279	
	$(0.015)^{**}$	
Constant	3.453	-6.945
	$(0.708)^{**}$	$(2.463)^{**}$
Observations	4894	2005
Log-Likelihood Value	-2490.726	-957.421
LR χ^2 Statistic	1234.09	5.18
Pr $> \chi^2$	0.000	0.159

Notes: The results are from maximizing the likelihood functions shown in equations B1 and B2.

using a Vuong (1989) test. The results indicate that the multinomial approach is closer to the truth (for the auction market, $Z = 5.89$, p-value $= 0.00$; for the posted-price market, $Z = 3.16$, p-value $= 0.00$).

CHAPTER III

Selling to Buyers with Correlated Values in Auction and Posted-Price Markets

I use a laboratory setting to study the pricing decisions of a monopolist in auction and posted-price markets. Experimental subjects set a price to sell a single, indivisible good to buyers as the level and nature of demand changes. The question of interest is whether sellers correctly recognize the role played by correlation among buyers' values. The prices set by subjects in the experiment closely match the risk-neutral benchmark predictions when demand follows the independent-private-values framework. In contrast, subjects fail to correctly account for correlation among buyers' values once the independence assumption is dropped. I offer two new models of pricing in a correlated-values environment. The model that suggests sellers ignore correlation outperforms both the benchmark and the model that suggests sellers incorrectly account for correlation.

Introduction

The distribution of buyers' values determines what fraction of the buyers have a willingness-to-pay at or below a particular price. A market's demand therefore can be characterized by analyzing the statistical and economic properties of the value distribution. The property of interest in this paper is the degree of correlation among buyers' values. When there is no correlation, values are independent and private, that is, i.i.d. random variables. When the degree of correlation increases, values are identically but no longer independently distributed random variables.

In this paper, subjects in a laboratory experiment are asked to set prices in auction and posted-price markets. I compare prices in the experiment to several theoretical models to understand how sellers incorporate correlation among buyers' values into their pricing decisions. Numerous experimental papers find that the benchmark model of pricing in auction and posted-price markets performs well when buyers' values follow the independent-private-values paradigm (e.g., Ketcham, Smith, and Williams (1984)). (The experimental results of the present paper also finds this to be the case.) My question is whether the same is true in a more complicated environment, in particular when buyers' values are correlated. Are experimental sellers equally likely to set the revenue-maximizing price in environments of uncorrelated and correlated values? If not, do models that account for optimization errors with respect to the role of correlation provide a better fit for the data?

By approaching these questions using data from a controlled laboratory setting instead of a naturally-occurring market, I can more carefully isolate the effect of changes in the economic environment on a seller's pricing decisions. Experimental papers that study market institutions typically focus on buyer behavior, seller behavior, or comparing mechanisms (Kagel 1995; Davis and Holt 1996). Because this paper studies sellers, I abstract from the strategic considerations of buyers and the design of or preferences over mechanisms. The experiment uses robotic buyers, meaning that buyers' bidding/purchase decisions are performed by the computer. The use of computerized buyers whose strategies are known to the seller sharpens the focus on the seller's pricing decisions by reducing the level of strategic uncertainty.

The question of how agents behave in complicated demand environments has received previous attention. Hortasu and Puller (2008) study a naturally-occurring electricity market that features complex strategic interactions between firms bidding to sell power in Texas. They find that large firms bid in a way that is more consistent with profit maximization, while small firms leave "money on the table" by bidding in ways that are inconsistent with profit maximization. While Hortasu and Puller discuss bidding behavior, their paper provides some insight into what changes we should expect in sellers' pricing behavior when the demand environments becomes more complicated.

The next section outlines the way in which a monopolist's revenue-maximizing price changes as the level of demand changes from low (two buyers) to high (five buyers). After presenting the experimental design and results, I introduce two new models of naive pricing. Each naive-pricing model collapses to the benchmark model when buyers' values are uncorrelated but misspecifies the role of correlation when values are correlated. Taking the three models to the data suggests that modifying the benchmark model to account for optimization errors provides a closer match of the level of subjects' prices and the comparative-static results in the correlated environment.

Benchmark Model

A risk-neutral monopolist offers for sale a single, indivisible unit of a good to n risk-neutral buyers whose participation decisions are exogenous. The seller's value for the good is set equal to 0. The buyers' values are symmetrically drawn from $F(v)$, which is assumed to be continuously differentiable. Let its first derivative $f(v)$ satisfy the monotone-likelihood-ratio property (Milgrom and Weber 1982). I use a conditionally-independent private-values (CIPV) model; buyers draw their values independently, conditional on a parameter that is common to all buyers. If μ denotes the common parameter, buyers' values are i.i.d. according to $F(v|\mu)$. The CIPV model is equivalent to the independent-private-values (IPV) model when $F(v) = F(v|\mu)$. Finally, let the distribution $G(\cdot)$ of the common component be continuously differentiable with first derivative $g(\cdot)$.

The two markets considered are the second-price sealed-bid auction and the posted-price market. In the auction market, the seller sets a (public) reserve price and the good is sold to the highest bidder if his bid is greater than or equal to the reserve price.[1] The selling price is the maximum of the reserve price and the second-highest bid. In the posted-price market, the seller sets a posted price and the good is sold to a buyer who is willing to pay the posted price. In the laboratory experiment described in the next section, robotic buyers execute the dominant strategy in each market: enter a truthful bid (i.e., a bid equal to the buyer's value) in the auction and choose to buy if doing so provides a non-negative payoff in the posted-price market. A second-price auction is appealing in this context because the strategy that robotic buyers will follow when bidding is easy for subjects to understand.

To think about optimal pricing, I express the monopolist's expected revenue $E(Rev)$ as a function of μ, then optimize over the reserve or posted price (Wang 1998). If $\mu \in [\underline{\mu}, \bar{\mu}]$ and $v_i \in [\underline{v}(\mu), \bar{v}(\mu)]$, then expected revenues in the two mechanisms are:

$$
\begin{aligned}
E(Rev_A) =& n \int_{\underline{\mu}}^{\bar{\mu}} \int_{r}^{\bar{v}(\mu)} \left(vf(v|\mu) + F(v|\mu) - 1\right) F(v|\mu)^{n-1} \, dv \cdot g(\mu) \, d\mu, \\
E(Rev_P) =& \int_{\underline{\mu}}^{\bar{\mu}} p \left(1 - F(p|\mu)^n\right) g(\mu) \, d\mu.
\end{aligned}
$$

The optimal reserve price satisfies[2]:

$$
0 = -n \int_{\underline{\mu}}^{\bar{\mu}} \left(rf(r|\mu) + F(r|\mu) - 1\right) F(r|\mu)^{n-1} g(\mu) \, d\mu, \tag{III.1}
$$

while the optimal posted price satisfies:

$$
0 = \int_{\underline{\mu}}^{\bar{\mu}} \left(1 - F(p|\mu)^n - npF(p|\mu)^{n-1} f(p|\mu)\right) g(\mu) \, d\mu. \tag{III.2}
$$

[1] Note that the common auction formats are not revenue equivalent when values are not independent. Second-price auctions revenue dominate first-price auctions (Milgrom and Weber 1982).

[2] Wang (1998) provides the second-order conditions, which are met by the distributions used in experiment.

When $F(v) = F(v|\mu)$, these optimality conditions become:

$$r = \frac{1 - F(r)}{f(r)}, \tag{III.3}$$

$$p = \frac{1 - F(p)^n}{nF(p)^{n-1} f(p)}. \tag{III.4}$$

I use there results to predict how the reserve and posted prices should change as the number of buyers increases. Values are uncorrelated when $F(v) = F(v|\mu)$ and correlated otherwise.

Parameterization of the Model

The laboratory experiment uses the affiliated-signals model of Kagel, Harstad, and Levin (1987), where buyers' values are determined in two stages:

1. μ is drawn from a uniform distribution on $[a, b]$,

2. then, the n buyers' values are independently drawn from a uniform distribution on $[\mu - \varepsilon, \mu + \varepsilon]$.

In summary, $G(\mu) = \frac{\mu - a}{b - a}$ and $F(v|\mu) = \frac{v - \mu + \varepsilon}{2\varepsilon}$.

The degree of correlation among buyers' values is captured by $b - a$. When $b - a = 0$, values are uncorrelated. Values become more highly correlated as a and b move further apart. The two environments considered are:

1. (Uncorrelated) Let $a = b = \varepsilon = 10$: buyers' values are determined in one stage, drawn uniformly from the integers $[0, 20]$.

2. (Correlated) Let $a = \varepsilon = 5$ and $b = 15$: μ is drawn uniformly from the integers $[5, 15]$, then buyers' values are drawn uniformly from the integers $[\mu - 5, \mu + 5]$.

The two-by-two-by-two design generates eight treatments: market (auction versus posted price), level of demand (two versus five buyers), and degree of correlation among buyers' values (uncorrelated versus correlated values). The optimal prices for each treatment are in Table 18 (found in Section III.5) and details are in Appendix III.7.

Within this framework, I test the following hypotheses that deal with how sellers' pricing decisions change in response to a change in the level of demand.

Hypothesis 1 *In the auction market, sellers do not change their reserve prices as the number of buyers increases in the uncorrelated environment.*

Hypothesis 2 *In the auction market, sellers reduce their reserve prices as the number of buyers increases in the correlated environment.*

Hypothesis 3 *In the posted-price market, sellers increase their posted prices as the number of buyers increases for a fixed degree of correlation.*

The predictions in the auction market are discussed in detail in Levin and Smith (1996). For the posted-price market, the predictions are intuitive and can be seen in the model of the present paper by inspection of the expected revenues in Appendix III.7.

Experimental Design and Procedures

Subjects were recruited to participate in an experiment whose purpose was to "observe pricing decisions." The functioning of each market was explained according to the instructions in Appendix III.8. Before being asked to set a price, subjects were told the number of buyers and whether buyers' values were uncorrelated or correlated. As can be seen in Figure 5, the description of the environment was shown at the time of each pricing decision. Subjects' prices were restricted to the real numbers between 0 and 20. Though they were not restricted to integers, no subject set a non-integer price.

It was explained to subjects that buyers' values were randomly drawn integers determined by the treatment in question. Subjects were told that buyers' values and (in the correlated environment) μ were redrawn between rounds, where μ is the mean of the first stage of the affiliated-signals model. Throughout the experiment, μ was referred to as X for clarity and it was explained to subjects that they would not be told X until after a price was entered. Further, subjects were told that buyers' actions were simulated and the dominant strategy that the robotic buyers would execute was explained. By using robotic buyers and monopolistic markets, I avoid having any interactions among subjects during the experiment and subjects' earnings depended only on the results of their own pricing decisions.

The experiment took place at Vanderbilt University during April and May of 2008. The thirty-five subjects had little experience in economic experiments and only two subjects had participated in a previous auction or posted-price experiment. There were 63 rounds and the total time from login to payment ranged from 30 to 45 minutes. For the eight treatments, rounds were distributed as follows: 40 live rounds (5 per treatment) and 23 practice rounds (with the following number before each round $(10, 5, 2, 2, 2, 2, 0, 0)$). The practice rounds exactly mimicked the live rounds, with a note prominently indicating that the round would not be one of the rounds used to determine take-home earnings. Subjects participated in treatments in random order, the order varied across subjects, and each subject participated in each of the eight treatments exactly once.

Take-home earnings had three components: \$5 for arriving at the experiment on time, the revenues from 10 randomly-selected (live) pricing rounds, and the revenue from a randomly-selected Holt and Laury (2002) lottery. The Holt-Laury procedure is a common way to estimate risk preferences and was used to check if relaxing the assumption of risk neutrality provided a better fit for the data. See Appendix III.9 for details. Dollar values during the experiment were expressed in experimental dollars. The instructions explained that the exchange rate was 10 : 1. At the end of the experiment, subjects saw which rounds were used to determine their take-home earnings and earnings were converted to American dollars. Earnings were advertised to be \$15 on average and, in fact, averaged \$15.24.

To check their understanding of the instructions, subjects took an ungraded and a graded quiz (the latter of which is shown in Figure 4). Subjects who failed to correctly answer 75% of the questions on the graded quiz had to speak with a monitor to clear up any confusion before retaking the quiz. Following the eighth and final treatment, subjects were asked to take the Holt-Laury risk survey as well as a demographic survey. Finally note that subjects were given feedback after each round to speed learning. Figures 6 and 7 are screenshots of two sample feedback pages. Subjects were shown their profit, all buyers' values, and (in the correlated environment) the value of X.

Results

Price Level

Though my focus is on a comparison across treatments, I begin with a discussion of how prices differ on average from those predicted by the benchmark model of the paper.

The results in Table 18 suggest that the benchmark model closely matches the level of prices in the uncorrelated environment. Only for the two-buyers posted-price treatment does a Wilcoxon nonparametric signed-ranks test report a failure of the model in terms of the level of prices (z=3.18, p-value=0.00) and even there the magnitude of the price difference ($0.54) is small. In the correlated environment however, subjects set prices that are meaningfully different than predicted. Now consider the comparative-static predictions.

Comparative-Static Results

Throughout, I compare the results from the relevant treatments using Kolmogorov-Smirnov (K-S) tests, which check for equality of empirical distributions. For each finding, I provide graphs of the relevant empirical cdfs using all subjects and all rounds.

Finding 1 *In the uncorrelated environment of the auction market, subjects do not change their reserve prices on average as the number of buyers increases but are more likely to set a low reserve price and less likely to set a high reserve price with five buyers relative to two buyers.*

See the left panel of Figure 2. I reject that the two-buyers and five-buyers distributions are equivalent (test statistic=0.26, p-value=0.00). A parametric comparison is useful here as well. While I fail to reject that the mean reserve prices are different for two and five buyers, the F statistic of a variance-ratio test is 0.54 (p-value=0.00). This suggests that the five-buyers distribution is a mean-preserving spread of the two-buyers distribution. I conclude that, while there is a meaningful amount of heterogeneity in the subject population, the overall response of subjects to an increase in the number of buyers in the uncorrelated environment of the auction market appears to be consistent with Hypothesis 1.

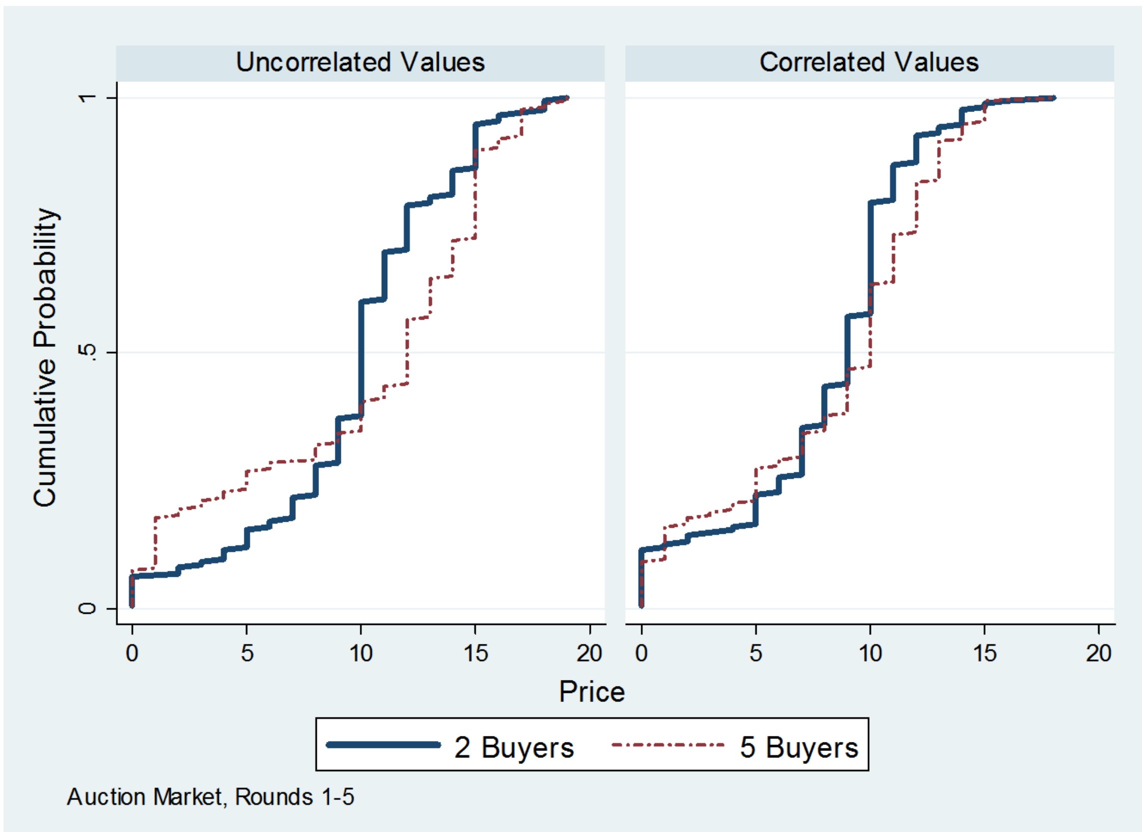


Figure 2. Empirical CDFs of Reserve Prices

Finding 2 *In the correlated environment of the auction market, subjects do not change their reserve prices as the number of buyers increases.*

From the right panel of Figure 2, I reject the equality of distributions using all rounds (test statistic=0.16, p-value=0.02) but fail to reject after excluding rounds 1 and 2 (test statistic=0.14, p-value=0.19). These results suggest that, in contrast to Hypothesis 2, subjects' behave similarly across the uncorrelated and correlated environments with respect to an increase in the number of buyers in the auction market.

Finding 3 *In the posted-price market, subjects increase their posted prices as the number of buyers increases for a fixed degree of correlation.*

The results seen in Figure 3 suggest that subjects set higher posted prices when selling to five buyers relative to two buyers, consistent with Hypothesis 3. K-S tests provide further support (uncorrelated-values test statistic=0.43, p-value=0.00; correlated-values test statistic=0.26, p-value=0.00). Price differences are more dramatic in the uncorrelated environment ($2.68) than in the correlated environment ($1.30). The result is not changed by excluding either round 1 or rounds 1 and 2.

I conclude from these findings that the benchmark model provides a good fit for pricing behavior in both the level of prices and the predictions across treatments in the uncorrelated environment. That the same is not true in the correlated environment is investigated now.

Naive-Pricing Models

The results of the previous section suggest that the pricing behavior of these subjects is broadly consistent with the comparative-static risk-neutral predictions. The

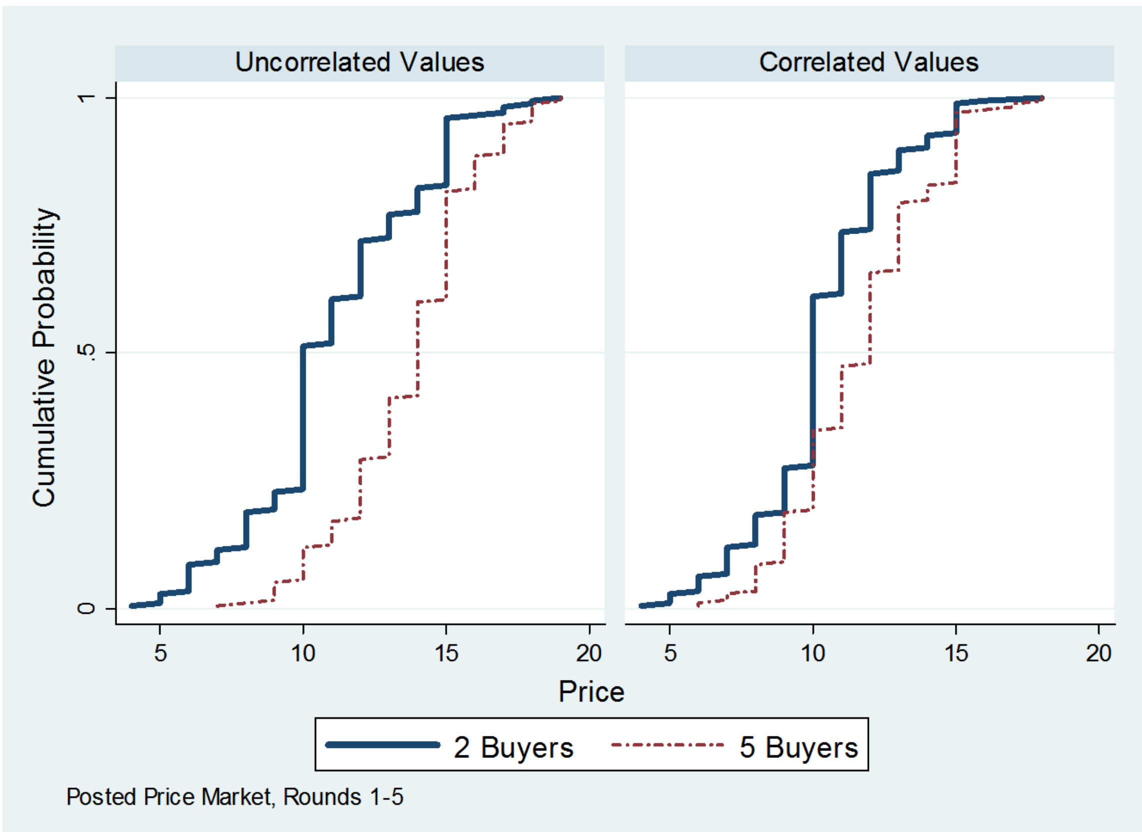


Figure 3. Empirical CDFs of Posted Prices

Table 17. Percent of Maximum Expected Revenue

	Uncorrelated		Correlated	
	2 Buyers	5 Buyers	2 Buyers	5 Buyers
Auction	0.916	0.941	0.863	0.783
	(0.010)	(0.008)	(0.017)	(0.024)
Posted Price	0.902	0.919	0.809	0.626
	(0.010)	(0.009)	(0.021)	(0.029)

Notes: Expected revenue is the revenue that a subject should expect ex ante to earn based on the price set. Percent of maximum expected revenue is the subject's expected revenue divided by the maximum expected revenue (which would be earned by setting the optimal price). Standard errors are shown in parentheses.

model does not perform well, however, in the correlated environment. To illustrate this point further, Table 17 shows the percent of maximum expected revenue earned by subjects in each treatment. This quantity tells us how subjects fare relative to the benchmark of revenue maximization. The table reinforces the conclusion that subjects do worse in the correlated environment.

Two explanations for subjects' difficulty in the correlated environment both generate testable models that can be taken to the data:

1. Subjects ignore correlation and set prices as if buyers' values are independently drawn from the ex post distribution of buyers' values. The ex post distribution is the unconditional distribution that ignores the common component μ, represented by the following trapezoidal distribution, $\tilde{F}(v) =$

$$\begin{array}{rl} 0 & v \in (-\infty, 0) \\ \frac{v^2}{150} & v \in [0, 5) \\ \frac{v}{15} - \frac{1}{6} & v \in [5, 15) \\ 1 - \frac{(20-v)^2}{150} & v \in [15, 20] \\ 1 & v \in (20, \infty) \end{array}$$

The optimal prices satisfy equations III.3 and III.4 after plugging in the ex post distribution.

2. Subjects incorrectly account for correlation in their pricing decisions. In particular, subjects consider the optimal price to be the weighted average of the optimal prices for each realization of μ. Informally, we can think of subjects taking the average of the optimal price for a low value of μ and the optimal price for a high value of μ. Formally, naive subjects set prices that satisfy the following two optimality conditions:

$$\begin{aligned} r =& \int_{\underline{\mu}}^{\bar{\mu}} \frac{1-F(r|\mu)}{f(r|\mu)} g(\mu) d\mu \\ =& \frac{2\varepsilon}{b-a} \int_a^b \left(1 - \left(\frac{r-\mu+\varepsilon}{2\varepsilon}\right)\right) d\mu, \end{aligned} \tag{III.5}$$

$$\begin{aligned} p =& \int_{\underline{\mu}}^{\bar{\mu}} \frac{1-F(p|\mu)^n}{nF(p|\mu)^{n-1} f(p|\mu)} g(\mu) d\mu \\ =& \frac{2\varepsilon}{b-a} \int_a^b \left(\frac{1-\left(\frac{p-\mu+\varepsilon}{2\varepsilon}\right)^n}{n\left(\frac{p-\mu+\varepsilon}{2\varepsilon}\right)^{n-1}} \right) d\mu. \end{aligned} \tag{III.6}$$

Both models predict prices in the uncorrelated environment that are equivalent to the benchmark risk-neutral predictions because $F(v) = F(v|\mu)$ in this case. In the correlated environment on the other hand, the prices predicted by the naive models are not optimal. Also notice that, in both models, the correlated environment now inherits the property of the uncorrelated environment that the reserve price is not a function of the number of buyers. The predicted prices under the naive-pricing models are shown in Table 18.

The results suggest that the naive models are a better fit for the data than the benchmark model. Both naive models match the comparative-static results in the corre-

Table 18. Predicted versus Experimental Prices

	Auction			
	Uncorrelated		Correlated	
	2 Buyers	5 Buyers	2 Buyers	5 Buyers
Benchmark	10.00	10.00	6.00	5.45
Ignore Correlation	10.00	10.00	8.75	8.75
Misspecify Correlation	10.00	10.00	7.50	7.50
Results	9.766	10.057	7.983	8.377
	(0.315)	(0.428)	(0.297)	(0.342)
	Posted Price			
Benchmark	11.55	13.98	9.11	9.75
Ignore Correlation	11.55	13.98	10.37	12.60
Misspecify Correlation	11.55	13.98	9.34	11.32
Results	11.011	13.697	10.326	11.646
	(0.224)	(0.178)	(0.181)	(0.180)

Notes: The table displays the reserve and posted prices predicted by the three models as well as subjects' prices in the experiment. Standard errors are shown in parentheses.

lated environment. To test between the two naive models, I compare prices levels. Nonparametric medians tests provide more support for the ignore-correlation model. In the auction market, I fail to reject that subjects follow the ignore-correlation model with two buyers (z=1.13, p-value= 0.26) and five buyers (z=0.02, p-value=0.99). In the posted-price market, I fail to reject with two buyers (z=0.08, p-value=0.94) but not with five buyers (z=5.71, p-value=0.00). I reject the misspecify-correlation model in all correlated-values treatments, except the five-buyers posted-price treatment (z=1.87, p-value=0.06), where the misspecify-correlation model outperforms both the benchmark model and the ignore-correlation model. In total however, the results are most favorable to the ignore-correlation model.

Discussion

The naive-pricing models proposed in this paper provide a better fit for the data than the benchmark model of how sellers set prices in auction and posted-price markets. The model that suggests sellers ignore the correlation among buyers' values outperforms both the benchmark and the model that suggests sellers incorrectly account for correlation. It would be interesting to compare these results to work that uses field data. Do sellers in naturally-occurring markets have similar difficulty in demand environments that are more complex than the independent-private-values framework? Providing an answer requires carefully isolating the causal link between correlation among buyers' values and seller pricing decisions. This is more easily done in the laboratory but it would be informative to bring field data to bear on this question. Recent econometric developments show how to recover the nature of correlation in the underlying demand structure (Li, Perrigne, and Vuong 2002). Using these insights, studying the effect of correlation on pricing decisions is possible and doing so would provide a worthwhile companion to this paper.

Appendix - Expected Revenues

Auction Market

In the correlated environment of the affiliated-signals model, expected auction revenues can be expressed as follow. For $r \in [0, 10]$:

$$\begin{aligned} E(Rev_A) =& \frac{n}{10}\int_{r+5}^{15}\int_{\mu-5}^{\mu+5}\left(\frac{v}{10}+\frac{v-\mu+5}{10}-1\right)\left(\frac{v-\mu+5}{10}\right)^{n-1}dvd\mu \\ &+\frac{n}{10}\int_{5}^{r+5}\int_{r}^{\mu+5}\left(\frac{v}{10}+\frac{v-\mu+5}{10}-1\right)\left(\frac{v-\mu+5}{10}\right)^{n-1}dvd\mu. \end{aligned}$$

The first term on the right-hand side corresponds to $\mu - 5 \geq r$, while the second term on the right-hand side corresponds to $\mu - 5 < r < 10$. For $r \in [10, 20]$:

$$E(Rev_A) = \frac{n}{10} \int_{r-5}^{15} \int_{r}^{\mu+5} \left(\frac{v}{10} + \frac{v - \mu + 5}{10} - 1 \right) \left(\frac{v - \mu + 5}{10} \right)^{n-1} dv d\mu.$$

Posted-Price Market

The optimal posted prices in the correlated environment of the affiliated-signals model can be derived from the following parameterization of the expected posted-price revenue function:

$$E(Rev_P) = \frac{1}{10} \int_{5}^{15} p \left(1 - \left(\frac{p - \mu + 5}{10} \right)^{n} \right) d\mu.$$

Appendix - Instructions

Today you will be participating in an experiment on how sellers set prices. You will play the role of a seller and are asked to set a price. Pricing will take place in two settings: an auction and a posted-price market. All monetary figures referred to in these instructions and during the experiment are in experimental dollars. Experimental dollars will be converted to American dollars at the end of the experiment and your take-home earnings will be paid in American dollars, including a \$5 show-up payment.

In the auction market, you, as the seller, will select a minimum bid. Bidding will begin at this price and no bids will be accepted below this amount. Buyers will see your minimum bid and are asked to place their bid. If no buyer enters a bid above your minimum bid, your item does not sell. Your profit on an unsold item is 0. If one and only one buyer enters a bid above your minimum bid, this buyer wins the auction and pays the minimum bid. In this case, your profit is the dollar value of your minimum bid. Finally, if more than one buyer enters a bid above your minimum bid, the highest bidder wins the auction and pays a price equal to the second-highest bid. In this case, your profit is the dollar value of the second-highest bid. For this reason, this type of auction is known as a second-price auction.

In the posted-price market, you will select a price to charge. Buyers will see your posted price and are asked whether or not they wish to buy the item. If no buyer chooses to buy your item, it does not sell. Your profit on an unsold item is 0. If at least one buyer chooses to buy your item, it sells at the posted price you selected. In this case, your profit is the dollar value of your posted price.

In today's experiment, the role of buyers will be performed by a computer. These simulated buyers will be assigned a value for your item. The term "value" refers to the maximum amount that a particular buyer is willing to pay; these values are unknown to you, the seller. The computer will assign a value to each buyer randomly in a particular way that will be described below. In the auction, the computer will then enter a bid for each buyer in the amount of that buyer's value. In the posted-price market, the computer will indicate that a buyer is willing to purchase your item if the price is below that buyer's value. The computer will indicate that the buyer is unwilling to purchase if the price is above that buyer's value.

We will now describe how buyers' values are determined. Buyers' values are determined in one of two environments:

A. For a portion of the experiment, values will be randomly selected from the integers between 0 and 20 inclusive (0,1,2,. . . ,18,19,20), with each integer being equally likely. Buyers' values will be reselected after each round, meaning that buyers will have a new value during each round.

B. For the remaining portion of the experiment, values will be determined in two steps: first a single number (that we will call X) is randomly selected from the integers between 5 and 15 inclusive (5,6,7,. . . ,13,14,15), with each integer being equally likely; once X is selected, buyers' values are then randomly selected from the integers between X-5 and X+5 inclusive, with each integer being equally likely. X will be reselected after each round. Buyers' values will also be reselected after each round. You will not be told X until after the round is completed.

Once you choose your minimum bid or price, values will be determined and you will be informed of your profits for the round. During the course of the experiment, you will sometimes be pricing in environment A, other times in environment B but it will always be made clear to you how values are being chosen before you set your price. The number of buyers to whom you are selling will also change but the number of buyers will also always be made clear to you before you set your price. Your take-home earnings depend entirely on your pricing decisions and are not affected by the actions of the other subjects in the room.

The conversion rate between experimental dollars and American dollars is 10 to 1. The take-home earnings that you receive for participating in this experiment will be based on 10 randomly-selected rounds during the experiment. You will not be made aware of which rounds are used to determine your take-home earnings until the experiment is completed. The first several rounds of each environment will be practice rounds. These rounds will not be used to determine your take-home earnings. You should use them to insure that you understand the environment and how to earn the highest profits. It will be made clear to you when you are pricing in the rounds that will be used to determine your take-home earnings. Do you have any questions?

Appendix - Measuring the Degree of Risk Aversion

Holt and Laury (2002) devise a procedure for eliciting risk preferences based on presenting subjects with a menu of lotteries. Table 19 reproduces their Table 1, with payoffs scaled up by a factor of four so that the expected payoff from the lottery experiment matches the expected payoff of the pricing experiment. I scale the payoffs because measuring risk aversion has been shown to depend critically on the stakes (Holt and Laury 2002). Subjects see the probabilities and payoffs associated with each option but not the expected payoff difference.

As argued in their original paper, the Holt-Laury procedure allow the researcher to measure a subject's risk preferences based on the decision (or the row in Table 19) at which the subject switched from Option A (the "safe" option) to Option B (the "risky" option). As the tenth decision involves a higher payoff with probability 1, subjects should choose Option B at some point in the sequence. Fairly weak assumptions on preferences would imply that subjects switch from Option A to Option B only once (or choose Option B in all decisions).

I use the results from the Holt-Laury procedure in two ways: (1) to group subjects according to the decision at which they first switched from Option A (the safe option) to Option B (the risky option); and (2) to group subjects according to the number of times

Table 19. Holt-Laury Risk Elicitation Procedure

Option A	Option B	Expected Payoff Difference
1/10 of \$8.00, 9/10 of \$6.40	1/10 of \$15.40, 9/10 of \$0.40	\$4.66
2/10 of \$8.00, 8/10 of \$6.40	2/10 of \$15.40, 8/10 of \$0.40	\$3.32
3/10 of \$8.00, 7/10 of \$6.40	3/10 of \$15.40, 7/10 of \$0.40	\$1.98
4/10 of \$8.00, 6/10 of \$6.40	4/10 of \$15.40, 6/10 of \$0.40	\$0.64
5/10 of \$8.00, 5/10 of \$6.40	5/10 of \$15.40, 5/10 of \$0.40	-\$0.70
6/10 of \$8.00, 4/10 of \$6.40	6/10 of \$15.40, 4/10 of \$0.40	-\$2.04
7/10 of \$8.00, 3/10 of \$6.40	7/10 of \$15.40, 3/10 of \$0.40	-\$3.38
8/10 of \$8.00, 2/10 of \$6.40	8/10 of \$15.40, 2/10 of \$0.40	-\$4.72
9/10 of \$8.00, 1/10 of \$6.40	9/10 of \$15.40, 1/10 of \$0.40	-\$6.06
10/10 of \$8.00, 0/10 of \$6.40	10/10 of \$15.40, 0/10 of \$0.40	-\$7.40

Notes: The payoffs have been scaled up by a factor of four such that the expected payoff matches the expected payoff of the pricing experiment.

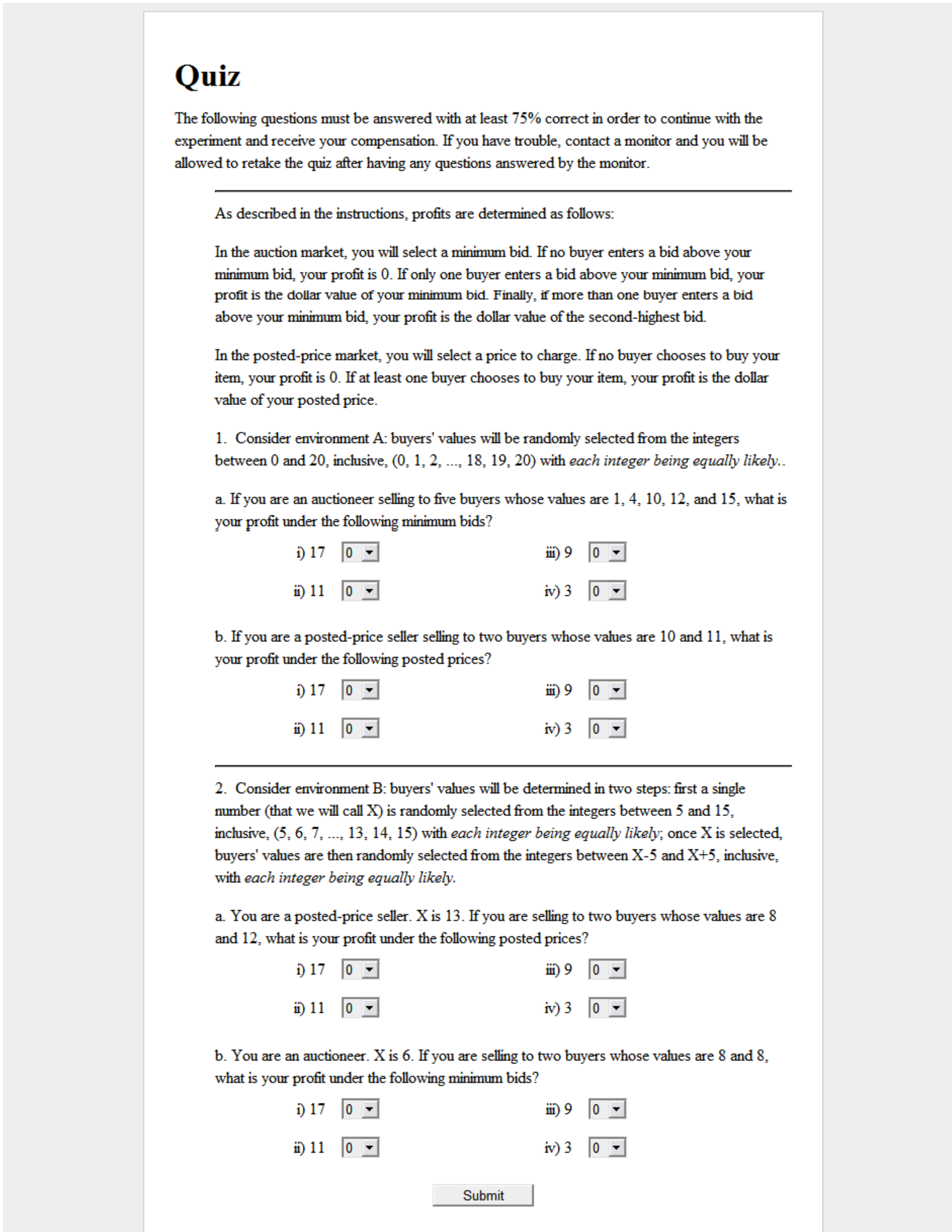
they switched between options. Subjects switching between Option A and Option B later in the sequence may reasonably be considered more risk averse, even without an exact estimation of their degree of risk aversion (which would depend on the function form of risk preferences). Subjects switching between Option A and Option B multiple times may reasonably be considered to have "different" behavior from those switching only once, either because of differences in their preferences or because they are less attentive. Under either interpretation, it is useful to check for differences across subjects who switched only once and those switching multiple times.

Risk neutrality predicts four safe choices, followed by six risky choices. The results of the lottery experiment can be summarized as follows:

- When considering the decision at which subjects first switched to the risky lottery, four subjects switched at decision two, one at decision three, seven at decision four, thirteen at decision five, four at decision six, four at decision seven, and two at decision eight.

- Nine subjects (25.7% of thirty five) switched between the safe and risky lotteries more than once. Four switched twice and one switched three times.
- The decision of the first switch and the number of switches are uncorrelated with price levels, which is surprising given that all three model detailed in this paper predicted lower prices in both markets as the degree of risk aversion increases.

Appendix - Screenshots



Quiz

The following questions must be answered with at least 75% correct in order to continue with the experiment and receive your compensation. If you have trouble, contact a monitor and you will be allowed to retake the quiz after having any questions answered by the monitor.

As described in the instructions, profits are determined as follows:

In the auction market, you will select a minimum bid. If no buyer enters a bid above your minimum bid, your profit is 0. If only one buyer enters a bid above your minimum bid, your profit is the dollar value of your minimum bid. Finally, if more than one buyer enters a bid above your minimum bid, your profit is the dollar value of the second-highest bid.

In the posted-price market, you will select a price to charge. If no buyer chooses to buy your item, your profit is 0. If at least one buyer chooses to buy your item, your profit is the dollar value of your posted price.

1. Consider environment A: buyers' values will be randomly selected from the integers between 0 and 20, inclusive, (0, 1, 2, ..., 18, 19, 20) with *each integer being equally likely.*.

a. If you are an auctioneer selling to five buyers whose values are 1, 4, 10, 12, and 15, what is your profit under the following minimum bids?

i) 17 [0] iii) 9 [0]

ii) 11 [0] iv) 3 [0]

b. If you are a posted-price seller selling to two buyers whose values are 10 and 11, what is your profit under the following posted prices?

i) 17 [0] iii) 9 [0]

ii) 11 [0] iv) 3 [0]

---

2. Consider environment B: buyers' values will be determined in two steps: first a single number (that we will call X) is randomly selected from the integers between 5 and 15, inclusive, (5, 6, 7, ..., 13, 14, 15) with *each integer being equally likely*; once X is selected, buyers' values are then randomly selected from the integers between X-5 and X+5, inclusive, with *each integer being equally likely.*

a. You are a posted-price seller. X is 13. If you are selling to two buyers whose values are 8 and 12, what is your profit under the following posted prices?

i) 17 [0] iii) 9 [0]

ii) 11 [0] iv) 3 [0]

b. You are an auctioneer. X is 6. If you are selling to two buyers whose values are 8 and 8, what is your profit under the following minimum bids?

i) 17 [0] iii) 9 [0]

ii) 11 [0] iv) 3 [0]

Submit

Figure 4. Screenshot of the Pre-Experiment Quiz

You are an auctioneer selling to two buyers in environment A: buyers' values will be randomly selected from the integers between 0 and 20, inclusive, (0, 1, 2, ..., 18, 19, 20) with each integer being equally likely.

Minimum Bid:

Enter

Figure 5. Screenshot of a Pricing Environment

You are an auctioneer selling to five buyers in environment B: buyers' values will be determined in two steps: first a single number (that we will call X) is randomly selected from the integers between 5 and 15, inclusive, (5, 6, 7, ..., 13, 14, 15) with each integer being equally likely; once X is selected, buyers' values are then randomly selected from the integers between X-5 and X+5, inclusive, with each integer being equally likely.

Your item sold. Your profits are 8.

This was a practice run. The results have not been recorded.

Your Minimum Bid	0
X	8
Highest Bid	13
Second-Highest Bid	8
Third-Highest Bid	5
Fourth-Highest Bid	4
Fifth-Highest Bid	3

Continue

Figure 6. Screenshot of the Feedback from a Practice Round with a Sold Item

You are a posted-price seller selling to two buyers in environment B: buyers' values will be determined in two steps: first a single number (that we will call X) is randomly selected from the integers between 5 and 15, inclusive, (5, 6, 7, ..., 13, 14, 15) with each integer being equally likely; once X is selected, buyers values are then randomly selected from the integers between X-5 and X +5, inclusive, with each integer being equally likely.

Your item did not sell. Your profits are 0.

Your Posted Price	9.11
X	6
Highest Value	4
Second-Highest Value	3

Continue

Figure 7. Screenshot of the Feedback from a Round with an Unsold Item

Thank you

Thank you for participating in this study. Please contact the proctor for information about receiving your take-home earnings.

Take-home earnings

Ten random rounds were selected from the pricing experiment to determine your take-home earnings. They are shown below, along with your profits from each one.

Treatment:	a5c	a2c	p5c	a2u	p5u	p2u	a2c	p2c	a5c	p5c
Profit:	13	10	9.75	10	13.98	11.55	0	9.11	19	9.75

In addition, one of the questions was selected from the survey. The selected question was:

- A: 3/10 chance of 8.00, 7/10 chance of 6.40
- B: 3/10 chance of 15.40, 7/10 chance of 0.40

You chose option A. A random number was chosen between 1 and 10. The number was 8. As a result, your profit from the question is 6.40. This will be added to your earlier profits.

Altogether, your profits in experimental currency were 112.54.

Your take-home earnings are 112.54 / 10 = $11.26.

You will also receive an additional $5.00 if you arrived at the experiment on time.

Your participant identification number is [redacted]. Please print this page and do not discuss your earnings with any other participants.

Figure 8. Screenshot of the Results Page

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