BUY IT NOW: A HYBRID INTERNET MARKET INSTITUTION

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ABSTRACT

This paper analyzes seller choices and outcomes in approximately 700 Internet auctions of a relatively homogeneous good. The 'Buy it Now' option allows the seller to convert the auction into a posted price market. We use a structural model to control for the conduct of the auction as well as product and seller characteristics. In explaining seller choices, we find that the 'Buy it Now' option was used more often by sellers with higher ratings and offering fewer units; and posted prices were more prevalent for used items. In explaining auction outcomes, we find that auctions with a 'Buy it Now' price had higher winning bids, ceteris paribus, whether or not the auction ended with the 'Buy it Now' offer being accepted, possibly reflecting signaling or bounded rationality. We also find that posting prices, by combining 'Buy it Now' and an equal starting price, was an effective strategy for sellers in the sample.

Keywords: market institutions, posted prices, auctions, e-commerce

1. Introduction

The Internet drastically alters absolute and relative transaction costs, and this, in turn, begins to alter market institutions. The posted offer institution dominated retail markets in the 20th century, but recently e-commerce has spurred the development of new auction institutions, as well as hybrids that combine aspects of auction and posted price institutions. As e-commerce takes hold in the retail sector—by 2006 the rapidly growing e-commerce share of retail sales reached 2.8%, or about $109 billion [US Census Bureau, 2007]—some patterns have begun to emerge. Amazon and other companies have created very efficient Internet versions of posted price institutions, and the evidence suggests that posted prices are more flexibly and finely adjusted in online settings [Smith et al., 2000]. Meanwhile, Internet auctions, led by eBay, have grown out from their original garage sale niche. As early as 2003, a substantial portion of eBay's $15 billion gross revenue[1] represented retail transactions [Hof, 2003]. Auctions and posted prices seem destined to coexist online, and for overlapping sets of goods.

What are the economic factors that determine the choice of market institution?[2] In this paper we present empirical evidence from recent Internet auctions on eBay that include the option for buyers to purchase immediately at a pre-specified 'Buy it Now' price. As explained in detail in Section 4, the option allows sellers to offer what is effectively a hybrid of auction and posted prices, or to choose a pure version of either institution. A 'Buy it Now' option may influence seller revenue in several different ways. The potential for a price premium for buyer impatience or risk aversion could account for the use of 'Buy it Now' prices if they were to raise final bids. Alternatively, transactions featuring such fixed prices may negatively impact profits due to under-pricing by naïve sellers or foregone premiums reflecting bidder excitement from auction competition.

To untangle the causes and consequences of sellers' choices, we estimate a structural model that factors in the predetermined characteristics of the seller, the good, and the transaction, while controlling for the endogenous conduct of the auction (e.g., the number of bids and bidders), to predict auction outcomes.

The remainder of the paper is organized as follows. Section 2 reviews some of the most relevant theoretical and empirical literature. Section 3 identifies variables of interest and the causal structure of the empirical model. Section

[1] This figure represents the total value of transactions, and not the net revenue figure reported in eBay's income statements. Based on figures in the company's latest annual report, this gross revenue figure had more than doubled by 2006.
[2] Our concern is with this specific issue of choice of market institution. Broader issues with respect to B2C e-commerce are summarized in Rajagopalan and Deshmukh [2005].

4 summarizes the data, obtained from over 700 completed eBay auctions, held during a period of five weeks, for a particular model of personal digital assistant (PDA). Section 5 presents results on seller characteristics and choices. For example, we find that the 'Buy it Now' option was used more often by sellers with higher ratings (awarded by previous buyers) and offering fewer units; and posted prices were more prevalent for used items.

Section 6 presents results on the conduct and outcome of the Internet auctions, focusing particularly on the role of the 'Buy it Now' seller option as a hybrid posted price institution. For example, we find that in auctions with a 'Buy it Now' price every dollar increase in the 'Buy it Now' price increased final bids by $0.29, ceteris paribus, whether or not the auction ended with the 'Buy it Now' offer being accepted. We conjecture that this effect reflects factors such as signaling or bounded rationality. We also find evidence that posting prices by combining 'Buy it Now' and an equal starting price was an effective strategy for sellers. Section 7 concludes with a summary of results, a discussion of their implications, and suggestions for future research. An appendix provides some subsidiary details on the variables and the estimation results.

2. Research on Market Institutions

The large theoretical literature on auctions, surveyed in McAfee and McMillan [1987] and more recently in Klemperer [2002], can be regarded as a special case of the analysis of market institutions. Comparisons across pricing institutions are less common. For example, Bulow and Klemperer [1996] provide a theoretical analysis of auctions versus some kinds of structured negotiations. Campbell and Levin [2006] examine the issue of when or when not to use an auction format for selling. They show that when buyers have interdependent valuations, auctions may lose their revenue-maximizing advantage for sellers, even if symmetry and independence of information are maintained. Peters and Severinov [2006] show that, even with many sellers, the buyers' optimal bidding strategies are independent of seller choices such as starting price.

Reynolds and Wooders [2004] present a model in which the 'Buy it Now' auction hybrid formats offered by eBay and Yahoo are revenue equivalent to ascending bid auctions if bidders are risk neutral, but can raise seller revenue in the presence of bidder risk aversion. Thus, with risk neutral bidders, there is no advantage to the seller from using a 'Buy it Now' option. Budish and Takeyama [2001] arrive at the same conclusions independently. Mathews [2004] develops a theoretical model in which sellers may use 'Buy it Now' prices where impatience is a factor on either side (or both), resulting in a Pareto improvement at lower transaction prices. Existing theory does not present us with sharply posed testable hypothesis but, as noted below, it is often suggestive.

We see three relevant strands of empirical literature. The first involves laboratory experiments. Plott and Smith [1978] is the first laboratory comparison of market institutions: the oral double auction vs. the posted price institution. Holt [1995] covers subsequent work examining market structure and institutions. More recently, Cason, Friedman and Milam [2003] contrast the posted price institution with one featuring haggling to determine prices. The authors find that efficiency is lower, sellers' prices higher, and prices stickier under haggling than under posted offer pricing.

A second strand, pioneered by Lucking-Reiley [1999], conducts "field experiments" by purchasing goods (e.g., collectable trading cards) and reselling them on the Internet, using alternative market institutions. Lucking-Reiley thus tested classical results from auction theory, such as revenue equivalence. Resnick et al. [2003] report a field experiment more directly relevant to our concerns. They find that the effects of seller reputation have the predicted positive effect on seller revenues when proper experimental controls are imposed. Durham et al. [2004] used this method, in conjunction with an uncontrolled, observed sample, to examine the impact of eBay's reputation mechanism and the inclusion of 'Buy it Now' prices on auction outcomes. They find evidence that newer sellers receive lower prices and that the likelihood of a sale ending with 'Buy it Now' decreases in the level of this fixed price.

Our work falls into a third strand of empirical research, involving the collection and analysis of transactions data from large numbers of related Internet sites – typically auctions conducted on web sites operated by eBay, Yahoo or Amazon. This approach typically uses specialized software to extract data samples from Internet sources. In one example, Houser and Wooders [2006] examine the effect of bidder and seller reputation on auction outcomes, concluding that seller reputations are correlated with auction success in *Pentium III* microprocessor auctions on eBay. Morgan and Baye [2001] analyze persistent price dispersion in posted price markets on the Internet. The timing of bids, and the impact of different methods of specifying auction deadlines are studied by Roth and Ockenfels [2002], Bajari and Hortaçsu [2003], and Ockenfels and Roth [2006], using data from eBay and/or Amazon. Lucking-Reiley et al. [2006] study price determination in eBay auctions of one-cent coins. We use the same data collection methods, described in Section 4 of the paper.

3. Key Variables and Hypotheses

The existing literature suggests a list of variables to be included in the empirical analysis, and, in some cases, provides specific hypotheses. The variables can be put into several general categories, as follows:

Product characteristics

Hedonic theory [Lancaster, 1971; Rosen, 1974] distinguishes quality characteristics (for which all consumers have ordinally equivalent preferences) from niche characteristics (for which different consumer segments may have marginal valuations with opposite signs.) Quality increments *ceteris paribus* imply higher transaction prices.

For our data, higher quality should be associated with "new" or "undamaged" products, and (due to rapid economic obsolescence) with earlier transaction dates. Niche characteristics, such as color or shipping location, are probably best dropped from the analysis because we have no information on buyers' characteristics.

Seller characteristics

The information regarding sellers in an online auction is indirectly observed, and often selected by the seller herself, and thus is highly imperfect. Information regarding seller characteristics, apart from that provided via seller choices (discussed below), includes the feedback ratings provided by previous customers and the number of auctions the seller is currently running.

The seller ratings may work in at least two dimensions, with a higher absolute number of ratings indicating more extensive experience, and with the auction site and the relative number of positive ratings more directly identifying seller quality. Ratings on eBay are represented by a numerical value, indicating the number of positive comments less the number of negative.[3] Durham et al. [2004] find evidence positively linking seller rating to final auction prices for silver dollars.

Other studies of the impact of feedback ratings in auctions suggest a non-linear relationship, with greater weight at low absolute value ratings and with the percentage of negative comments mattering more than rating levels [Lucking-Reiley et al., 2006; Brown and Morgan, 2006].[4] To better analyze the information provided by such ratings, we transform the feedback rating into two variables: NEGRATIO (the ratio of negative to total comments), and LNSLRTNG (natural log of positive comments net of negative comments). Thus lower NEGRATIO and higher LNSLRTNG indicate two aspects of better seller reputation.

Any rating measures will be imperfect signals of underlying characteristics, such as the trustworthiness of the seller to accurately represent the product and follow through in the transaction in good faith. Theoretically, a more trustworthy seller will obtain higher prices in a separating equilibrium *ceteris paribus* [e.g., Fudenberg and Tirole, 1991]. Other factors may also influence perceptions of trustworthiness. For instance, a higher volume seller may appear more stable and professional, thus attracting more bidders and increasing the transaction price. The difficulty in separating high volume from longer history based on an individual's seller rating requires some further classification of sellers. Thus we categorize sellers within our sample according to the volume of sales within the sample period as detailed below.

Conversely, sellers with many similar items to sell may utilize 'Buy it Now' pricing to price discriminate based on the relative patience or reservation prices of bidders**.** Such practices will be reflected in higher volume for some sellers but at a lower average price. If prevalent, such uses of 'Buy it Now' prices should be apparent in the data. To take account of these factors, in addition to our two reputation measures, we control for how frequently a seller appears in the sample by categorizing sellers by the number of auctions conducted during the sample period (MULTSLR codes 2-10 auctions and FREQSLR codes 11-50), a proxy for seller volume. If such discrimination exists we should see more use of 'Buy it Now' and higher transaction prices for these higher volume sellers, controlling for reputation. If negative feedback adversely affects 'Buy it Now' transactions, the data should reveal lower accepted prices and fewer transactions as a result.

Seller choices[5]

Investments that signal trustworthiness, once sunk, presumably will increase transaction price, since otherwise the seller would have little reason to make them: these investments are therefore part of a separating equilibrium where the seller's characteristics are unknown, *ex ante*. Such investments might possibly include use of photographs of the item, more detailed descriptions, buying a "featured" billing, or links to websites with further information regarding the seller.[6] A higher auction starting price or 'Buy it Now' price specified by the seller could serve a similar purpose in signaling product quality.

If buyers are price takers, a higher private (or, in eBay's terminology, 'secret') reserve price will trade off a lower probability of a sale against a higher transaction price conditional on a sale. If buyers react to a secret

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[3] The positive and negative classifications are selected by transacting buyers and sellers who leave the feedback. The rating value is represented as a hyperlink, which leads one to a more detailed listing of the brief comments (limited to 80 characters).

[4] Malaga [2001] identifies a range of problems with reputation mechanisms from major e-commerce sites, and offers some possible solutions. A good reputation signals trustworthiness: Kim and Benbasat [2003] consider the general issue of trust building, including neutral third-party judgments, across a variety of e-commerce sites.

[5] We take as given the seller's choice of eBay as the selling channel. Walczak et al. [2006] analyze the important prior choice of which auction site to sell at, comparing eBay with Yahoo and Amazon.

[6] These choices serve as control variables, but are not the focus of our analysis. Detlor et al. [2003] investigate consumer preferences with respect to product displays for browsing as well as targeted search.

reservation price per se, there could be other effects. In a field experiment, Katkar and Lucking-Reiley [2005], comparing public and secret reserve prices, found that the use of a secret reserve reduces both the probability of a sale and the transaction price.[7]

Apart from providing minimum revenue and potentially signaling relative quality the starting bid selected by a seller has the potential to reduce the number of bids submitted in a given auction. Such restriction will not adversely impact the final price if it reflects only fixed private values of bidders. However, there is some evidence suggesting that bidders, once engaged in an auction, may receive positive utility from winning an auction [Standifird et al., 2005; Ku et al. 2005]. This has the potential to raise the final sales price in auctions with more active bidding. To the degree that such 'arousal effects' occur, lower minimum bids could encourage bidder participation and affect transaction prices.

The seller choice of the 'Buy it Now' option is a focus of our analysis. Note that the seller can replicate a posted offer by setting a 'Buy it Now' price and an equal minimum bid price. The choice of posted price vs. straight auction mainly involves a trade-off between (a) expected losses due to mis-pricing a posted price, against (b) reduced demand due to buyers' higher participation costs in auctions. The higher participation costs arise from the loss of immediacy—buyers must wait until the end of an auction to know whether they transacted—and potential 'shoe leather costs' of monitoring one's auction progress as buyers adjust their maximum bids over time.[8] Hence sellers who have relatively precise beliefs about demand will tend to prefer a posted price or 'Buy it Now.' If some auctions include the 'Buy it Now' option, and others involve straight auctions, then in a separating equilibrium, more risk averse and/or impatient buyers will opt for the 'Buy it Now' price [Reynolds and Wooders, 2004; Mathews, 2004].

Under-pricing by replacing the auction with a fixed price may result in losses in several ways. Apart from the obvious mistake of selecting a price below market equilibrium, to the extent that bidders gain utility from winning a competitive auction, posting prices may bypass opportunities to capture any premiums resulting from bidder competition. The impact is similar to, but more pronounced than the effects of setting a high minimum bid, discussed above.

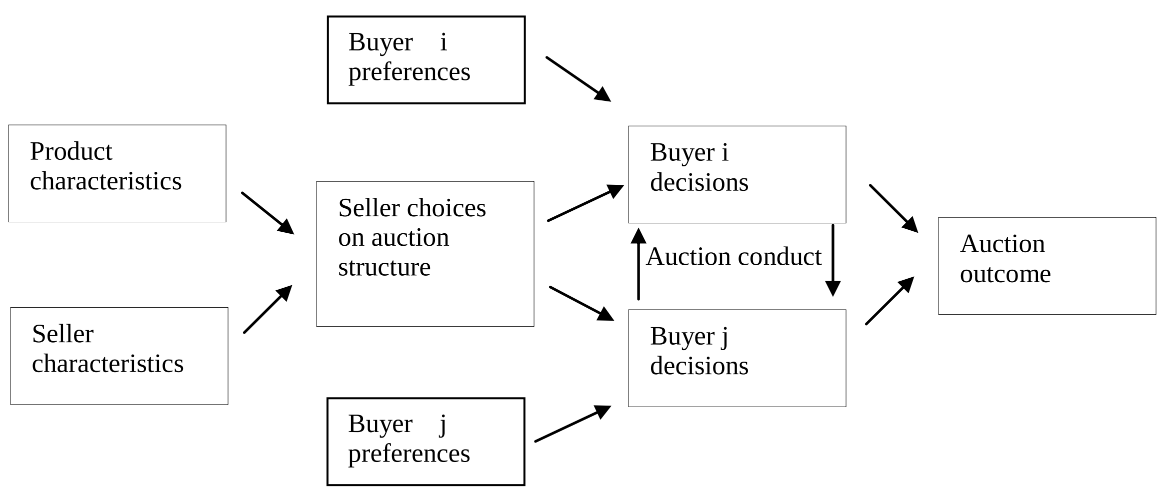

Figure 1: Decision Making Sequence in an Auction

Figure 1 illustrates the sequence of decisions that we analyze. We take the product and seller characteristics as exogenous, determining the seller choices on auction structure. These choices, together with exogenous buyer preferences, determine the dynamic course of the auction (or hybrid market when the 'Buy it Now' option is used) and the ultimate outcomes.

Our strategy for analyzing the data accordingly has two parts. First, we use the observable product and seller characteristics to explain the main seller choices, using Ordinary Least Squares (OLS) for continuous choices and Logit for binary choices. Section 5 presents those results, and notes when they support or cast doubt on the testable

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[7] One caveat to these results is that the authors found some informal evidence that sellers were using the secret reserve to circumvent eBay's fee structure by personally contacting high bidders after unsuccessful auctions. Anderson et al. [2007] found that the probability of a sale was lower, but the transaction price higher, when a secret reserve price was used.

[8] In private value auctions, eBay's proxy bidding system should eliminate the need to adjust bids as the auction end approaches. However, the well documented practice of "bid sniping" by submitting last second bids above the existing high bid indicates that bidder strategies indeed incorporate timing. Roth and Ockenfels [2002] provide some potential explanations for such behavior.

hypotheses presented above. Next, we use relevant exogenous characteristics, as well as instruments for the endogenous seller choices, to explain the market outcomes, via Two Stage Least Squares (2SLS). In doing so, we restrict attention to completed auctions. Thus, our main analysis is conditional on the auction resulting in a sale.[9] Section 6 presents the results for this aspect of the auction. Section 7 is a summary conclusion.

4. Data Overview

Our hypotheses are best examined with a reasonably large sample of auctions for selling a homogeneous good over a short period of time. Therefore we gathered data from eBay, the largest Internet auction site, for one of the highest volume (at the time) and most homogenous items, the Palm Vx PDA. We collected complete data on 1177 Palm Vx auctions on eBay from August 6 to September 11, 2001 using a web-crawling "spider" similar to that described in Lucking-Reiley et al. [2006]. This gave us a reasonably large sample in a short period of time, during which environmental conditions could be taken to be relatively static. In particular, product innovation and the severe 9-11 effect led to us not collecting further data. Given the maturity of eBay auction institutions by 2001, we believe that the data and analysis based on it are still of relevance and interest. Of course similar analysis as ours can be performed on new data sets to test the robustness of our results. As we have noted in the literature review, our data collection strategy and sample size and period are similar to several other works in this area, and quite standard in this respect.

eBay Auction Rules

A review of eBay's basic rules is in order before presenting the data. The seller provides information on the item, such as a description and picture, terms of payment and shipping, and chooses the duration of the auction, either 3, 5, 7, or 10 days. The seller also chooses a minimum first bid (starting price), and whether to enter a private reserve price. (Potential buyers know when a private reserve price exists but don't know its value until someone bids above it.) Sellers may also provide links to their own "home pages" on the web, which can be a source of further information for buyers.

Potential buyers can bid on any item they find on eBay's web site, and bid histories are available to them. The auction ends at the pre-specified time, and the item goes to the highest bidder at the highest bid price. Shipping and payment are left up to the buyer and seller, although eBay services here are available at an additional fee. Finally, eBay also collects buyers' comments about sellers, so that sellers can build and maintain reputations. Potential buyers have access to these comments, as well as all seller-provided information.

The seller also can specify a 'Buy it Now' price. By so doing, the seller commits to sell the item immediately to any buyer who accepts that price, thus ending the auction early. The 'Buy it Now' option is extinguished (and disappears from the item's auction site) when any buyer enters a bid that is at least as great as the minimum first bid, even if the first bid is lower than the 'Buy it Now' price. The seller can prevent this by specifying a starting price or a secret reserve price at (or above) the 'Buy it Now' price. As noted earlier, such price combinations are equivalent to a posted price.[10] Used by itself, the 'Buy it Now' option creates a hybrid institution, a mix of an auction and a posted price, with buyer behavior determining which of the two institutions is activated for the transaction.

The Data

Of the 1177 auctions for which we collected data, 1008 were successfully completed, ending in a sale. We focus on these completed auctions in the regression analysis.[11] Furthermore, of the 1008 completed auctions, 286 were conducted by two high volume sellers. We omit these auctions from our regression analysis because their distinctive behavior would distort the overall results.[12] This leaves 722 observations for analysis. We also separately analyze sub-samples: auctions where the 'Buy it Now' option was not offered (510), those where it was (212), 'Buy it Now'

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[9] There are two reasons for our focus on completed auctions. First, our regression analysis straightforwardly seeks to explain the level of the winning bid – allowing for incomplete auctions would require a different analysis, since those auctions essentially have a missing dependent variable. Second, there could be problems of interpretation, since failed auctions can be relisted on eBay once, at no cost to the seller beyond the time delay.

[10] By using a high secret reserve price to "protect" the 'Buy it Now' option, the seller allows bidding to continue, but fruitlessly. Buyer comments suggest that they find the practice annoying and they may avoid the auction. Using a high starting price is just as effective and more transparent. Since this sample was collected, eBay has begun allowing sellers to offer goods exclusively at a 'Buy it Now' price, explicitly making the offering to a posted offer.

[11] See footnote 6 for a justification of this focus. Anderson et. al [2007] found that auctions involving a secret reserve price were less likely to end in a sale, and that more experienced sellers in the sample very rarely failed to sell an item. Additionally, a sale was somewhat more likely when sellers made 'Buy it Now' offers.

[12] We may label these sellers as 'retailers.' Anderson et al. [2007] analyzed these retailers separately: their behavior differs in important ways from the lower volume sellers. In brief, they had higher ratings, and they always used the pure 'Buy it Now' option. Both used minimal ($0.01) starting prices and avoided secret reserve prices. Thus they took full advantage of the hybrid, 'Buy it Now' institution by using it to provide a quick sale to impatient buyers, yet encouraging as much bidding up of the price as possible if no impatient buyer happened to be shopping at the time.

auctions in which there was an auction and the ‘Buy it Now’ price was not the transaction price (121), and ‘Buy it Now’ auctions which ended through the exercise of the option, so that effectively no auction took place (91).[13]

5. Seller Characteristics and Choices

To examine the hypotheses presented in section 3, we use summary statistics as well as a detailed regression analysis of the data, including the various subsets of auctions. Table 1 presents the average values of the variables. The first column reports the full sample of completed transactions, the second and third report the sub-samples with and without the 'Buy it Now' option, and the last two divide the latter sub-sample according to whether or not the ‘Buy it Now’ option was exercised. The sample sizes in appear in the bottom row. Complete definitions of variables appear in the Appendix.

Table 1: Sample and Sub-sample Means

Variable	All Sales	“Buy it Now” not Offered	“Buy it Now” Offered	“Buy it Now” not Accepted	“Buy it Now” Accepted
Product Characteristics					
NEW	0.389	0.376	0.420	0.496	0.319
DAMAGE	0.026	0.024	0.033	0.017	0.055
EXTRAS	0.436	0.414	0.491	0.521	0.451
QUANTITY	1.252	1.337	1.0471	1.083	1
DAYS806	18	18	18	18	19
Seller Characteristics					
SINGLSLR	0.440	0.465	0.382	0.413	0.341
MULTSLR	0.298	0.278	0.344	0.273	0.440
FREQSLR	0.262	0.257	0.274	0.314	0.220
RETAILER	0.025	0.030	0.015	0.013	0.017
NEGRATIO	0.440	0.465	0.382	0.413	0.341
LNSLRTNG	3.538	3.214	4.319	4.110	4.597
Seller Choices					
SLRHOME	0.129	0.106	0.184	0.182	0.187
STARTPRC	$79.97	$57.88	$133.10	$81.45	$201.78
LOWSTPRC	0.395	0.455	0.25	0.438	0
PRIVTRES	0.255	0.235	0.302	0.273	0.341
FEATURED	0.026	0.037	0	0	0
DSCLNGTH	4165	4266	3922	4144	3628
IMAGE	0.713	0.661	0.840	0.860	0.813
SCRPYDUM	0.722	0.692	0.792	0.810	0.769
POSTDPRC	0.125	0	0.425	0.008	0.979
STRTBYNW	0.294	0	1	1	1
BYNOWPRC	$217.16		$217.16	$227.97	$202.79
Auction Outcomes					
DURATION	4.875	5.156	4.198	5.645	2.274
ENDBYNOW	0.139		0.429	0	1
NUMBIDS	15.878	18.910	8.585	13.198	2.451
UNIQBIDR	9.026	10.669	5.075	7.537	1.802
WINBID	$199.01	$197.96	$201.53	$201.35	$201.78
Sample Size	**722**	**510**	**212**	**121**	**91**

The observable product characteristics—whether the item is new, whether it is damaged or includes any extra accessories—are dummy variables. The entries hint that the ‘Buy it Now’ option is less likely to be offered but more likely to be accepted on new items, which constitute 28.3% of the sample. Table 1 indicates that both measures of seller rating are better on average in the ‘Buy it Now’ sub-samples, and best when ‘Buy it Now’ is accepted, and that higher frequency sellers make up a greater proportion of these auctions offering ‘Buy it Now’ prices.

[13] In all but one of these 91 auctions, the seller effectively used ‘Buy it Now’ to post a price. Thus, the ‘Buy it Now’ option was accepted, but the only bidding alternative for the buyer was to try a different seller. For the remaining 121 auctions that started with ‘Buy it Now,’ only one also had a posted price.

Seller choices are summarized in the next section of Table 1. Minimum bid prices average about $80, but diverge for accepted and not accepted ‘Buy it Now’, probably reflecting the fact that the vast majority (97.9%) of ‘Buy it Now’ transactions represent an effective posted price. Private (secret) reserve prices are used in 25.5% of all auctions, and more frequently when a ‘Buy it Now’ price is accepted. Some 29.4% of auctions in our sample offer the ‘Buy it Now’ option; of these, 42.5% actually are posted prices.

The OLS and Logit regressions in Tables 2 and 3 more explicitly examine hypotheses relating seller characteristics to seller choices. The explanatory variables are the exogenous product and seller characteristics, omitting the dummy variable for FREQSLR (21-50 auctions). The first column of Table 2 shows that the starting price (minimum bid) is higher (on the order of $50-60) for the infrequent sellers and slightly higher for sellers with better measured reputations.

Table 2: Seller and Product Characteristics and Seller Choices (OLS Regression)

Independent Variable	**Dependent Variables**		
	Starting Price	**Description Length**	**‘Buy it Now’ Price**
NEW	1.50	-406	20.02***
	(0.226)	-(1.309)	(3.877)
DAMAGE	-20.91	-31.00	-32.16**
	-(1.119)	-(0.037)	-(2.324)
EXTRAS	4.36	-334	3.59
	(0.681)	-(1.042)	(0.628)
QUANTITY	0.71	138	-11.10***
	(0.273)	(0.755)	-(2.857)
DAYS806	-0.16	-7.00	0.15
	-(0.502)	-(0.398)	(0.555)
SINGLSLR	51.81***	-2835***	22.08***
	(6.817)	-(8.062)	(3.425)
MULTSLR	59.77***	-1712***	10.39
	(7.552)	-(4.261)	(1.607)
NEGRATIO	5.45	22830***	-453.25***
	(0.148)	(6.921)	-(5.143)
LNSLRTNG	4.27**	234***	-2.64**
	(2.319)	(3.066)	-(2.040)
Sample Size	722	722	212

Note: 1 to 3 asterisks represent 10%, 5%, 1% significance, respectively

The regression analysis of the 212 auctions featuring the ‘Buy it Now’ option, presented in the third column of Table 2, confirms the observation from Table 1 that new items are more likely to conclude using the ‘Buy it Now’ option, even when controls are included, though the significance level is marginal. As one would expect, items that are characterized as ‘new’ have higher ‘Buy it Now’ prices, while items identified as damaged have lower ‘Buy it Now’ prices.[14] This is consistent with the signaling motive discussed in Section 3.

From Table 2, column 3 we see that sellers with a high ratio of negative comments set lower ‘Buy it Now’ prices. Infrequent sellers tend to set higher ‘Buy it Now’ prices. The ‘Buy it Now’ option is chosen more often by sellers with better reputations, conditional on the auction having been completed.[15] The selling frequency does not have a significant impact on use of ‘Buy it Now.’

The Low Starting Price regression (Table 3) examines the decision to set an initial bid below $20. The results for the impacts of seller characteristics on this decision are similar to those for the continuous choice of a starting

[14] The 2SLS regressions in Table 4 below indicate similar effects on final prices of completed transactions.

[15] This condition means that the impact of the seller’s reputation on the ‘Buy it Now’ option being observed may be indirect, through the ‘Buy it Now’ option affecting the probability of a sale differentially across reputational levels. This is taken up in detail in Anderson et al. [2007].

price level presented in the first column of Table 2.[16] A secret reserve price was used less often for new items and by less frequent sellers. Further, this decision is inversely related to the seller rating variable, LNSLRTNG. This may reflect a seller desire for protection against lack of measured trustworthiness.

Table 3: Seller and Product Characteristics and Seller Choices (Logit)

Variable	'Buy it Now'	Low Starting Price	Secret Reserve	Secure Payments	Include Photo	5-Day Auction	7-Day Auction	10-Day Auction	Posted Price
NEW	0.38*	0.21	-0.72***	0.45**	0.22	-0.28	-0.13	-1.99**	-0.86**
	(1.905)	(1.107)	-(3.280)	(2.205)	(1.036)	-(0.931)	-(0.488)	-(2.291)	-(2.354)
DAMAGE	0.34	0.28	-0.33	0.53	1.61**	-1.15	0.23	-0.70	1.05
	(0.634)	(0.565)	-(0.549)	(0.909)	(2.044)	-(0.943)	(0.299)	-(0.537)	(1.083)
EXTRAS	0.33*	-0.05	0.06	0.27	0.14	0.39	0.64**	0.29	-0.23
	(1.771)	-(0.315)	(0.318)	(1.466)	(0.740)	(1.318)	(2.482)	(0.582)	-(0.713)
QUANTITY	-0.57***	0.01		-0.24***	-0.07	-0.08	0.02	0.19	
	-(3.284)	(0.098)		-(3.345)	-(0.829)	-(0.696)	(0.194)	(1.393)	
DAYS806	0.00	-0.01	-0.01	-0.01	0.00	0.00	-0.00	0.03	-0.01
	(0.03)	-(1.248)	-(0.702)	-(0.574)	(0.277)	(0.285)	-(0.236)	(1.337)	-(0.324)
SINGLSLR	-0.08	-1.38***	-0.31	-0.57**	-0.98***	1.28***	2.53***	2.53**	0.19
	-(0.328)	-(5.750)	-(1.197)	-(2.179)	-(3.294)	(3.238)	(6.202)	(2.174)	(0.419)
MULTSLR	0.39	-1.12***	-0.96***	-0.01	-0.91***	0.39	1.46***	1.33	0.88*
	(1.544)	-(4.720)	-(3.397)	-(0.050)	-(3.090)	(1.022)	(3.708)	(1.139)	(1.880)
NEGRATIO	-8.17***	-14.18***	-1.07	0.75	1.58	-5.68**	-7.45***	-44.79	1.45
	-(3.311)	-(5.953)	-(0.614)	(0.449)	(0.916)	-(2.270)	-(3.064)	-(1.541)	(0.240)
LNSLRTNG	0.35***	0.05	-0.22***	0.16***	0.37***	0.30***	0.10	0.50***	0.32***
	(6.563)	(1.012)	-(4.001)	(2.941)	(6.448)	(3.455)	(1.365)	(3.490)	(3.032)
Sample Size	722	722	722	722	722	510	510	510	212
% correct predictions	69.9	68.8	74.0	71.3	73.3				67.0
% false negative	22.3	24.5	25.1	2.1	6.0		See Table 3a		22.6
% false positives	7.1	6.6	1.0	26.6	20.8				10.4

Notes: (1) Coefficients are reported, with t-statistics in parentheses. (2) 1 to 3 asterisks represent 10, 5, 1% significance, respectively. (3) Seller choice of a 3-day auction is the omitted category for auction duration choices

Table 3a: Frequencies of Actual and Predicted Auction Length

Actual Length	**Predicted Length (days)**				
	3	**5**	**7**	**10**	**Total**
3 days	132	3	63	0	198
5 days	37	7	54	0	98
7 days	38	2	149	1	190
10 days	2	1	20	1	24
Total	209	13	286	2	510

The results from Columns 4 and 5 of Table 3 show a positive relationship between the use of these seller choices and seller experience, as indicated by both the within sample frequency dummy variables and overall rating (LNSLRTNG). Choice of auction length does not exhibit any clear pattern.

The last column of Table 3 considers the choice to create a posted price (by entering a starting price equal to the 'Buy it Now' price) in the 212 auctions with the 'Buy it Now' option, and shows that it is less likely for new items and more likely for experienced sellers (as indicated by LNSLRTNG). There is a marginally significant difference in the use of posted prices by multiple sellers (the highest frequency category). From Table 1, the average winning bid

[16] This alternative allows us to test for nonlinear impacts.

for the entire sample was just about equal between posting a price (almost all the cases where 'Buy it Now' was accepted) vs. using a higher 'Buy it Now' price without making it a posted offer. However, posting a price reduces the auction duration to less than half of the average for our sample as a whole, *ceteris paribus*. Therefore, impatience may have been a seller motivation for using 'Buy it Now' to post a price.[17]

6. Auction Outcomes

We now examine how observed seller characteristics and choices influence auction outcomes, conditional on a sale. We are particularly interested in how the 'Buy it Now' option affects final price, i.e., the winning bid. The last part of Table 1 contains the auction outcomes, including the number of bids, number of unique bidders, and the winning bid. Winning bids averaged $199, and tended to be about $3.50 higher for sellers offering the 'Buy it Now' option, whether or not it was accepted.

We use two-stage least squares (2SLS)[18] to control for endogeneity of auction conduct. For example, if the final price were affected by the excitement generated by the bidding process, then we would make incorrect inferences if we ignored the number of bids, which is endogenously determined. We instrument for these endogenous auction conduct variables—the duration,[19] the number of bids, the number of unique bidders, and whether the auction ended with 'Buy it Now.' At the auction conduct stage, the seller choices are predetermined. A dummy variable for auctions beginning with the 'Buy it Now' option measures the impact of its inclusion. Table 4 presents the 2SLS results for explaining the final price in the overall sample of online sales and the subsets based on the existence and acceptance of the 'Buy it Now' option.

Our measures of seller reputation, which one would expect to provide valuable information to bidders, do not consistently boost the final price. It is possible that the primary impact is indirect, via the effects of reputation on the number rather than the level of bids. If so, our regressions account for this by controlling for the number of bids in the first stage regressions and more bids do positively impact price, as discussed below.[20]

In the results for the entire sample of concluded transactions, the choice to include the 'Buy it Now' option does not have a statistically significant impact on the final price.[21] However, when sellers indicate a 'Buy it Now' price, as in sub-samples presented in columns 4 and 5, every dollar increase in the 'Buy it Now' price increases final bids by $0.29.[22] This effect occurs whether or not the auction concludes via buyer acceptance of the 'Buy it Now' price. Thus the evidence suggests that the election by sellers to offer a fixed price, not the acceptance of such prices by buyers, accounts for this modest increase in final transaction prices.

Now we turn to the hypothesis that experienced sellers intentionally set starting bids low to exploit bidder competition within the auction (more bids). Winning bids are lower for less frequent relative to more frequent sellers in auctions without a 'Buy it Now' price. The conditional means (not reported here) for the non-'Buy it Now' sub-sample indicate that less frequent sellers started their auctions with prices that were over $41 higher, on average, than did more frequent sellers. Furthermore, the regression analysis in Table 2 indicates a relationship between higher starting prices and frequency of selling. The less frequent sellers also attracted about nine fewer bids and six fewer bidders per auction than frequent sellers. To the degree that bidding enthusiasm translates into higher final bids, this could be a source of the lower auction transaction prices for this group.

Two features of our analysis provide evidence to this end. Controlling for the endogenous factors which influence bid frequency, we see (Table 4) that the number of bids positively impacts sale prices across auctions excluding those ending with a 'Buy it Now' price. This effect is partially offset by an opposite impact from a higher number of unique bidders, indicating that multiple bids by individuals and not a greater number of bidders which push up final prices.

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[17] Conversely given that the final prices (WINBID) were, on average, similar for posted price auctions and other 'Buy it Now' auctions, sellers do not seem to be able to use posted prices to extract an impatience or risk premium from buyers.

[18] Since the model is linear with standard assumptions, 2SLS is appropriate and simpler to implement and interpret than the more general GMM approach. See, for example, Greene [2000], Example 11.6.

[19] The variable indicating the duration of the auction was only endogenous in the 'Buy it Now' sub-samples, so it was instrumented there and not elsewhere.

[20] Our result here can be seen as complementary to those of Ku et al. [2005], who examine auctions of unique or otherwise hard-to-price items, and find evidence for competitive arousal and similar effects.

[21] Thus, our results provide a caveat to the suggestion of Park and Bradlow [2005] that the 'Buy it Now' feature may be overused. They base this statement on Korean notebook computer auctions, and as a consequence of a negative impact of the 'Buy it Now' option on willingness to bid. The latter effect is present in our first stage regression, but the final effect on the winning bid is not negative in our sample.

[22] Standifird et al. [2005], while focusing on the fact that below market 'Buy it Now' prices are not necessarily accepted, do not find this positive relationship between the 'Buy it Now' price and the transaction price. However, they have relatively small samples, and use data on auctions for low value items.

Table 4: Auction Characteristics and Value of Winning Bid (2SLS)

Variable	**All Sales (1)**	**No BuyNow (2)**	**Only BuyNow (3)**	**BuyNow Rej. (4)**	**BuyNow Acc. (5)**
NEW	7.700***	7.429**	7.058**	3.201	16.744*
	(3.570)	(2.378)	(2.288)	(0.642)	(1.922)
DAMAGE	-20.089**	-20.510	-16.662	16.909	-62.391***
	-(2.115)	-(1.448)	-(1.304)	(0.859)	-(3.291)
EXTRAS	2.722	6.092	2.379	-3.027	8.943
	(1.053)	(1.614)	(0.914)	-(0.733)	(0.911)
QUANTITY	-4.698***	-3.685***	-1.719	-5.071	
	-(3.930)	-(2.772)	-(0.533)	-(1.075)	
DAYS806	-0.165	-0.281*	0.069	0.125	0.168
	-(1.446)	-(1.865)	(0.461)	(0.500)	(0.482)
SINGLSLR	-9.910***	-13.879***	8.744	-1.487	40.203***
	-(2.850)	-(2.968)	(1.530)	-(0.160)	(2.701)
MULTSLR	-12.939***	-15.524***	2.474	-0.628	26.371*
	-(3.696)	-(3.467)	(0.479)	-(0.063)	(1.952)
NEGRATIO	-40.864*	-34.522	29.200	162.464*	-326.95**
	-(1.717)	-(1.260)	(0.459)	(1.691)	-(2.398)
LNSLRTNG	-1.940***	-2.101**	-2.343**	-2.173	-1.240
	-(3.307)	-(2.504)	-(2.330)	-(1.525)	-(0.511)
SLRHOME	-2.404	-0.794	8.386**	7.399	29.557***
	-(0.649)	-(0.134)	(2.324)	(0.978)	(3.516)
STARTPRC	-0.346***	-0.034	0.140	0.596*	
	-(2.823)	-(0.181)	(0.716)	(1.784)	
SQRSTPRC	0.0026***	0.0012*	0.0010*	0.000	
	(8.191)	(1.732)	(1.864)	-(0.122)	
LOWSTPRC	-14.326*	-2.589	14.694	36.070*	
	-(1.928)	-(0.253)	(1.173)	(1.783)	
PRIVTRES	12.210***	11.147***	-1.205	16.975***	-14.774
	(4.963)	(2.994)	-(0.346)	(2.805)	-(1.104)
DSCLNGTH	0.0009*	0.0012*	0.001	0.001	0.000
	(1.807)	(1.782)	(1.095)	(1.607)	(0.037)
IMAGE	-1.454	-2.233	0.421	5.858	10.101
	-(0.402)	-(0.499)	(0.129)	(0.850)	(0.970)
SCRPYDUM	-4.719*	-4.889	0.737	-2.771	13.136
	-(1.754)	-(1.364)	(0.205)	-(0.450)	(1.384)
FEATURED	10.188	29.823			
	(0.444)	(1.065)			
POSTDPRC	-2.718		6.949	20.751*	42.044
	-(0.635)		(1.072)	(1.668)	(1.474)
STRTBYNW	2.417				
	(0.882)				
BYNOWPRC			0.284***	0.290***	
			(2.800)	(3.291)	
(P)DURATION	1.018*	1.082	2.132	3.871	2.628
	(1.932)	(1.429)	(0.847)	(1.288)	(0.917)
PENDBYNW	-14.310***		12.873**		
	-(3.170)		(2.085)		
PNUMBIDS	3.326**	3.997***	1.373*	1.791*	-0.523
	(2.562)	(2.735)	(1.704)	(1.958)	-(0.344)
PNUMBDRS	-3.769*	-5.294**	4.436**	4.919**	11.408**
	-(1.668)	-(2.047)	(1.960)	(2.137)	(2.206)
R-Squared	0.2574	0.0188	0.6685	0.3295	0.2645
Sample Size	722	510	212	121	91

This leads us to the argument [Peters and Severinov, 2006] that buyers' optimal bidding strategies are independent of seller choices such as starting price. Our results suggest that this may not be completely true in practice, because of two complicating factors. First, the starting price may affect the subsequent conduct of the auction, in terms of number of bids and bidders.[23] Second, a higher starting price has a small positive and nonlinear effect on the final price (Table 4, columns 2 and 3), whether or not a 'Buy it Now' option is used. In fact, the effect is clearest in auctions where the 'Buy it Now' option is present, but not availed of by a buyer before bidding begins (Table 4, column 4). One possibility is that a higher starting price signals product quality or seller valuation. On the other hand, the economic significance is small, since the impact on the selling price is only about $0.60.

7. Conclusions

The dynamic nature of e-commerce presents fertile ground for research into the influence of institutions on market performance. EBay's rich menu of seller options allows us to observe transactions across institutional structures. In particular, sellers can incorporate elements of the posted price institution to varying degrees. The behavior of sellers operating in this market environment and the resulting outcomes yield some insight into this institution-performance relationship.

Sellers' decisions regarding features such as initial bid levels and use of private reserve prices affect the conduct of the auction in dimensions relevant to the outcome. We found that auctions run by frequent sellers or featuring damaged items tended to have lower minimum bids. This strategy generated more active auctions, which tend to increase final sales prices, *ceteris paribus*. A secret reserve price was less likely for new items and frequent sellers, and more likely for sellers with home pages.

The practice of offering items at a fixed, 'Buy it Now' price occurred widely across most product characteristics. The existence of a 'Buy it Now' price did not have a significant impact on the sale price, although the estimated effect was positive. However, in the subsample where 'Buy it Now' offers were made, a higher 'Buy it Now' price offer resulted in a significantly higher sale price, possibly through a signaling effect.

Some sellers convert their auction into a take-it-or-leave-it posted price market by setting the initial bid equal to the 'Buy it Now' price. Sellers with higher seller ratings and a higher frequency of selling in our sample were more likely to choose this posted price option. New items were less likely to be offered at a posted price. This practice allows a greater degree of control over the minimum price they receive, making it attractive to risk averse sellers. Less patient sellers could also be utilizing a posted price to move their goods more quickly. In practice, this choice appears to have no statistically significant impact on the sale price, though in some regressions the coefficient magnitudes are large ($20-$40). The indirect effect of 'Buy it Now' prices suggests signaling or bounded rationality effects in these online market transactions.

Contrary to predictions from the trustworthiness hypothesis, higher sale prices were achieved by less frequent sellers in our sample, relative to our more frequent-seller group. The sharp difference in transaction prices for these two types when they posted a price (recalling that essentially every 'Buy it Now' accepted price was posted) vs. when they did not, combined with the observation that successful posted prices are only slightly higher on average than all sales in the sample, suggests that some less experienced sellers used posted prices to overcome potential disadvantages, such as buyer wariness of their inexperience, to transact at prices near the expected equilibrium sales price.

Our results are also supportive of a corollary of the theoretical model of Reynolds and Wooders [2004]. They show that, with risk neutral bidders, there is no advantage to the seller from using a 'Buy it Now' option. In our case, this is borne out since winning bids are about equal, on average, whether the 'Buy it Now' offer is accepted or not. Buyers reject 'Buy it Now' offers when a seller attempts to capture a premium, while accepting those with little or no premium over the auction alternative.

Possible extensions of our research include broadening the sample to include multiple goods, and investigating in greater depth the relationship between seller characteristics and market outcomes. Field experiments would allow better control over seller characteristics, and enable exploration of 'Buy it Now' prices in other dimensions. Further theoretical work is also needed to inform future empirical research regarding such hybrid market structures.

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[23] See the earlier discussion of such arousal effects. Standifird et al. [2005] also find evidence that auctions have entertainment value. Table A2 suggests a rather non-obvious nonlinear relationship between starting price and number of bids and bidders, especially when auctions with a 'Buy it Now' option are included in the regression.

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APPENDIX

Table A1: Variable Names and Definitions

Variable	Description
NEW	Dummy variable equal to one, if the item is definitively described to be "sealed, in the box, and new" in either the title of the auction listing or in the description text.
DAMAGE	Dummy variable equal to one, if any significant damage to the item is mentioned in either the title or the description text.
EXTRAS	Dummy variable equal to one, if the item is being offered with significant accessories, mentioned in either the title or the description text.
QUANTITY	Number of items sold in a single, particular auction.
DAYS806	Number of days between the start of the auction and the date of the first auction in the sample (8/6/01).
SINGLSR	Dummy variable equal to one, if the seller only held one auction during our sample.
MULTSLR	Dummy variable equal to one, if the seller held more than one auction but no more than ten auctions during our sample.
FREQSLR	Dummy variable equal to one, if the seller held more than ten auctions but no more than fifty auctions during our sample.
RETAILER	Dummy variable equal to one, if the seller held more than fifty auctions during our sample.
LNSLRTNG	This is the natural logarithm of the difference between the number of unique, positive comments about the seller and the number of unique, negative comments.
NEGRATIO	The ratio of the number of unique, negative comments to the total number of unique comments listed in the seller's feedback page.
SLRHOME	Dummy variable equal to one, if the seller posts a link to his website in the description text of the auction listing.
STARTPRC	Initial price to start the bidding, posted by the seller at the beginning of the auction.
SQRSTPRC	Square of the seller's starting price.
LOWSTPRC	Dummy variable equal to one, if the seller posts an initial price below twenty dollars.
POSTDPRC	Dummy variable equal to one, if the seller sets the initial price equal to a displayed, 'Buy it Now' price.
STRTBYNW	Dummy variable equal to one, if the seller offers buyers the option to buy the item immediately at a displayed, 'Buy it Now' price.
BYNOWPRC	Seller's price if displayed at the beginning of the auction as a 'Buy it Now' offer.
PRIVTRES	Dummy variable equal to one, if the seller displays a notice that actual sale is subject to a buyer at least bidding as high as some unknown, private, reserve price.
FEATURED	Dummy variable set equal to one, if the seller paid extra to have the item(s) listed at the top of the listings, no matter what the potential buyer's search criteria was.
DSCLNGTH	Number of text characters in the description of the item, composed by the seller for the auction listing page, minus the number of HTML tags.
IMAGE	Dummy variable set equal to one, if the seller included at least one image in the description of the item.
SCRPYDUM	Dummy variable set equal to one, if the seller accepts credit cards, PayPal, or eBay Online Payments.
DURATION	Duration of the auction, initially set by the seller to a maximum of 3, 5, 7, or 10 days; may turn out to be lower if 'Buy it Now' option is used..
ENDBYNOW	Dummy variable equal to one, if the auction ends with a buyer accepting a seller's 'Buy it Now' option.
NUMBIDS	Number of bids on the item(s) in a particular auction.
UNIQBIDR	Number of unique bidders for the item(s) in a particular auction.
WINBID	Dollar value of the final bid in an auction that resulted in a sale.

First-Stage Regression Results for 2SLS

First-stage regression results are reported in Tables A2 and A3. They indicate how exogenous characteristics and seller choices affect our regression results indirectly, through their impact on the endogenous conduct of the auction. Squares of some of the explanatory variables used in the second stage are added in the first stage regressions, to ensure that the instruments are not collinear with the other regressors in the second stage. In Table A2, for the sample as a whole first three columns), as well as for auctions where a ‘Buy it Now’ option was not made available (last two columns), the characteristics of the goods have the expected impacts on the number of bids and bidders, and on whether a ‘Buy it Now’ option was accepted.

Amongst seller characteristics the most interesting first-stage result is that the proportion of negative comments in the seller’s rating appears to have a significant positive impact on both the number of bids and the number of unique bidders for the whole sample and the sub-sample. At the same time, the log of the seller rating was insignificant. The results on seller choices in Table A2 support the conjecture of a decrease in enthusiasm from bidders if the seller chooses a high starting price or chooses a private reserve price. Both of these choices have a significant, negative impact on the number of bids and of bidders for the whole sample and the non-‘Buy it Now’ sub-sample. We have noted that such choices appear to mostly occur among the relatively inexperienced sellers in our sample. The choice to pay eBay an additional fee to feature an item, though rarely undertaken in our sample, does have a significant, positive impact in attracting both more bids and bidders.

With respect to our focus on the ‘Buy it Now’ institution, the most interesting, though anticipated, result is a significant negative impact of the seller’s choice to make the ‘Buy it Now’ option available, on the number of bids. Also, as we have mentioned, almost no ‘Buy it Now’ option was accepted unless the seller chose to use ‘Buy it Now’ to effectively post a price. This characteristic of the auctions in our sample is again reflected in Table A2 (middle column) by the strong, significantly positive coefficient on posting a price, for the endogenous outcome of the auction ending with the ‘Buy it Now’ option being accepted.

Turning to Table A3, note that the duration of the auction is an additional endogenous variable in all auctions where the seller made a ‘Buy it Now’ option available, and hence is no longer an explanatory variable. We expect duration to be affected by the product characteristics, and by seller characteristics and choices, as are the other conduct variables, and this generally appears to be the case. New items enjoy significantly less time at auction before being purchased, on average, while damaged items spend relatively more time being bid upon. It appears more likely (Table A2) that a first bidder will cut the auction short and purchase a new item at the ‘Buy it Now’ price and it appears less likely that a first bidder will do so for a damaged item. Product characteristics are not as significant in explaining the duration of the auction for the sub-sample where the ‘Buy it Now’ option is not accepted, because auction duration reverts to whatever was initially chosen by the seller.

Selling frequencies significantly impact the auction duration. Both single sellers and slightly more experienced sellers had significantly shorter auctions than more frequent sellers (the omitted category), whether their ‘Buy it Now’ price was accepted or not. There appear to be significant, negative impacts on the number of bidders and on the number of bids, from being a less frequent seller for the sub-sample where the ‘Buy it Now’ option was accepted. However, this result is solely due to one auction in our sample with a buyer that “trembled” and bid above the ‘Buy it Now’ price. Since the ‘Buy it Now’ price did not disappear in this case, it appears that another bidder then was able to actually underbid the first bidder and still win the item, according to eBay’s rules for ‘Buy it Now.’ The seller for this particular auction was a more frequent seller, but with a relatively high ratio of negative comments in his or her seller rating. If it were not for this one auction, the only significant endogenous impacts would occur on auction duration and not on the number of bids or bidders in the sub-sample where the ‘Buy it Now’ option was accepted.

Overall, for the sub-sample where the ‘Buy it Now’ option was not accepted by the first bidder, most of the significant impacts on endogenous variables were on the number of bids, and not on the auction duration or the number of unique bidders. The lack of impact on the auction duration is understandable, since duration reverts to the seller’s initial choice. For this sub-sample, results in Table A3 indicate experience may have differing significant impacts on the duration of the auction vs. the number of bids or bidders: less-experienced sellers set auction durations that were significantly shorter, yet attracted both significantly more bids and bidders, on average, than more frequent sellers in our sample. It appears that lower starting prices can increase the participation in the auction (the number of bids), when the ‘Buy it Now’ option was not accepted. Also, selling a greater quantity of Palm Pilot Vx’s in a single auction significantly decreased the number of bids and bidders, while new items attracted significantly more bids and bidders in our sample.

Table A2: First Stage Regressions for Instrumenting Conduct Variables

	All Auctions			No "Buy it Now" Option	
Variable	**Num. Bids**	**Num. Bidders**	**End BuyNow**	**Num. of Bids**	**Num. Bidders**
NEW	1.365**	0.413	-0.376	1.060	0.257
	(2.233)	(1.429)	-(0.455)	(1.287)	(0.639)
DAMAGE	-3.593**	-0.543	-0.221	-3.737**	-0.916
	-(2.267)	-(0.659)	-(0.079)	-(2.273)	-(1.385)
EXTRAS	0.168	-0.517**	-0.602	0.138	-0.582*
	(0.312)	-(2.047)	-(0.791)	(0.190)	-(1.701)
QUANTITY	-8.980***	-4.713***		-9.221***	-5.065***
	-(3.670)	-(3.462)		-(3.482)	-(3.455)
DAYS806	0.072	0.716	0.127***	-3.963	-0.369
	(0.014)	(0.278)	(2.576)	-(0.601)	-(0.101)
SINGLSLR	6.462**	2.610	1.353	6.569	1.818
	(2.017)	(1.562)	(0.725)	(1.414)	(0.712)
MULTSLR	6.200	2.088	0.241	1.961	-0.814
	(1.487)	(0.950)	(0.138)	(0.333)	-(0.243)
NEGRATIO	73.522***	28.060***	-17.641	90.722***	38.886***
	(3.767)	(3.289)	-(1.025)	(3.949)	(3.754)
LNSLRTNG	-0.844	-0.347	0.411	-1.260*	-0.595
	-(1.352)	-(1.097)	(1.520)	-(1.751)	-(1.524)
SLRHOME	-0.353	-0.350	0.698	-0.062	0.276
	-(0.345)	-(0.653)	(0.613)	-(0.036)	(0.283)
STARTPRC	-0.649***	-0.452***	0.092*	-0.740**	-0.347**
	-(3.102)	-(4.891)	(1.646)	-(2.229)	-(2.105)
SQRSTPRC	0.0009***	0.0005***	-0.0002	0.0009**	0.0003
	(3.601)	(4.893)	-(0.981)	(2.024)	(1.363)
LOWSTPRC	3.401	3.140***		4.745	2.887**
	(1.178)	(2.717)		(1.393)	(1.963)
PRIVTRES	-2.051***	-0.774***	1.580	-2.316***	-0.897***
	-(3.535)	-(2.884)	(1.497)	-(3.213)	-(2.634)
DSCLNGTH	0.0003	-0.0003	-0.0001	0.0002	-0.0004
	(0.359)	-(0.905)	-(0.683)	(0.251)	-(0.876)
IMAGE	-0.493	-0.802**	0.640	-2.087**	-1.505***
	-(0.641)	-(2.217)	(0.721)	-(2.021)	-(2.926)
SCRPYDUM	-0.268	0.0614	-0.011	0.271	0.262
	-(0.356)	(0.165)	-(0.013)	(0.293)	(0.557)
FEATURED	57.538***	39.781***		58.40***	40.873***
	(8.883)	(10.437)		(8.348)	(10.146)
DURATION	-0.807	-0.608		-2.180	-1.586
	-(0.383)	-(0.582)		-(0.834)	-(1.216)
STRTBYNW	-375.06	-405.08***	7.84		
	-(0.975)	-(2.670)	(1.266)		
BYNOWPRC	0.230	0.367	-0.044		
	(0.364)	(1.460)	-(1.514)		
POSTDPRC	0.412	-0.012	8.873***		
	(0.277)	-(0.015)	(4.182)		
PENDBYNW	-0.309	0.035			
	-(0.221)	(0.045)			
R Squared	0.7672	0.8353		0.7629	0.8377
Log-Likelihood			-32.846		
Sample Size	722	722	722	510	510

Notes: (1) Coefficients are reported with t-statistics below in parentheses. (2) 1 to 3 asterisks represent 10, 5, 1% significance, respectively. (3) The results for the number of bids and bidders are from OLS first-stage regressions. The results for accepting "Buy it Now" are from a Logit regression

Table A3: First Stage Regressions for Instrumenting Conduct Variables (continued)

	"Buy it Now" Accepted			**"Buy it Now" Not accepted**		
Variable	**Auction Duration**	**Number of Bids**	**Number of Bidders**	**Auction Duration**	**Number of Bids**	**Number of Bidders**
NEW	-1.321***	-0.888	-0.592	0.499	3.083**	0.996**
	-(2.666)	-(1.278)	-(1.657)	(1.193)	(2.571)	(2.070)
DAMAGE	2.238***	4.019**	1.794	-0.935	-3.897	-0.559
	(2.723)	(2.135)	(1.174)	-(0.902)	-(1.075)	-(0.285)
EXTRAS	-0.051	-0.540	-0.625	0.809	-0.528	-0.276
	-(0.074)	-(0.609)	-(1.337)	(1.313)	-(0.424)	-(0.514)
QUANTITY				3.271	-14.117*	-12.919***
				(1.197)	-(1.707)	-(3.707)
DAYS806	-2.866	0.555	0.464	-6.206	18.994	24.525***
	-(0.872)	(0.151)	(0.238)	-(1.120)	(1.032)	(3.285)
SINGLSLR	-15.989***	-39.774***	-12.165**	-6.742***	9.823	7.587**
	-(3.014)	-(3.676)	-(2.566)	-(2.901)	(1.225)	(2.354)
MULTSLR	-15.023***	-34.905***	-7.713*	-10.633***	37.179***	17.281***
	-(3.425)	-(3.347)	-(1.809)	-(3.018)	(3.899)	(4.241)
NEGRATIO	-4.483	189.636***	69.766***	-39.903	45.184	-34.150
	-(0.178)	(4.293)	(3.634)	-(0.949)	(0.373)	-(0.803)
LNSLRTNG	-0.825	-1.282	-0.018	-0.024	-0.795	0.305
	-(1.201)	-(1.156)	-(0.036)	-(0.028)	-(0.503)	(0.372)
SLRHOME	-1.537**	-0.694	-0.569	-0.486	1.549	-1.107
	-(2.021)	-(0.554)	-(0.831)	-(0.727)	(0.673)	-(1.031)
STARTPRC				-0.189	-0.907	-0.715**
				-(0.726)	-(1.323)	-(2.202)
SQRSTPRC				0.000	0.0013*	0.001***
				(0.986)	(1.732)	(2.872)
LOWSTPRC				-1.150	4.257	0.519
				-(0.276)	(0.336)	(0.094)
PRIVTRES	0.142	3.905***	1.976***	-0.348	-2.570	-1.356*
	(0.295)	(5.686)	(5.854)	-(0.564)	-(1.327)	-(1.676)
DSCLNGTH	-0.0002	-0.0007	0.0008	0.0004	0.0013	-0.0003
	-0.131	-(0.359)	(0.584)	(0.573)	(0.710)	-(0.305)
IMAGE	1.085*	-0.091	0.395	-0.490	3.840*	0.787
	(1.790)	-(0.091)	(0.866)	-(0.589)	(1.781)	(1.031)
SCRPYDUM	0.366	-1.177	-0.849*	-0.497	-2.028	0.004
	(0.653)	-(1.389)	-(1.777)	-(1.060)	-(1.304)	(0.007)
BYNOWPRC				0.140	-0.333	0.036
				(0.415)	-(0.272)	(0.091)
POSTDPRC	1.131	-1.200	-0.385	-2.150	2.442	0.142
	(0.533)	-(0.855)	-(0.415)	-(1.281)	(0.499)	(0.068)
R Squared	0.3542	0.7178	0.6766	0.4183	0.6884	0.7116
Sample Size	91	91	91	121	121	121

Notes: See Table A2