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Assessing Sale Strategies in Online Markets Using Matched Listings†

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We use data from eBay to identify hundreds of thousands of instances in which retailers posted otherwise identical product listings with targeted variation in pricing and auction design. We use these matched listings to measure the dispersion in auction prices for identical goods sold by the same seller, to estimate nonparametric auction demand curves, to analyze the effect of buy it now options, and to assess consumer sensitivity to shipping fees. The scale of the data allows us to show that the estimates are robust to narrower criteria for matching listings, thereby addressing plausible concerns about endogeneity and selection biases. (*JEL* D44, L11, L81)

The Internet has dramatically reduced the cost of changing prices, displays and information provided to consumers, and of measuring the response to these types of changes. As a result internet platforms, retailers and advertisers increasingly can customize and vary their offers. One effect of this flexibility is to facilitate learning. Google, for instance, conducts thousands of experiments each year to refine its search platform (Varian 2010), and Microsoft constantly experiments with its advertising platform (Athey 2011). Our goal in this paper is to illustrate how the ubiquitous variation in pricing and sales strategies by market participants can be used at scale, with appropriate care, to address traditional economic questions about consumer behavior and market outcomes.

Our analysis focuses on eBay, the largest e-commerce platform and a primary sales channel for tens of thousands of retailers. We use complete data on the platform to identify instances in which a given seller lists a given item multiple times while varying pricing or auction parameters. This practice—analogues of which

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can be observed in other internet markets, such as for sponsored search or display advertising—is extremely common. Of the hundred million listings appearing on eBay on a given day, it is possible to find for more than half a near-duplicate listing of the same item by the same seller, with modified sale parameters.

The use of targeted variation in sale parameters may be driven by active experimentation, but it is unlikely that every price or auction design change is motivated purely by the desire to experiment. We use alternative matching criteria as a way to address potential endogeneity and selection biases. For instance, we compare listings that appeared concurrently and, hence, faced the same consumer demand, and separately analyze matched listings that appeared sequentially and therefore were less likely to be part of a consumer segmentation strategy. A somewhat surprising finding is that our most straightforward matching strategy yields results that prove to be similar to those obtained from narrow matching strategies that control for potential biases.

We start our analysis by constructing a very large sample of matched listings, in which the same seller offered the same item in multiple listings over the course of a year. Then, to examine a given sales strategy, we identify the matched sets with variation in the relevant pricing or auction design parameter. We use fixed effects regressions to estimate the effects of the price or design choice. The scale of the data permits us to examine how the estimates vary by product category or at different parts of the price distribution. We take this approach to four main analyses.

First, we estimate the variability in auction prices, holding fixed both the product and the seller. In an environment where physical search costs are extremely low, one might expect auction prices for a given item sold by a given seller not to vary much and, if the seller also offers the item at a posted price, to be capped above by the posted price. Instead, we find that auction prices vary substantially. The average coefficient of variation is 10–15 percent when we compare equivalent auctions in the same calendar month. At the same time, we find that auction prices generally do not rise above equivalent (i.e., same seller, same item) posted prices, an event that was more common a decade ago (Malmendier and Lee 2011; Einav et al. 2013). We reconcile the high level of variation with the lack of excessively high prices by showing that on average auction prices are well below equivalent posted transaction prices.

Second, we estimate auction demand using variation in auction start prices. Intuitively, when a seller raises her auction start (or reserve) price, she lowers the probability of sale but raises the expected final price conditional on selling. Variation in the start price therefore traces out a familiar demand curve in price-quantity space. Our nonparametric demand curve estimates have a rather unexpected feature: they are highly convex, so their associated marginal revenue curves are not downward sloping. An implication is that very low and very high start prices should be preferred to intermediate ones. Consistent with this, we show that the observed distribution of start prices is bimodal. We also use the same start price variation to examine a behavioral hypothesis of Ku, Galinsky, and Murnighan (2006) and Simonsohn and Ariely (2008) that low start prices can create bidding escalation that leads ultimately to higher final prices. We find some patterns that are consistent with this effect, but as a general principle it does not hold.

Third, we analyze the effect of buy-it-now options in consumer auctions. A buy-it-now option allows a buyer to preempt the auction by purchasing the item at a posted price set by the seller. In theory, this can allow a seller to discriminate between impatient but possibly high value buyers, and bargain hunters who are willing to wait and bid in the auction. We find that the effect of offering a buy-it-now option depends on how the buy price is set. At the typical level used by sellers, the effect on revenue is negligible. Consistent with the price discrimination theory, however, sellers generate additional revenue by setting a relatively high buy price. We also evaluate the hypothesis that buy prices might act as a reference point in subsequent bidding, and again find only weak evidence for this behavioral effect.

Fourth, we revisit a finding of Tyan (2005), Hossain and Morgan (2006), and Brown, Hossain, and Morgan (2010) that consumers underweight shipping fees relative to regular prices. This application illustrates how our empirical strategy allows us to exploit the scale of internet data. We expand from the 5 specific items studied by Tyan (2005), and the 20 CD and Xbox titles, and 2 specific iPod models in the latter papers, to analyze targeted shipping fee variation for over 6,000 distinct items. In this large sample, we estimate that moving from a small shipping charge to free shipping increases the expected auction price by more than \$2. We also confirm the earlier finding that once fees are positive, consumers do not fully internalize increases. We estimate that every \$1 increase in the shipping fee reduces the auction sale price by only around \$0.82.

The empirical strategy we pursue in this paper, while quite simple, differs from most prior studies of eBay and other internet markets. One approach in prior work has been to focus on a small set of products and attempt to control for quality variation across sellers and items using observed covariates (e.g., Bajari and Hortaçsu 2003). An alternative has been to run field experiments in which a researcher sells a small number of identical items while varying one or a few sale parameters (e.g., Lucking-Reiley 1999). In both cases, the analysis typically is limited to a handful of products and tens or hundreds of sales. Elfenbein, Fisman, and McManus (2012, 2014) were the first to use matched listings in studying charity contributions by eBay sellers, and subsequently certification of sellers as top-rated.[1]

We view their matched listings approach, which we apply here to thousands of products and tens or hundreds of thousands of sales at a time, as a useful way to resolve a tension in analyzing large-scale internet data. The tension arises in trying to leverage the vast scale of the data, while still obtaining plausible identification of economic effects. We elaborate on this trade-off in Section III. We demonstrate some pitfalls in trying to obtain large-sample estimates without a narrow matching strategy. We also show that economic effects can vary greatly across products, limiting the conclusions that can be drawn from small-scale experiments. Researcher-conducted field experiments also cannot be used retrospectively to study how consumer behavior or pricing incentives have changed over time.

We already have highlighted a main limitation of comparing matched listings. While the internet makes it easy and desirable for sellers to experiment, it is surely the case that not every pricing or auction design change is orthogonal to demand conditions.

[1] Einav et al. (2013) use the approach developed here, applied to data from multiple years, to explain why sellers on eBay have moved over time from selling by auction toward posted prices. Ostrovsky and Schwarz (2009) is an example of a very large-scale field experiment, in their case to study reserve prices in Yahoo! search advertising auctions.

We construct matched sets of listings to incorporate both episodes of explicit experimentation and pricing changes that effectively amount to experiments because they are cost-driven or occur within a short time window, while potentially confounding changes in demand are slow-moving. Comparing matched listings also rules out omitted variable biases due to differences across listings in seller or item quality.

Nevertheless, if demand-driven pricing or sales design changes are sufficiently prevalent, our estimates may not approximate the effects of random price changes. Our strategy for dealing with this, as mentioned above, is to use alternative and more stringent criteria to match listings, and then compare how the estimates change as we narrow the sample to eliminate specific threats to identification. We find that the estimates are surprisingly similar across these more refined matching criteria, such as matching only contemporaneous listings to eliminate endogenous responses to demand changes. We provide more detail in Section ID.

The remainder of the paper proceeds as follows. Section I describes the use of duplicate listings by retail sellers on eBay, our data construction, and summary statistics. Section II analyzes the problems described above: price variability, auction demand, buy-it-now prices, and shipping fees. Section III compares the matched listings approach to using more heterogeneous observational data, and also shows why results from a limited set of products may not be representative. In Section IV, we conclude by discussing why sellers vary their pricing parameters so often and so widely. A lengthy online Appendix provides many additional analyses that address various potential endogeneity and selection biases. We replicate all the results using a range of samples and specific approaches to matching listings, showing that the results are highly consistent across these alternatives.

I. Background, Data, and Empirical Strategy

A. *Background and Empirical Challenge*

The e-commerce platform eBay had approximately 90 million active users and $57 billion in gross merchandise volume in 2009, the year of our data. The site includes large and active submarkets for collectibles, electronics, clothes, tickets, toys, books, jewelry and art, both new and used. Products are offered by thousands of professional retailers, and millions of individual users. The platform's scale, and the ease of collecting data and running experiments, has made it a focal point for research on online markets.[2]

Sellers on eBay have considerable flexibility in designing a sales strategy. Sellers select a listing title and picture of their product, a longer item description, a shipping fee, and a sales mechanism. Traditionally, most sellers have used ascending auctions. This means specifying an auction duration, a start price, and perhaps an additional secret reserve price, or a buy-it-now price at which a bidder can purchase the item before an initial bid is made. Sellers also can use regular posted prices.

[2] Bajari and Hortaçsu (2004) and Hasker and Sickles (2010) review dozens of papers using data from eBay.

Nowadays, posted price transactions account for more than half of eBay's sales volume. It is easy for sellers to change these sale parameters from listing to listing.

The diversity of selling strategies creates an opportunity to learn about how consumers respond to different pricing and sales mechanisms, and to test hypotheses about consumer behavior. At the same time the diversity of sellers and products poses a challenge. We illustrate this point and how it motivates our empirical strategy in Figure 1.

Figure 1A shows the eBay listings displayed following a search for "taylormade driver" (a type of golf club) on September 12, 2010.[3] The market for even this narrowly defined product is large (over 2,500 listings) and heterogenous. The products are differentiated (different models and sizes, new and used), as are the sellers (by location, reputation score, whether they are top-rated), the sales mechanisms (posted prices, auctions, buy-it-now auctions), and the shipping arrangements and fees. As a result, it is challenging to attribute consumer responses to specific sales strategies, despite observing thousands of contemporaneous listings in a narrow product category. This problem has motivated the use of field experiments in which researchers post a small number of listings, say fifty or a hundred, that vary on only one or two pricing dimensions.

Ideally one would like an empirical strategy that preserves the type of variation in the field experiment approach, but can be scaled to study the larger marketplace. The key idea of this paper is the observation that sellers frequently change the way they list a given item by narrowly varying their pricing or choice of sales mechanism. Figure 1B provides an example. It shows a subset of 31 listings located by the search query above. They are for the same item, and have been listed by the same retailer (user name *budgetgolfer*). However, they are not completely identical. Eleven of them offer the driver for a fixed price of \$124.99, while the other 20 are auctions scheduled to end within the next week. Also, the listings have different shipping fees, either \$7.99 or \$9.99. So this group of listings can be used to identify the dispersion in auction prices, and their relationship to posted transaction prices, or to assess whether auction prices fully adjust to account for shipping fees.

As we describe below, posting near-identical listings with varying prices, fees, and sales mechanisms—either contemporaneously or over time—is extremely common. We discuss below several reasons for this, but one factor is simply mechanical. Auctions on eBay are for a single unit, so a retailer who wants to sell multiple units must post multiple listings. Once a retailer is making multiple listings, there is little cost and some informational benefit to trying different approaches, even concurrently given that eBay's search algorithm will typically spread the listings across multiple pages of results rather than in head-to-head competition.[4] The next sections describe how we search eBay's data to identify such matched listings and our approach to aggregating them.

[3] Consumers shopping on eBay find items either by typing in search terms or browsing through different categories of products. Products are displayed as listings similar to Figure 1A, and can be sorted in various ways. The default sort is based on a relevance algorithm. Consumers then click on individual listings to see more detailed item information, place bids, or make purchases.

[4] The advice to experiment with different strategies is common on websites and discussion boards that cater to eBay sellers. For instance, in a post picked somewhat at random from the reviews.ebay.com site, the user *cjackc* advises that sellers review historical data on the best day to end an auction, "... and then experiment with your own unique listing to see if you can find even more success...." because "... your items are unique and what works for others may not work best for you." (http://reviews.ebay.com/Is-Sunday-Really-the-Best-Listing-Day?ugid=10000000008235490)

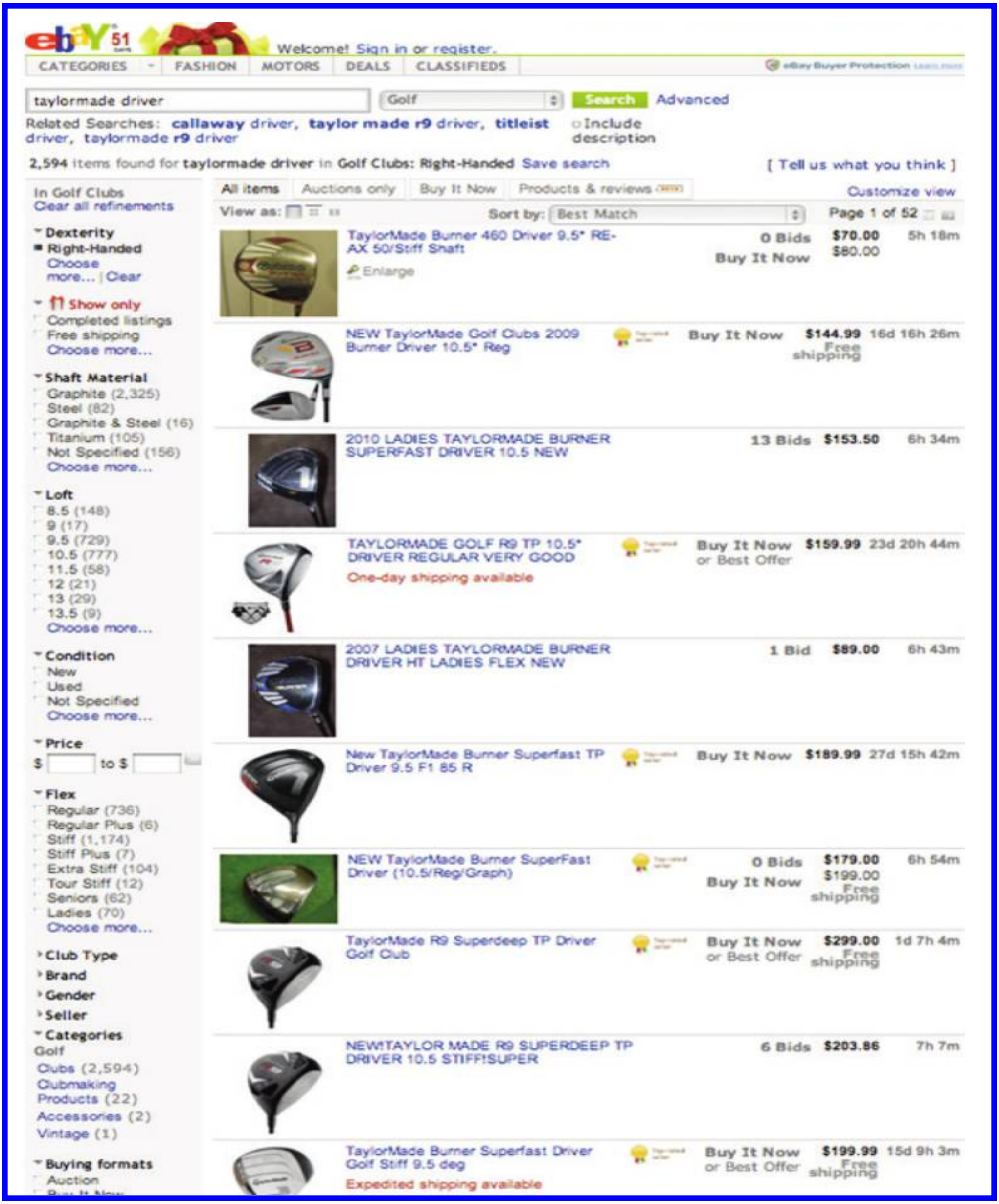

FIGURE 1A. A STANDARD SEARCH RESULTS PAGE ON EBAY

Note: The figure presents a screenshot of listings on eBay following a search for "taylormade driver" on 9/12/2010.

B. *Matched Listings Data*

We construct our data from the universe of eBay.com listings in 2009. We exclude only auto and real estate listings, which have a different institutional structure. We look for matched sets of listings that involve the same seller offering the same product. Because most eBay listings do not include a well-defined product code, we use the listing title and subtitle to identify products.

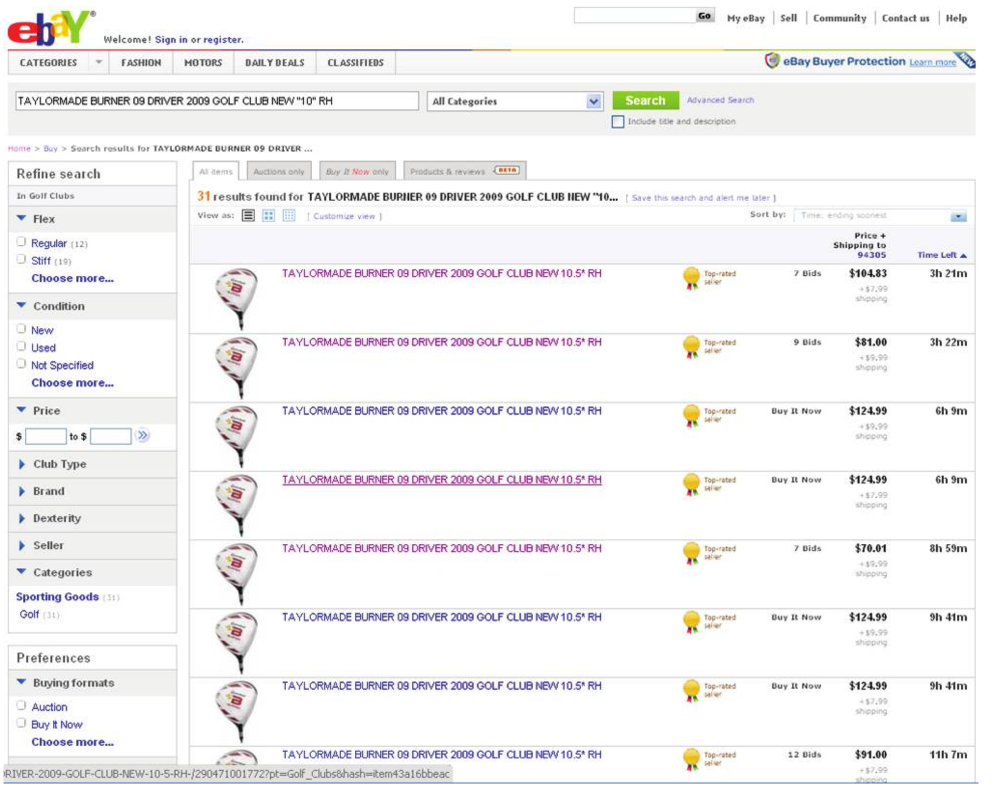

Figure 1B. An Example of a Matched Set

Notes: The figure illustrates a matched set. It shows the first 8 out of 31 listings for the same golf driver by the same seller. All the listings were active on 9/12/2010. Of the 8 listings in the figure, 4 are offered at a fixed price (Buy It Now) of \$124.99. The other four listings are auctions. The listings also have different shipping fees (either \$7.99 or \$9.99).

Specifically we identify all sets of listings that have an exact match on four variables: seller identification number, item category, item title and subtitle. We then drop single listings that have no match. This leaves around 350 million listings, grouped into 55 million matched sets. As an example, the listings in Figure 1B, together with any additional matched listings that were active before or after the day of the screenshot, comprise one set of matched listings.[5]

Our empirical strategy relies on variation within matched listings in sale parameters and outcomes. In this paper, we focus primarily on auction listings and outcomes, which leads us to refine the data in several ways. In particular, we restrict attention to matched sets that include at least two auction listings and at least one successful posted price listing. The former is necessary to have within-set auction comparisons. The latter, as we explain below, provides a useful way to normalize prices in order to make matched sets comparable and compute average treatment effects. Finally, we

[5] Note that by using title and subtitle to identify items, we exclude cases in which a seller might have offered the same item with varied listing titles. On the other hand, it is also possible that we might include certain cases in which a seller offered different items under the same title or used different photos for the same item, although we manually checked a random sample of the data and did not find any examples of this, so we suspect that such instances are not common.

Table 1—Baseline Dataset

	Baseline sample (1)					All auction matched sets (2)	Random eBay (3)
	Obs. (millions)	Mean	SD	25th percentile	75th percentile	Mean	Mean
Panel A. Listings							
Start price ($)	7.69	42.47	194.48	5.45	20.89	26.96	27.90
Fraction with BIN option	7.69	0.73				0.29	0.24
BIN price ($) (if exists)	5.60	47.70	202.14	7	24	54.16	63.60
Fraction with secret reserve	7.69	0.006				0.006	0.009
Secret reserve price ($) (if exists)	0.05	355.23	605.45	99	354	323.69	322.39
Fraction with flat rate shipping	7.69	0.95				0.88	0.85
Fraction with free shipping	7.69	0.77				0.27	0.21
Shipping fee ($) (if flat and > 0)	1.65	8.13	16.55	3.99	6.00	8.12	7.41
Auction duration (days)	7.69	3.2	2.5	1.0	7.0	4.5	5.6
Seller feedback score (000s)	7.69	327.0	472.1	4.6	308.0	24.40	26.6
Seller feedback (pct. positive)	7.65	99.3	2.0	98.9	99.8	99.36	97.5
Fraction with a catalog number	7.69	0.21				0.05	0.06
Fraction with associated:							
Fixed price listings	7.69	1.00				0.18	—
Fixed price transactions	7.69	1.00				0.13	—
Overlapping auctions	7.69	0.81				0.53	—
Most frequent category		Cell phones, PDAs (24.2%)				Clothing (23.2%)	Clothing (18.8%)
2nd most frequent category		Video games (19.5%)				Jewelry and watches (14.9%)	Jewelry and watches (11.9%)
3rd most frequent category		Electronics (13.1%)				Collectibles (7.7%)	Collectibles (10.8%)
4th most frequent category		Computers, networking (6.4%)				Home and garden (4.2%)	Toys and hobbies (5.3%)
5th most frequent category		Cameras, photo (5.3%)				Video games (4.1%)	Sports mem, cards (5.3%)
Fraction sold	7.69	0.35				0.27	0.39
Panel B. Transactions							
Price ($)	2.69	67.39	172.95	8.50	73.01	32.29	38.22
Price including shipping ($)	2.69	69.54	174.96	8.99	76.00	37.18	43.55
Start price/sale price ratio	2.69	0.63	0.44	0.03	1.00	0.70	65.14
Number of bids	2.69	6.4	8.7	1.0	10.0	3.9	4.4
Number of unique bidders	2.69	3.6	3.9	1.0	6.0	2.4	2.7

Notes: A unit of observation is a listing. Column 1 presents statistics for the baseline sample. Column 2 presents statistics for all auction matched sets (that is, including those for which we do not have a corresponding fixed price transaction). Column 3 presents statistics for the population of the entire eBay listings during the same period.

include only those matched sets where the listings have a nonempty subtitle. This is a convenient way to reduce the size of the data to make it manageable, while focusing on more professional retailers who tend to use subtitles. In the online Appendix, we also report all our results for a random 20 percent subsample of the matched sets that meet our initial criteria.

This generates our baseline dataset: 244,119 matched sets with a total of 7,691,273 listings. The data include cases in which a seller posts multiple overlapping auctions and in which a seller runs multiple nonoverlapping auctions, as well as combinations thereof. Table 1 presents summary statistics, along with corresponding statistics for the entire matched listings data and for a large random sample of eBay

Table 2—Baseline Dataset

	Baseline sample (1)					All auction matched sets (2)	
	Obs. (000s)	Mean	SD	25th percentile	75th percentile	Obs. (000s)	Mean
Number of (auction) listings	244.1	31.5	113.3	2	19	54,984.3	6.4
Fraction with positive sales	244.1	0.728				54,984.3	0.579
Number of (auction) sales	244.1	11.0	49.5	0	7	54,984.3	1.8
Fraction associated with a fixed price listing	244.1	1.000				54,984.3	0.1
Associated fixed price listings	244.1	6.9	22.6	1	6	4,047.4	4.4
Fraction associated with a fixed price sale	244.1	1.000				54,984.3	0.038
Associated successful fixed price listings	244.1	2.9	6.6	1	3	54,984.3	1.3
Matched set "duration" (days)	244.1	56.2	72.4	8	77	54,984.3	38.2
Matched set sale rate	244.1	0.411	0.383	0.000	0.778	54,984.3	0.306
Matched set average sale price	177.6	101.41	303.64	10.21	89.00	31,854.0	42.75
Matched set median sale price	177.6	101.09	303.36	9.99	88.95	31,854.0	42.62
Sale price variation within matched set:							
Coefficient of variation (two sales or more)	143.9	0.111	0.147	0.018	0.148	13,548.8	0.152
75th to 25th pctile difference ($) (4+ sales)	92.5	8.297	26.660	0.000	8.000	4,494.6	5.299
90th to 10th pctile difference ($) (10+ sales)	50.0	13.224	42.378	0.950	13.500	1,410.8	8.326
75th to 25th pctile ratio (4+ sales)	92.5	1.554	103.019	1.000	1.204	4,494.6	1.400
90th to 10th pctile ratio (10+ sales)	50.0	1.543	13.856	1.050	1.386	1,410.8	2.183
(75th pctile–25th pctile)/median (4+ sales)	92.5	0.153	1.058	0.000	0.188	4,494.6	0.252
(90th pctile–10th pctile)/median (10+ sales)	50.0	0.273	1.207	0.049	0.332	1,410.8	0.570

Notes: A unit of observation is a matched set. Column 1 presents statistics for the baseline sample. Column 2 presents statistics for all auction matched sets (that is, including those for which we do not have a corresponding fixed price transaction).

auction listings. In the baseline data, just over a third of the listings result in a sale, with an average price around $67.

By construction, the items in our sample are less unique and idiosyncratic than many items sold on eBay, and the sellers relatively professional. This is reflected in Table 1 in the fraction of items that are catalogued, the experience of the sellers, and their tendency to use sophisticated sale strategies such as a Buy-It-Now (BIN) option. It also shows up in the distribution of items across product categories. Relative to the rest of eBay, our sample includes more cell phones, video games and electronics, and less clothing, jewelry and collectibles. Essentially we are looking at professional and semi-professional retailers, while eBay as a whole also includes a vibrant consumer-to-consumer market.

Table 2 provides summary statistics at the matched set level. The average set in our baseline data has 32 auction listings. About 70 percent of the matched sets have at least one sale. Figure 2 shows the distribution of set sizes. Roughly 45 percent of the matched sets have four or fewer listings, but there are also many (much) larger

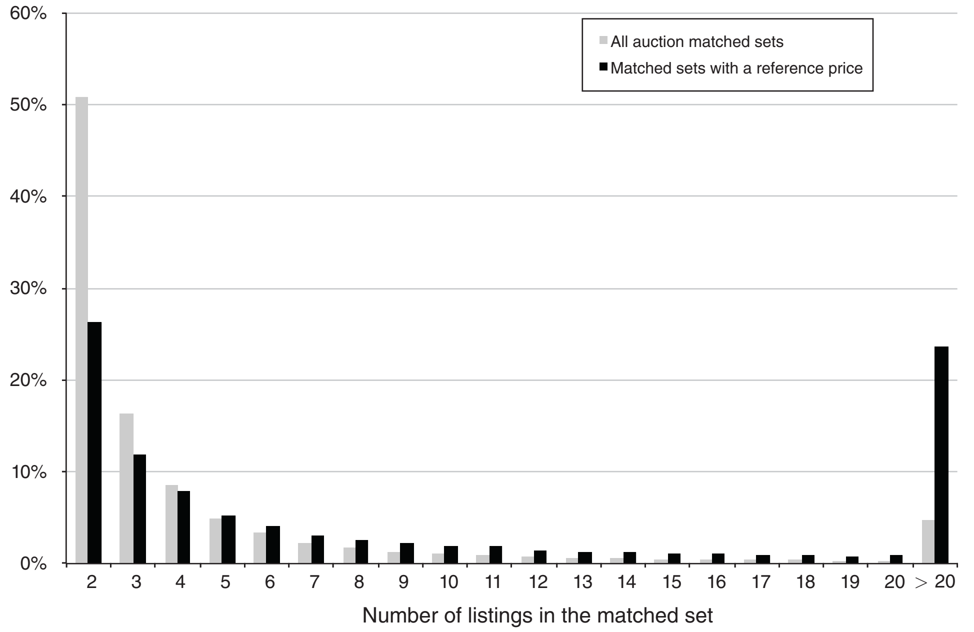

Figure 2. Number of Listings in Each Matched Set

Note: The figure presents the distribution of the set "size" (number of listings) in the entire matched listings data (gray) and in our baseline sample (black).

sets. The typical set includes multiple listings that occur over a relatively short time period, just under two months on average.

Our empirical strategy relies on the fact that when sellers post multiple listings for the same item, they regularly vary different sale parameters. The amount of variation in the data is large. Table 3 reports the number of matched sets that contain variation in different sale parameters of interest. The first column shows that of the 244,119 sets in the baseline sample, more than 140,000 have variation in the auction starting price, more than 17,000 have variation in the shipping fee, more than 90,000 have variation in the BIN option, and more than 92,000 have variation in the auction duration. The remaining columns show that we can find large numbers of matched sets with variation in a given sale parameter even if we condition on other sale parameters being held fixed. We rely on this below to construct samples of matched sets in which we seek to pinpoint specific pricing effects.

C. *Empirical Strategy*

Our data includes a large number of distinct items and sellers. We aggregate using fixed effects regressions. Let i index matched sets, t index listings within sets, and z_{it} denote a listing parameter whose effect we want to know. For a given outcome of interest y_{it}, we estimate regressions of the form:

$$y_{it} = \alpha_i + f(z_{it}) + \varepsilon_{it}, \tag{1}$$

Table 3—Within Set Variation

	Sample	Baseline sample	Large matched sets (10+ listings)	Listings with start price below \$1	Listings with free shipping	Listings without a BIN option	Listings without a secret reserve	Auctions that last (exactly) 7 days
	Total number of matched sets	244,119	89,670	35,391	143,106	125,282	237,815	114,745
Within set variation in:	Start price	142,653	79,107	17,350	82,423	62,148	139,526	57,045
	Shipping rate (flat rate only)	17,718	8,979	2,127	0	7,229	16,869	8,096
	Free shipping indicator	11,917	4,902	1,633	0	5,566	11,178	4,553
	Shipping fee (flat rate only, nonfree)	10,350	6,026	1,032	0	3,897	9,936	5,485
	BIN (any variation)	90,404	53,788	4,312	51,006	0	87,728	37,962
	BIN option indicator	24,052	9,754	2,383	13,154	0	22,788	8,487
	BIN price	46,920	25,244	2,058	26,156	0	45,218	19,532
	Secret reserve (any variation)	5,267	1,009	1,093	2,165	2,374	0	1,950
	Secret reserve indicator	2,918	652	386	1,215	1,264	0	1,036
	Secret reserve price	2,879	581	748	1,152	1,312	0	1,059
	Auction duration	92,226	48,132	12,908	57,069	43,403	89,905	0
	Day of week (starting date)	208,896	88,020	28,300	121,900	100,685	203,383	81,896
	Day of week (ending date)	211,554	87,785	29,096	123,260	102,585	205,988	84,626

Notes: The table presents the extent of within set variation in the baseline sample. Each entry in the table reports the number of matched sets that contain within set variation in the listing parameter that is defined by the row header, out of the sample defined by the column header. The first column uses the entire baseline data, and the other columns stratify the baseline data based on various criteria.

where α_i is an item-seller fixed effect and ε_{it} is an error term assumed to be independent of z_{it} within sets.

There are at least two reasons to pool matched sets as in our specification. First, many are small, so pooling provides greater statistical power. Second, it seems easier and more digestible to report an average effect rather than thousands of distinct effects for individual items. We break out estimates by item value, and discuss heterogeneity across item categories in Section III.

One challenge in aggregating effects is that the items have different value. A \$1 increase in the auction reserve price may be important for a \$5 item but not so important for a \$500 item. To address this, we define a reference value for each item, and evaluate price changes for an item relative to its reference value. Specifically, we define each item's reference value v_i as the average price across posted price transactions of that item.[6] Then when we consider auction sales, we focus on the normalized price $p_{it}^n = p_{it}/v_i$ rather than the auction price p_{it}. Similarly, in studying auction reserve prices, we use the normalized reserve price $s_{it}^n = s_{it}/v_i$ rather than the dollar reserve price s_{it}. A more general alternative would be to estimate treatment effects of the form $f(s_{it}, v_i)$ rather than $f(s_{it}/v_i)$ but we find, rather surprisingly that there seems to be little gain from doing this.

We rely on two further assumptions to identify average treatment effects. The first is that the idiosyncratic effects of each item denoted by α_i enter in an additive and separable way. The second is that sale parameters within each matched set are

[6] Recall that in selecting matched sets into our baseline sample, we required each set to have at least one successful posted price listing. Note that we use posted price transactions and not listings so that the reference value is not affected by excessively high posted prices that never sell. We also experimented with modifications to this definition, for example using the median transaction price or trimming outliers before taking averages, and the results (not reported) remain virtually the same.

not correlated with factors that bear directly on auction outcomes. This assumption deserves some discussion, which we turn to next.

D. *Threats to Identification*

In our baseline analysis, we group listings of a given item by a given seller over a period of up to a year, and estimate treatment effects using variation in auction parameters within these matched listings. Our intention is to capture sellers who are experimenting with prices or auction design, or are making changes for idiosyncratic or cost-based reasons. However, an obvious concern is that we also capture changes in sale parameters that are reactions to changing demand. If so, our estimates will suffer from a standard endogeneity bias. A related concern is selection bias, which might arise if sellers change their sale parameters only after an initial strategy has failed.

The most direct way to investigate whether our results are driven by endogenous pricing changes is to restrict attention to narrower time windows, reducing the potential variation in demand or in the seller's information at the time of posting. The most extreme version is to match listings only if they are exactly contemporaneous, starting and ending on the exact same day. We implement this in online Appendix A, where we repeat all the estimates in the paper using this more stringent criterion, as well as an intermediate criterion that focuses on 30-day time windows. The results in both cases are similar, suggesting that endogenous pricing changes do not drive our results.

We use the broader matching criterion in the main paper because relying on short time windows, or contemporaneous listings, has a different set of limitations. It throws out a great deal of potentially useful data, for instance from sellers who are experimenting over time. It also raises the concern that matched listings may interact. While the structure of the eBay search algorithm spreads duplicate listings across many pages of search results, somewhat mitigating this concern, it is plausible that buyers might arbitrage between parallel auctions held by the same seller for the same product. That could lead to less price dispersion for parallel listings than for sequential listings. Or an auction with a high start price might get fewer bids if conducted at the same time as an identical auction with a low start price. While the interaction concern could also be raised about many online field experiments, it seems especially pronounced if we narrow attention to exactly concurrent matched listings.

A natural way to address concerns about interaction is to restrict attention instead to matched listings that *do not* overlap in time. In online Appendix A, we also repeat all of the estimates in the paper using a matching criterion that selects only the matched sets for which the listings are truly sequential and do not overlap. We also report results using a related criterion with no listing overlap but where matched listings are completed within 30 days of one another. Again, the results are similar, suggesting that even if interaction effects are present, they do not appear to be a major factor in driving our results. The online Appendix also reports estimates for a few additional samples and selection criteria, for example sets where the listings are overlapping but not necessarily contemporaneous, for large matched sets only, or for a sample in which all auctions occurred in the presence of a parallel posted price listing. The results remain strikingly similar.

We emphasize that even with these robustness checks, some caution is needed in interpreting the results. Our goal is to provide a simple, scalable method to investigate questions about pricing and consumer behavior across a huge range of submarkets using observational data. Almost by definition, we are not going to obtain the exact variation that might characterize an equivalently large set of field experiments. However, the robustness of the results to alternative matching criteria that should capture the most obvious threats to identification lend some assurance that we are capturing meaningful demand responses to pricing changes. For this reason, the main text proceeds in straight-ahead fashion, without continual references to maintained assumptions about identification.

II. Learning from Matched Listings

In this section, we use the matched listings data to analyze four issues related to pricing and auction design: price dispersion, auction demand, buy-it-now options and shipping fees. We relate our results to prior findings and behavioral theories along the way. We focus mainly on what the empirical approach can tell us about consumer behavior. In Einav et al. (2013), we show how our empirical strategy can provide insight into seller incentives and the evolution of selling strategies over time. The estimates we report in this section are all platform average effects, pooling items from many product categories. We discuss heterogeneity across product categories in the next section.

A. *Price Dispersion and Excessive Bidding*

We start by reporting some large-sample findings about the variability in auction prices. The first is that auction prices for identical items sold by the same seller vary substantially, by around 10–15 percent, even if one focuses on auctions that occur close in time. The second is that auction prices generally do not rise above equivalent posted prices. A third finding that reconciles the first two is that auction prices, on average, are significantly below equivalent posted prices.

These findings relate to an ongoing debate about price dispersion and consumer search in online markets. In principle, the low physical search costs on the internet should limit price dispersion. Yet studies by Bailey (1998); Smith and Brynjolfsson (2001); Baye, Morgan, and Scholten (2004); and Ellison and Ellison (2009), all report substantial dispersion in posted prices, even on structured price comparison websites.[7] Recent work by Malmendier and Lee (2011) also provides a striking failure of consumer search. They document an episode on eBay in 2004 in which a particular board game was available from two sellers for $129.95, while other sellers offered the game for auction. Malmendier and Lee find that auction prices exceeded the posted price more than 40 percent of the time, often by $10 or more. They argue that this is inconsistent with rational search and that a significant number of consumers are irrationally overbidding.

[7] Ambrus and Burns (2013) provide a recent state-of-the-art theory of rational bidding behavior when bidders are not fully focused on an auction, and show that a wide range of price outcomes can be consistent with equilibrium.

Table 4—Summary of Auction Price Variation in Different Samples

	Baseline sample (1)		All auction matched sets (2)	
	Obs. (000s)	Mean	Obs. (000s)	Mean
All matched sets (with 2+ sales)	143.9	0.11	13,548.8	0.15
Within same calendar month	125.3	0.10	16,427.6	0.13
With start price < \$1	43.0	0.19	4,970.2	0.20
With start price >\$1	104.5	0.07	8,556.1	0.12
With no BIN option	73.7	0.15	10,336.9	0.16
With BIN option	74.6	0.07	3,121.4	0.10
Sold by experienced sellers (feedback > 5,000)	68.7	0.08	3,939.1	0.14
Sold by inexperienced sellers (feedback < 250)	26.7	0.15	3,545.2	0.16
With any posted price listings	143.9	0.11	1,373.2	0.13
With any posted price sale	143.9	0.11	970.5	0.12
With posted price at ending time	91.2	0.10	91.2	0.10
With posted price at ending time and no BIN	43.8	0.14	43.8	0.14
Only within category:				
Clothing, shoes, accessories	20.6	0.06	126.2	0.13
Jewelry and watches	10.6	0.13	963.0	0.13
Video games	13.6	0.09	151.9	0.13
Cell phones, PDAs	11.2	0.08	116.4	0.14
Electronics	6.9	0.14	600.2	0.18

Notes: The table presents the average coefficient of price variation across matched sets in the-baseline sample (column 1) and entire sample of all auction matched sets (column 2), and for narrower subsamples.

A complicating factor in existing studies is that prices are compared across retailers, and the prices being compared are typically posted prices rather than transaction prices. This makes it difficult to disentangle differences in retailer attractiveness from frictions in consumer search, or in some cases to rule out the possibility that consumers mostly ignore high-priced alternatives. Our matched listings data allow us to identify the transaction price variability across auctions by a single seller, both on average and for different types of sellers and products. In addition, by focusing on auctions that overlap with the presence of an equivalent (same seller, same item) posted price listing, we can examine the Malmendier and Lee overbidding hypothesis for a sample of hundreds of thousands of items.

We report our findings on price dispersion in Table 4. We use as our metric the coefficient of price variation, or the standard deviation of a group of auction prices divided by the mean price. We compute the coefficient of price variation for each matched set, and for a refinement in which we partition each set by calendar month. The average coefficient of price variation is 0.11 (0.10 with the finer partition of each matched set). The degree of variation climbs to 0.15 if we also consider matched sets of auction listings (same seller, same item) that do not have a matched fixed price sale. In contrast, there is less variability for experienced sellers, or when the seller uses a BIN option or a higher reserve price. Overall, however, 10 to 15 percent price variation across equivalent auctions appears to be a pervasive feature of the market.

Next, we report on how auction prices compare to equivalent posted prices. Recall that we defined an item's reference price or value v_i to be the average price across posted price sales of the item by the same seller. For a successful auction with price p_{it}, define p_{it}/v_i to be the relative price. Figure 3, panel A plots the distribution of relative auction prices for items with values less than \$10, between \$10 and \$30, between \$30 and \$100, and between \$100 and \$1,000. Our data also include a few goods that sell for posted prices above \$1,000, but they are sufficiently rare that we drop them to focus the analysis.

Auction prices are strikingly low compared to equivalent posted prices. The average relative price is around 0.84, and the median is around 0.87. So around half of the auction sales we observe occurred at a discount of 13 percent or more relative to the posted price. We also can examine the prevalence of excessive bidding in which the auction price exceeds the reference value. This is relatively atypical. Less than 20 percent of auction prices exceed the reference price, and most of these episodes involve very small overpayments. To see this, panel B of Figure 3 plots the analogous distribution of $p_{it} - v_i$, the absolute (dollar) difference between the auction and reference price. Of the 1,178,855 successful auctions in our sample, only about 5 percent result in prices more than \$10 above the item's posted price.

To be consistent with subsequent analysis in the paper, Figure 3 compares auction prices to the average posted sale price of the same item over the course of the year. If one is looking for overbidding, a more apt comparison might be to a concurrent posted price offered by the same seller, should one exist. In the online Appendix, we repeat the analysis, limiting attention to auctions for which there was a matched posted price offer available at the auction close (when most bidding occurs). Our data includes 98,536 successful auctions that meet this criteria. When we replicate Figure 3 for this smaller sample and compare the auction prices to the lowest posted price available at the close of the auction, the results remain qualitatively similar, with the vast majority of auction sales occurring below the (concurrent) posted price and very few meaningfully above (see online Appendix Figure G.3).[8]

The evidence from these hundreds of thousands of matched auction listings indicates that auction prices vary widely. On average they are well below matched posted prices, and exceed them only rarely. A possible interpretation of the latter finding is that consumers who buy at posted prices pay a premium for the convenience of an immediate and guaranteed purchase. We explore this hypothesis and its implications, and show that the auction discount was not present in the early days of internet commerce, in Einav et al. (2013).

B. *Auction Start Prices and Demand Curves*

In this section, we show how variation in auction start prices (or reserve prices) can be used to test some basic principles of auction theory and to trace out nonparametric auction demand curves. In a standard second-price auction with private

[8] Specifically, in this smaller sample we find that the auction sells on average at a relative price of 0.90 (the median price is the same), that 19.7 percent of the auctions sell above the (concurrent) posted price, and that only 4.4 percent sell at more than \$10 above the concurrent posted price.

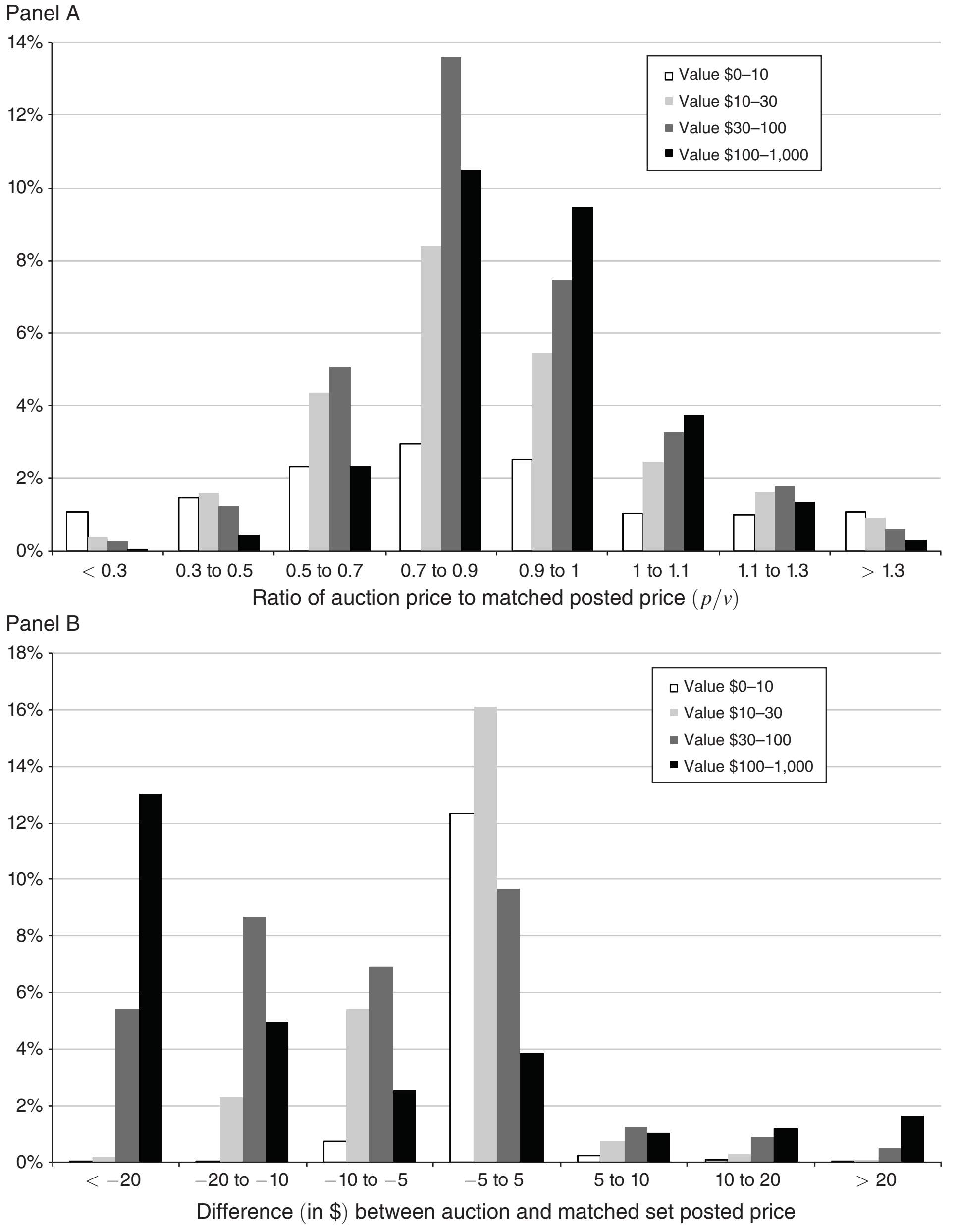

Figure 3. Auction Sale Price Dispersion

Notes: The figure shows the distribution of transacted auction prices p relative to the reference value v of the same item. The reference value for each item is defined as the average price across equivalent posted price transactions. The top panel shows the distribution of p/v, while the bottom panel shows the distribution of $p - v$. The figure omits items with a reference value greater than $1,000. These comprise just 1.9 percent of the matched sets and 0.5 percent of the listings in our baseline data.

values, an increase in the reserve price lowers the probability of a successful sale, but raises the price conditional on sale. The price increase occurs because increasing the reserve price from s to s' either eliminates sales that would occur at prices between s and s' or forces their price up to s'. Conditional on the auction price increasing above s', the distribution of sale prices is the same whether the reserve price was s or s'.

There are other models of auctions in which reserve prices can have more nuanced effects. These include models with entry or bidding costs, or with common value elements, or behavioral models. For instance, Ku, Galinsky, and Murnighan (2006) argue that bidders may exhibit escalating commitment so that lower start prices increase the odds of a sale and also the price conditional on sale. They present supporting evidence of this based on a sample of Persian rug and digital camera auctions on eBay. Simonsohn and Ariely (2008) found that while lower start prices did not necessarily increase the price conditional on sale, they did increase the price conditional on it being at the upper tail of the price distribution—again consistent with a bidding frenzy theory. In contrast, other researchers (Kamins, Drèze, and Folkes 2004; Reiley 2006; Lucking-Reiley et al. 2007) have found that lower start prices generally lead to lower prices conditional on sale, without testing the upper tail.

We take a large-sample approach to these hypotheses using our matched listings data. There are 142,653 matched sets in our baseline sample with variation in the start price. To limit the variation in other auction parameters, we restrict attention to listings with free shipping, no secret reserve price, and no BIN option. This leaves 19,777 matched sets with start price variation, encompassing a total of 494,170 listings, or about 25 listings, on average, per set. As above, we normalize start and sale prices by the items' reference values, so a start price of 0.35 means that a particular auction started at a price that was 35 percent of the item's posted price.

There is a stunning amount of variation in start prices. The top panel of Table 5 shows the overall distribution of start prices for items of different values. The bottom panel summarizes the within-set price variation. For the latter, we find the minimum and maximum start price for each matched set, and cross-tabulate the sets according to these numbers. It is quite common for a seller to auction the same item multiple times with widely different start prices. For instance, of the 3,262 sets that contain at least one very low start price ($p_{it}^n < 0.05$), 1,401 (43 percent) have at least one listing with a start price of $p_{it}^n > 0.85$, and several hundred have at least one start price of $p_{it}^n > 1$. As we discuss below, there are fewer intermediate start prices, but still enough to obtain robust estimates.

We use this variation to estimate fixed-effects regressions, where the dependent variable is either an indicator for a successful sale or the price conditional on sale. We allow the start price to have a flexibly estimated nonlinear effect by using a set of indicator variables for different start price levels. The regression results are presented in Table 6, and in Figure 4.

Panel A of Figure 4 plots the effect of the (normalized) start price on the probability of sale. A sale is almost guaranteed when the start price is very low, but the sale probability drops to less than 0.2 for high start prices. The figure shows separate sales curves for each of our four value categories. These come from separately estimated regressions, so that each plot is an average sales curve for a set of items of roughly similar value. The sales curves are remarkably similar (and close to linear) across price categories. Thus, it appears that the probability of sale depends a great deal on the start price relative to the item's value, but not so much on the value of the start price per se.

Table 5—Variation in Auction Start Price within and across Matched Sets

		Item reference value				
		< \$10	\$10–30	\$30–100	\$100–1,000	All listings
	Number of listings	92,925	184,652	125,326	91,269	494,170
Ratio of auction start price to reference value	< 0.05	6.5%	7.3%	20.3%	25.3%	13.8%
	0.05 to 0.15	6.7%	3.6%	0.5%	0.8%	2.9%
	0.15 to 0.30	5.3%	0.7%	1.5%	0.2%	1.7%
	0.30 to 0.45	2.1%	1.8%	2.2%	0.7%	1.7%
	0.45 to 0.60	5.5%	2.9%	3.5%	1.3%	3.2%
	0.60 to 0.85	12.9%	21.7%	17.4%	8.4%	16.5%
	0.85 to 1.00	42.1%	44.7%	37.0%	44.4%	42.2%
	1.00 to 1.20	11.5%	12.5%	13.8%	16.1%	13.3%
	> 1.20	7.3%	4.8%	3.8%	3.0%	4.7%

		Maximum (within matched set) ratio of auction start price to reference value						
		< 0.05	0.05 to 0.45	0.45 to 0.85	0.85 to 1.00	1.00 to 1.20	> 1.20	Total
Minimum (within matched set) ratio of auction start price to reference value	< 0.05	489	627	745	908	343	150	3,262
	0.05 to 0.45		473	1,077	545	119	126	2,340
	0.45 to 0.85			2,027	3,121	728	357	6,233
	0.85 to 1.00				2,627	2,436	1,068	6,131
	1.00 to 1.20					550	667	1,217
	> 1.20						594	594
	Total	489	1,100	3,849	7,201	4,176	2,962	19,777

Note: The table presents the distribution of (normalized) start prices, and the amount of variation within matched sets, for the sets we use to analyze the effect of auction start price.

Panel B of Figure 4 plots the effect of the auction start price on the final sale price. The relationship is estimated only for auctions that result in a sale. The estimates are again remarkably similar across price categories. For start prices below 0.6, the expected auction price conditional on sale is generally around 0.8. One interpretation of the flat price curve for lower start prices is that there is enough competition in the market to keep auction prices from slipping very far even if the start price is very low. For higher start prices, of course, start prices must exceed 0.8, and indeed the estimated price curves are upward sloping in this range.

In panel C of Figure 4, we combine these estimates to obtain auction demand curves. For each possible start price, we plot the probability of sale against the expected price conditional on sale on the y-axis. As the start price varies, we trace out demand curves. To make the figure clear, we only show the auction demand curve for a sample that pools all value categories, the value-specific demand curves are very similar. A somewhat unexpected finding is that the auction demand curve is highly convex, and the associated marginal revenue curve is not downward sloping as in standard analyses. Instead, the marginal revenue is roughly U-shaped, as shown in panel C, which plots a (smoothed) marginal revenue curve for the pooled sample.[9] With this type of demand, a seller would prefer either a high start price or

[9] To construct the marginal revenue curve in Figure 4, panel C, we smooth the demand estimates. The exact procedure is described in online Appendix B, which also shows the smoothed and unsmoothed plots. The smoothed and unsmoothed demand curves look nearly identical, but small wiggles in the unsmoothed curve create a few outlier points in the unsmoothed plot of marginal revenue.

Table 6—The Effect of Auction Start Price

	Item reference value							
	< \$10		\$10–30		\$30–100		\$100–1,000	
Panel A. Dependent variable: Sale indicator								
Start/value ratio indicator:								
0.05–0.15	−0.066	(0.013)	−0.042	(0.010)	−0.015	(0.022)	−0.086	(0.021)
0.15–0.30	−0.150	(0.011)	0.075	(0.019)	−0.086	(0.015)	−0.123	(0.039)
0.30–0.45	−0.273	(0.017)	−0.166	(0.012)	−0.171	(0.014)	−0.214	(0.028)
0.45–0.60	−0.416	(0.013)	−0.246	(0.010)	−0.193	(0.010)	−0.373	(0.015)
0.60–0.85	−0.522	(0.012)	−0.476	(0.007)	−0.421	(0.007)	−0.539	(0.008)
0.85–1.00	−0.645	(0.011)	−0.588	(0.007)	−0.597	(0.006)	−0.695	(0.006)
1.00–1.20	−0.674	(0.013)	−0.646	(0.008)	−0.648	(0.007)	−0.775	(0.007)
> 1.20	−0.721	(0.013)	−0.694	(0.010)	−0.760	(0.010)	−0.807	(0.012)
Constant	0.932	(0.010)	0.881	(0.007)	0.906	(0.005)	0.973	(0.004)
Number of listings	92,925		184,652		125,326		91,267	
Number of matched sets	3,769		7,183		4,772		4,053	
Panel B. Dependent variable: Sale price (conditional on sale)								
Start/value ratio indicator:								
0.05–0.15	0.146	(0.036)	0.006	(0.006)	0.024	(0.013)	0.038	(0.007)
0.15–0.30	0.084	(0.034)	−0.043	(0.011)	−0.022	(0.009)	0.031	(0.014)
0.30–0.45	0.135	(0.050)	−0.038	(0.007)	−0.014	(0.009)	0.011	(0.011)
0.45–0.60	0.233	(0.039)	−0.008	(0.006)	−0.005	(0.007)	−0.050	(0.007)
0.60–0.85	0.255	(0.035)	0.045	(0.005)	0.039	(0.005)	0.032	(0.004)
0.85–1.00	0.413	(0.035)	0.185	(0.005)	0.150	(0.005)	0.118	(0.003)
1.00–1.20	0.533	(0.045)	0.323	(0.007)	0.273	(0.007)	0.208	(0.004)
> 1.20	0.762	(0.048)	0.608	(0.010)	0.500	(0.012)	0.544	(0.012)
Constant	0.610	(0.026)	0.769	(0.004)	0.817	(0.002)	0.855	(0.001)
Number of sales	39,174		72,067		60,375		42,285	
Number of matched sets	3,010		5,889		3,762		2,831	

Notes: The table presents regression results of listing outcomes on (normalized) starting price, using matched set fixed effects. The dependent variable in the top panel is a dummy variable that is equal to one when the listing transacts. The dependent variable in the bottom panel is the transaction price (conditional on sale).

a very low one, depending on his marginal cost, and not an intermediate start price, consistent with bimodal distribution reported in Table 5.

How do our estimates relate to the various theories described above? That the estimated demand is downward sloping, while hardly surprising, runs counter to the strong version of the bidding escalation theory. It is also interesting to investigate the weaker version of this hypothesis, namely that *conditional on reaching a given price*, an auction that started at a lower price will continue longer. In contrast, the textbook private value auction model predicts that the upper tail of the price distribution (say, above some price p) should not depend on the start price (for any start price less than p).

To investigate this, panel D of Figure 4 plots, for low, medium, and high start prices, the probability of the auction price rising above different thresholds. The plot suggests that low and high start prices raise the (unconditional) probability of getting a high final price relative to an intermediate start price. One potential explanation is that low start prices attract more bidder attention. However, the evidence does not particularly support the escalation hypothesis, as the figure also shows that

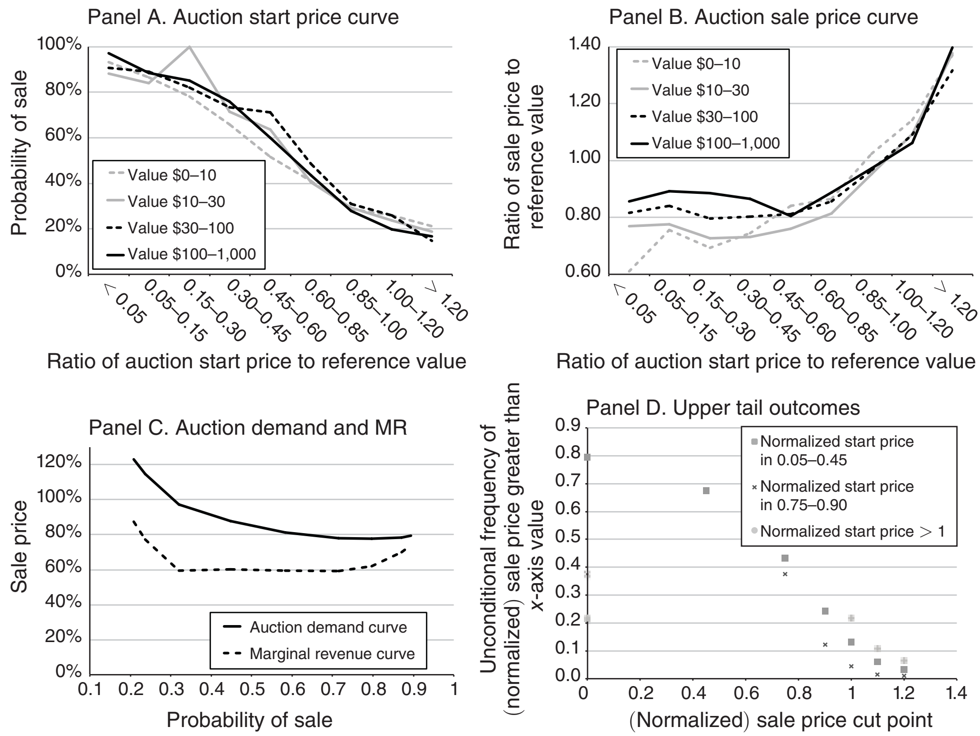

Figure 4. The Effect of Auction Start Price

Notes: Panels A and B show the effect of auction start price on listing outcomes, based on the regression results in Table 6. Panel A shows the effect on the probability of sale; Panel B shows the effect on expected sale price. Panel C pools all value categories and presents the implied auction demand curve and its corresponding marginal revenue curve; see the main text and online Appendix B for additional details. Panel D plots the probability a listing results in an auction price above certain levels, for different start prices (see text for further discussion).

high start prices, which attract fewer bidders, also lead to higher prices than intermediate start prices.

C. *Auctions with Buy It Now Prices*

Sellers on eBay can adjust a variety of auction design parameters apart from the reserve price. For a small fee of 5 to 25 cents, a seller can specify a buy-it-now (BIN) price at which a buyer can preempt the auction and immediately purchase the item. The BIN price disappears if the item receives a qualified bid, and a standard auction ensues.

The mechanism has generated a lot of theoretical interest (e.g., Budish and Takeyama 2001; Matthews 2004). Consider the benchmark case of an ascending auction with exogenous participation, where bidders draw independent private values from the same distribution, and the reserve price is set optimally. A very high BIN price will have no effect on revenue, and a lower BIN price reduces expected revenue. At the same time, a BIN price may increase revenue if bidders are impatient so that participating in an auction is costly, or risk-averse and willing to pay a premium to guarantee victory.

Several studies have tried to evaluate the effects of buy-it-now prices. Standifird, Roelofs, and Durham (2004) auctioned silver dollars and found that buyers tended not to use the buy-it-now option even when the BIN price was set low. Ackerberg, Hirano, and Shahriar (2006) analyzed Dell laptop auctions and found that sellers using a BIN option had revenue that was \$29 higher. Anderson et al. (2008) collected data on sales of Palm handheld devices, and found that the BIN option was used more often by experienced sellers. In their summary statistics, the prices of BIN auctions are slightly higher but they do not report a comparison after controlling for seller or item characteristics.

The matched listings approach allows us to provide large-scale evidence that extends and sharpens these earlier analyses. We first identify the 90,404 matched sets in our baseline sample that have variation in the BIN price, or in whether the BIN option is used at all. To avoid confounding BIN choices with other auction parameters, we restrict attention to listings with free shipping, no secret reserve price, and a start price that is effectively nonbinding (specifically listings with a value of at least \$10 and a start price of less than \$1). This leaves us 3,239 matched sets with BIN variation, and a total of 123,757 listings. Table 7 documents the amount of variation in (normalized) BIN prices, both across the whole sample (top panel), and within matched sets (bottom panel). Most BIN prices fall between 80 and 120 percent of an item's average posted price, with considerable variation in this range.

We use the within-set variation to identify the BIN effect on sale outcomes. By focusing on listings with essentially nonbinding reserve prices, almost all (98 percent) end in a successful sale, so the resulting outcome is only whether the item sells via the BIN price or instead via the auction mechanism (but not whether the item sells at all).

The top panel of Table 8 reports results from fixed effect regressions in which the dependent variable is a dummy equal to one if an item sells via the BIN price, and zero if the item sells by auction or not at all (items with no BIN option are not included in this regression). Items are quite unlikely to sell via BIN at high BIN prices, especially prices more than 10 percent above the item's reference value. It is more common for a buyer to exercise the BIN option when the BIN price is less than 90 percent of the reference value, but it still happens only for a minority of listings. The top panel of Figure 5 plots the results.

The bottom panel of Table 8 and the middle panel of Figure 5 include items with no BIN option, and show the relationship between the BIN price and auction revenue. The results are based on fixed effects regressions in which the dependent variable is the transaction price. The median (normalized) BIN price in our sample is between 0.95 and 1.00. Setting a BIN price at this level has a negligible effect on revenue. Setting a lower (under-priced) BIN price reduces seller revenue, while setting a high (over-priced) BIN price modestly increases revenue. These results are consistent with the theories above in which a high BIN price can raise revenue from impatient or risk-averse buyers.

A more subtle question is whether a BIN option that is *not* exercised might affect subsequent bidding, for example by anchoring subsequent bids. The anchoring mechanism is arguably unlikely in that the BIN price disappears once a qualified bid is received. Nevertheless, we can provide some evidence by looking at how BIN prices affect the probability of obtaining a very low sale price, i.e., at the lower

Table 7—Variation in BIN Price Within and Across Matched Sets

		Item reference value				
		< \$10	\$10–30	\$30–100	\$100–1,000	All listings
	Number of listings	15,277	11,360	65,041	32,079	123,757
Ratio of BIN price to reference value	No BIN	47.2%	42.9%	20.7%	28.2%	27.9%
	< 0.90	8.5%	6.0%	8.4%	15.8%	10.1%
	0.90 to 0.95	1.0%	2.5%	17.5%	17.9%	14.2%
	0.95 to 1.00	19.6%	16.2%	16.3%	13.2%	15.9%
	1.00 to 1.10	8.6%	10.9%	15.2%	13.4%	13.5%
	> 1.10	15.1%	21.5%	21.9%	11.5%	18.3%

		Maximum (within matched set) ratio of BIN price to reference value						
		No BIN	< 0.90	0.90 to 0.95	0.95 to 1.00	1.00 to 1.10	> 1.10	Total
Minimum (within matched set) ratio of BIN price to reference value	No BIN	0	108	55	522	440	648	1,773
	< 0.90		55	40	102	50	65	312
	0.90 to 0.95			18	52	59	33	162
	0.95 to 1.00				139	128	148	415
	1.00 to 1.10					140	134	274
	> 1.10						303	303
	Total	0	163	113	815	817	1,331	3,239

Note: The table presents the distribution of (normalized) BIN prices, and the amount of variation in BIN prices within matched sets, for the sets we use to analyze the effect of BIN price.

tail of the auction price distribution. The bottom panel of Figure 5 shows that the likelihood of receiving below 60 percent of the reference value is essentially the same whether the seller sets a high BIN price, a low BIN price, or no BIN price at all, consistent with limited anchoring effects.

D. *Other Aspects of Auction Design*

The matched listings data provides a rich laboratory to explore the effects of other auction design parameters. We briefly mention a few that we have explored.

A number of studies have found that longer auctions seem to generate higher revenue (Lucking-Reiley et al. 2007; Haruvy and Popkowski Leszczyc 2010), or have analyzed the effect of ending auctions on different days of the week or at different times of the day (Simonsohn 2010). Using a similar empirical strategy to the one employed so far, we identified 92,266 matched sets with variation in auction duration, 129,955 matched sets with variation in the ending time, and 126,027 matched sets with variation in the ending day. Our results suggest that overall the effect of the auction duration is small. On average, we find that longer auctions with a BIN option are slightly more likely to succeed while auction duration makes little difference for the sale probability of standard auctions with no BIN option. The effects are not large, however, and are less robust than most of our other findings. We also find little effect of the day of the week on which the auction ends, and we confirm existing results that auctions that end late at night (midnight to 5am) perform slightly worse.

Another issue that has attracted some debate is the effect of keeping auction reserve prices secret. On eBay, the seller sets a public reserve price in the form of the auction

Table 8—The Effect of BIN Price

	Value \$10–30, Starting price < \$1		Value \$30–100, Starting price < \$1		Value \$100–1,000, Starting price < \$1	
Fraction sold	0.982		0.987		0.978	
Panel A. Dependent variable: Sale via BIN option indicator						
BIN price to value ratio indicator:						
< 0.90	(omitted)		(omitted)		(omitted)	
0.90–0.95	−0.086	(0.036)	−0.055	(0.009)	−0.020	(0.011)
0.95–1.00	−0.122	(0.028)	−0.074	(0.009)	−0.029	(0.013)
1.00–1.10	−0.165	(0.033)	−0.122	(0.011)	−0.096	(0.013)
> 1.10	−0.246	(0.036)	−0.240	(0.015)	−0.110	(0.017)
Constant	0.355	(0.026)	0.249	(0.009)	0.215	(0.009)
Number of listings	5,959		50,584		22,254	
Number of matched sets	368		665		624	
Panel B. Dependent variable: Sale price (conditional on sale)						
BIN price to value ratio indicator:						
< 0.90	−0.102	(0.018)	−0.092	(0.004)	−0.113	(0.005)
0.90–0.95	−0.031	(0.022)	−0.049	(0.004)	−0.053	(0.005)
0.95–1.00	0.000	(0.009)	−0.007	(0.004)	−0.001	(0.004)
1.00–1.10	0.038	(0.012)	−0.003	(0.003)	0.011	(0.004)
> 1.10	0.083	(0.013)	0.012	(0.005)	0.046	(0.009)
Constant (No BIN)	0.825	(0.005)	0.850	(0.002)	0.883	(0.003)
Number of listings	11,013		64,012		31,200	
Number of matched sets	662		1,026		908	

Notes: The table presents regression results of listing outcomes on (normalized) BIN price, using matched set fixed effects. The sample includes all items with reference value greater than \$10 and only listings with starting price that is less than \$1, so that virtually all items in the sample transact. The regressions in the top panel only use listings with a BIN price, while the bottom panel also uses listings with no BIN option. The dependent variable in the top panel is a dummy variable that is equal to one when the listing transacts via the BIN price (rather than via the regular auction). The dependent in the bottom panel is the transaction price (via BIN or auction).

start price we analyzed earlier, but (for an additional fee) can also set a secret reserve price that is not known to potential bidders. When a seller sets a secret reserve price, bidders know that it exists, but learn its level only if bidding in the auction exceeds it. Various factors might make a secret reserve price more or less profitable than a public reserve price. For instance, Katkar and Reiley (2006) auctioned 100 Pokemon cards, half with a public reserve price of 30 percent of the item value and half with a secret reserve of 30 percent of the item value (and effectively a zero starting price). They found that secret reserve prices resulted in lower revenue.

To investigate this question using our data, we match listings of the same item into groups that have similar levels of public and private reserve prices (specifically, we do this in multiple ways: either by matching listings that have exactly the same reserve price, or—to increase statistical power—by matching listings with reserve prices within 10 percent of each other). Because the use of secret reserve prices has been discouraged by eBay (less than one percent of eBay listings use a secret reserve), our power is much lower than in previous exercises. Nevertheless, we do find 403 matched sets of listings, so we can estimate the effect of using a secret reserve price versus a public reserve price of the same magnitude. Our results indicate that in this sample, there is not much difference in auction outcomes between the public and secret reserve price sales.

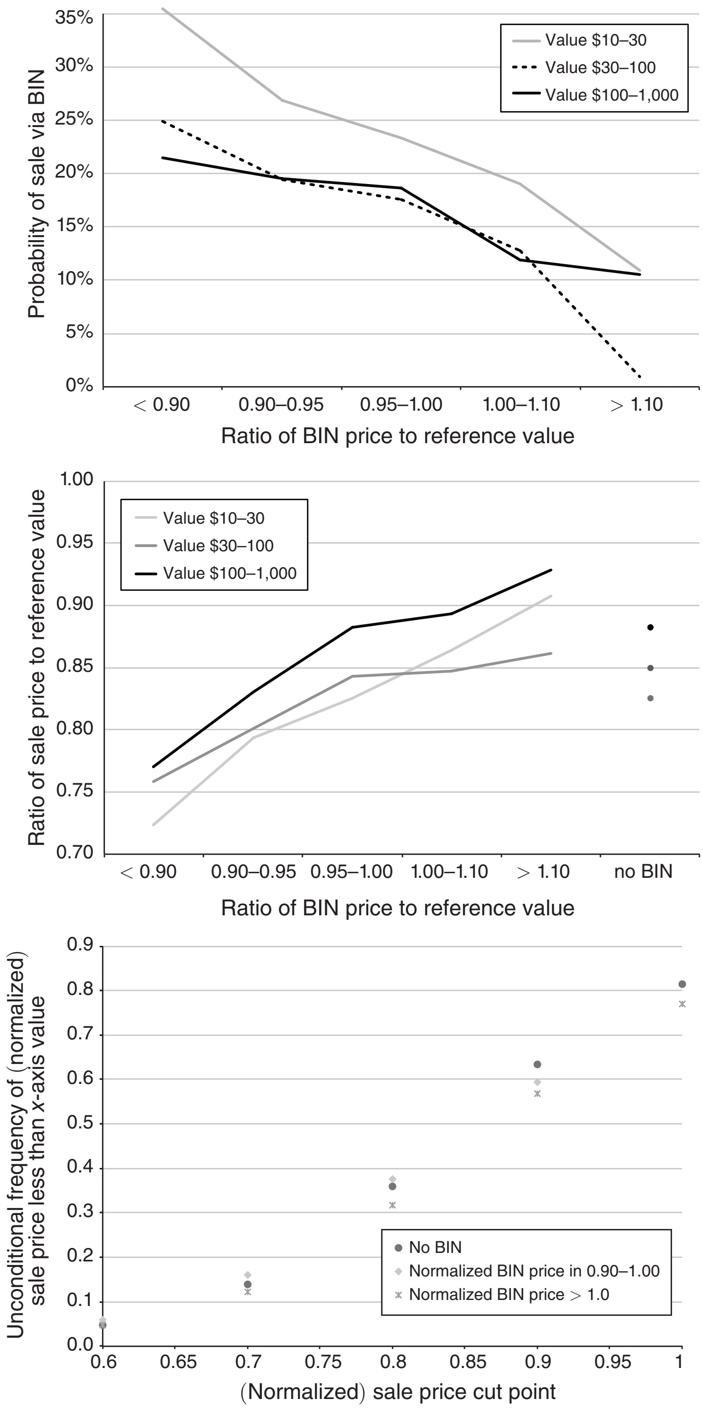

Figure 5. The Effect of BIN Price

Notes: The top two panels show how the seller's choice of BIN price affects the probability the auction sells at the BIN price, and the listing revenue. The sample focuses on items with a starting price of less than one dollar, so essentially all listings sell. The plots are based on the regression results in Table 8. The bottom panel plots the probability the sale occurs at prices below certain levels, for different BIN prices (see text for further details).

TABLE 9—WITHIN AND ACROSS MATCHED SET VARIATION IN SHIPPING RATE

		Item reference value				
		< $10	$10–30	$30–100	$100–1,000	All listings
	Number of listings	12,726	30,929	40,812	32,735	117,202
(Flat) shipping rate	Free	26.5%	51.1%	37.9%	38.3%	40.3%
	0 to $2.50	19.9%	4.0%	1.2%	0.4%	3.7%
	$2.50 to $5	37.5%	22.5%	11.8%	2.7%	14.9%
	$5 to $10	11.0%	13.5%	24.0%	13.3%	16.8%
	$10 to $20	4.6%	6.9%	19.0%	26.2%	16.3%
	> $20	0.4%	1.8%	6.0%	19.3%	8.0%

		Maximum (within matched set) shipping rate					
		0 to $2.50	$2.50 to $5	$5 to $10	$10 to $20	> $20	Total
Minimum (within matched set) shipping rate	Free	385	1,277	995	519	315	3,491
	0 to $2.50	91	219	3	0	0	313
	$2.50 to $5		559	332	29	2	922
	$5 to $10			504	371	10	885
	$10 to $20				516	176	692
	> $20					352	352
	Total	476	2,055	1,834	1,435	855	6,655

Notes: The table uses the baseline sample, and shows the extent of variation in shipping fees. The top panel presents statistics on the variation in (dollar) shipping fees across matched sets, while the bottom panel presents variation within sets.

E. *Shipping Fees*

Shipping arrangements are an important part of internet commerce, and internet retailers frequently compete to offer free or expedited shipping. At the same time, one often hears the idea that shipping fees can act as a hidden price that buyers do not fully internalize in making shopping decisions. Tyan (2005), Hossain and Morgan (2006), and Brown, Hossain, and Morgan (2010) all have studied data from eBay and found that increases in shipping fees can increase total seller revenue (inclusive of the shipping fee), suggesting that a dollar increase in the shipping fee does not lead bidders to reduce their bids by a full dollar to compensate. Sellers also can have another reason to favor shipping fees: until recently, eBay commissions were not applied to the shipping component but rather to the pre-shipping fee sale price.

We are interested in whether buyers internalize shipping fees. To analyze this, we follow the empirical strategy we have been employing throughout, and select matched sets from our baseline data that have variation across listings in the shipping fee. To avoid complications, we consider only listings with flat shipping fees that are independent of the buyer location.[10] The resulting data contains 117,202 listings grouped into 6,655 matched sets, with an average of 18 listings per set. A substantial fraction of these listings offer free shipping. Table 9 presents the distribution of shipping rates across the listings, and also the within-set variation in shipping fees. In parallel with our earlier analyses, we see sellers trying a range of shipping fees.

[10] Five percent of the listings in our baseline data are associated with a shipping fee that depends on the location of the buyer. To simplify, our analysis focuses on the remaining 95 percent. Further excluding listings with contradictory shipping information in the data leaves us with 89 percent of the listings that have a flat shipping rate.

Table 10—The Effect of Shipping Fees

	Baseline sample		Only listings with positive shipping rate		Value < $30 and start price < $1		Value in $30–1,000 and start price < $1	
Panel A. Dependent variable: Sale indicator								
Shipping > 0 (indicator)	−0.014	(0.0042)	—	—	−0.056	(0.0130)	−0.002	(0.0049)
Shipping fee ($)	−0.001	(0.0002)	−0.001	(0.0003)	−0.015	(0.0023)	−0.0003	(0.0003)
Constant	0.639	(0.0024)	0.621	(0.0037)	0.882	(0.0066)	0.959	(0.0025)
Number of listings	117,202		70,023		16,990		34,529	
Number of matched sets	6,655		6,655		1,076		1,742	
Panel B. Dependent variable: Sale price (conditional on sale)								
Shipping > 0 (indicator)	−2.521	(0.3120)	—	—	−1.571	(0.2307)	−2.940	(0.5063)
Shipping fee ($)	0.181	(0.0202)	0.523	(0.0468)	0.362	(0.0440)	0.039	(0.0329)
Constant	93.734	(0.1576)	93.945	(0.5662)	16.398	(0.0858)	122.066	(0.2533)
Number of sales	73,034		43,064		13,403		42,335	
Number of matched sets	5,156		4,679		847		2,624	

Notes: The table presents regression results of listing outcomes on (dollar) shipping fee, using matched set fixed effects. Column 1 reports results for the baseline sample, while the other columns cut the data in different ways. The dependent variable in the top panel is a dummy variable that is equal to one when the listing transacts. The dependent variable in the bottom panel is the transaction price (conditional on sale). Note that the transaction price includes the shipping fee, so in a frictionless market the coefficient on shipping fee should be zero.

Table 10 reports results on sale probability and auction revenue (conditional on sale) for several different subsamples. The effect of shipping fees on the probability of sale is minimal, so we focus on the price effect. Unlike our earlier analyses, we run the price regression without normalizing by the item value, as this helps in facilitating the quantitative interpretation of the estimated effects. With this specification, a coefficient of zero on shipping rate implies that bidders respond to shipping fee changes one-for-one, so that a higher shipping fee is fully canceled out by a lower sale price, and the effect on total revenue (sale price plus shipping) is zero. As Table 10 indicates, our estimates suggest a positive coefficient of around 0.2 to 0.3, suggesting that only 70 to 80 percent of the shipping fee is internalized in the bidding.

In addition, we find a distinct effect at zero. Free shipping is associated with an average revenue increase of around $2.50, with a larger dollar effect for more expensive items. The free shipping effect may be some combination of buyers responding to a free offer (Shampanier, Mazar, and Ariely 2007) and eBay's strategy of prioritizing free shipping in the search results. Figure 6 provides a graphical illustration of our regression estimates. As shown in the figure, our estimates suggest that low shipping fees on eBay, of roughly less than $10, are suboptimal. Sellers could increase profits by either reducing the shipping rate and making it free, or by increasing the shipping rate and benefiting from the fact that bidders would only partially internalize this increase. The observed distribution of shipping fees is largely consistent with these incentives: only a small fraction of the listings are associated with low (but positive) shipping fees (top panel of Table 9).

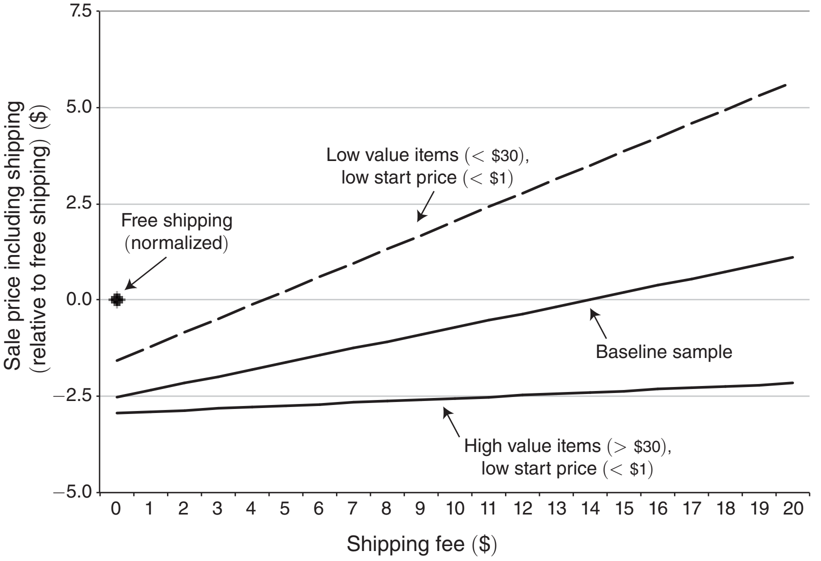

Figure 6. The Effect of Shipping Fees

Note: The figure shows the effect of shipping fees on seller revenue, based on the regression results in Table 10.

An even more finely targeted way to analyze the effect of shipping fees is to focus on cases where an increase in the shipping fee was matched by a reduction in the start price. A textbook economic analysis would suggest that an auction with free shipping and a start price of $10 should be *identical* to an auction with a 0 start price and a $10 shipping fee. That is, they should have the same probability of sale and expected revenue conditional on sale. Following this logic, we identified duplicate listings with same inclusive start price, that is, the same sum of start price and shipping fee. We then asked whether the division mattered. We found 279 such matched sets in our baseline sample (and many more where the inclusive start prices were within a 10 cent or 10 percent range). Our finding in this sample was similar: increases in the shipping fee reduce the sale price, but less than one-for-one.

III. The Advantage of a Matched Listings Approach

Our empirical strategy provides a simple, scalable way to assess a wide range of selling strategies, and we have argued that it allows for plausible identification despite pooling large numbers of sellers and products. In this section, we consider first whether one could obtain equally credible large-scale estimates without targeting such narrowly matched listings, and exactly what the benefits of large-scale estimates might be relative to tightly defined field experiments that ensure even cleaner randomization and identification.

A. *Cross-Item Observational Data*

The key concern with cross-item comparisons in Internet markets is the heterogeneity of items that are listed for sale and the sellers doing the listing. This makes it difficult to specify an appropriate set of control variables, particularly when many item attributes such as the listing title, item pictures and description are relatively unstructured. We use a variant of the start price analysis from the previous section to illustrate this point. Our illustration entertains what researchers might have done if they had access to the same data, but were not able to identify matched listings as we do.

Absent such a grouping, a researcher presumably would have tried to define comparable sets of products in some other way. One natural way to group items is to rely on eBay's product categories. eBay classifies products using a hierarchical category structure. At the highest level, listings are partitioned into almost 35 meta categories, such as electronics, collectibles, baby items, and so on. At the finest level, products are partitioned into 37,636 leaf categories, such as "iPod and MP3 players" and "developmental baby toys." Thus, one way a researcher could analyze the effect of start price is to compare listings within a given leaf or (less ideally) meta category.

We examine this strategy by running our start price exercise in three different ways: grouping listings in our baseline sample according to their meta category, their leaf category, and by matched listings. In the former two cases, we average item reference values within each category to create a category-specific reference value, as if all items within the category were perfectly comparable. We then use this average value to normalize the start price for each listing in the category, and reestimate the effect of start price on an indicator for a successful sale and the final (normalized) price conditional on sale, including fixed effects for the relevant item groupings, but also omitting the fixed effects for comparison. For simplicity, we report results only for the probability of sale, and not the price conditional on sale.

We report the results in Figure 7, which plots the differently estimated sales curves as a function of start price. The estimates for which we group items by (either meta or leaf) category are dramatically different from what we obtain by grouping identical listings into matched sets. To understand the difference, we can interpret the solid black curve in Figure 7 as an average estimate of how the sale probability changes with the start price for a fixed item (and seller). In comparison, the solid grey curves are constructed so that the composition of the items offered at different start prices is not the same, although they are all in the same product category. The differences in the estimated sales curves indicate that items offered at very low and very high start prices are generally more appealing (in the sense of having a higher probability of sale) than those offered at medium start prices.

Two other patterns in Figure 7 are worth noting. First, the inclusion of fixed effects in all three analyses makes very little difference. That is, it appears that—at least for this analysis—the effect of grouping listings into eBay product categories or into sets of identical items is captured mostly in the construction of the reference value by which we normalize the start price. Second, it is interesting to note that although the meta category level is an extremely crude way to categorize products while the leaf category level is an extremely precise classification, the results obtained from these two exercises are very similar, and both are dramatically different from the fixed item and seller grouping we rely on using the matched listings approach.

Overall, the analysis points to a considerable problem of accounting for heterogeneity in large diverse markets such as eBay. This is presumably one reason

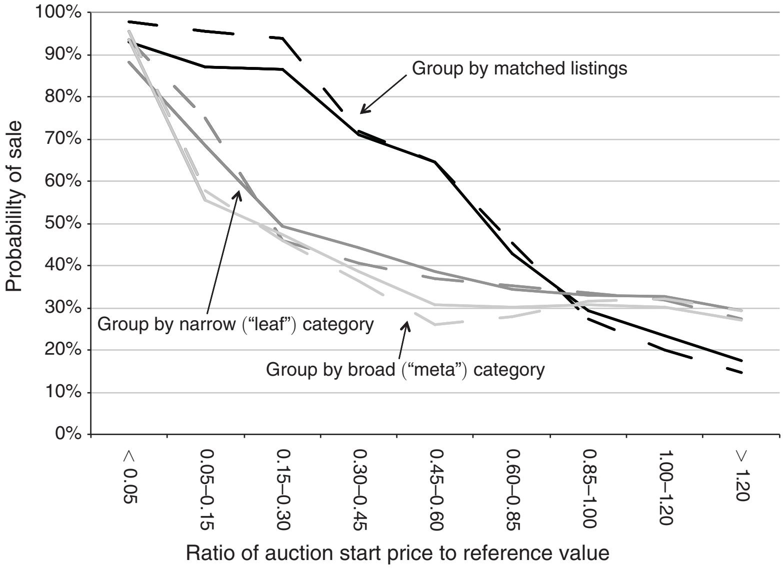

Figure 7. Matched Listings Approach versus Cross-Item Observational Data

Notes: The figure presents the relationship between auction starting price and the probability of sale for the different regressions. The black lines represent start price variation within matched sets, which is the type of variation used throughout the paper. The dark grey lines represent variation within narrow (leaf) product categories as defined by eBay; there are more than 37,000 such categories. The light grey lines represent variation within broad (meta) product categories as defined by eBay; there are 35 such categories. There are two lines for each grouping. The dashed lines represent specifications with no fixed effects, so that groupings are used to generate a reference value (average fixed price transactions for matched sets, and average sale price in each category for the category grouping). The solid lines repeat the same exercise, but are based on regressions that also include group (matched set or category) fixed effects.

researchers working with data from eBay or other online markets typically have restricted attention to a very narrowly defined groups of products, such as particular pop-music CDs, collectible coins, Pokemon cards, or board games. A narrowly drawn set of products may (or may not) mitigate the problem just identified, but even if it does, as in the case of a researcher-conducted experiment, it raises the concern that the results apply only to a narrow context. It is to this separate concern that we now turn.

B. *Structured Field Experiments*

The same ease of listing and selling items that makes duplicate listings so prevalent on eBay and other online platforms also makes these settings appealing for researcher-initiated field experiments. Administering and funding experiments is costly, however, so although researcher experiments are common, they are typically quite small in scale and scope, focusing on one of a few items, in limited quantity, and varying just one or a few sale parameters to identify a very limited number of treatment effects.

To illustrate why this is limiting, we again return to our analysis of auction start price, and rerun the exercise separately for each product meta-category. To facilitate a graphical illustration, we estimate a linear effect of the (normalized) start price on both the probability of sale (by regressing an indicator equal to one if the item sold

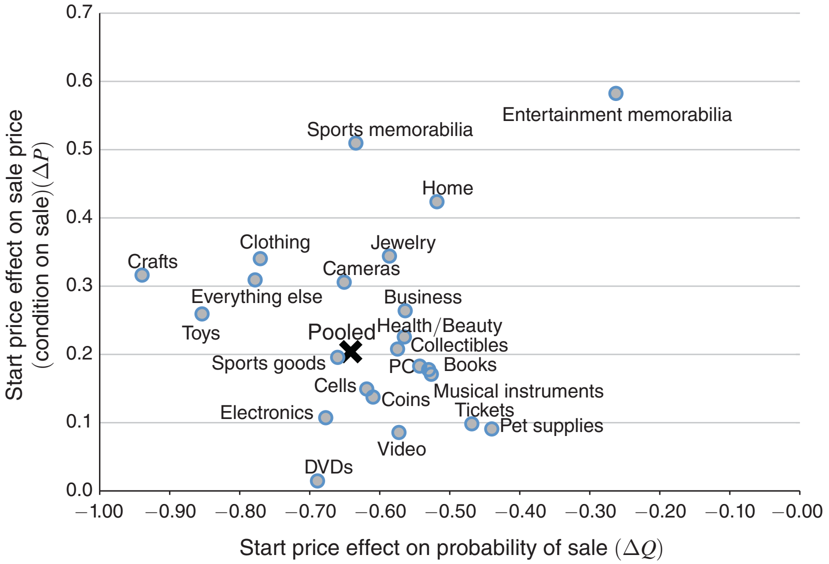

Figure 8. Category Heterogeneity

Notes: The figure presents the relationship between auction starting price and the probability of sale (horizontal axis) and transaction price (vertical axis) for different product categories, parallel to the regression results reported in Table 11. For each category, we run a simplified linear regression of the probability of sale on the (normalized) starting price p/v, and (separately) a regression of the transaction price (conditional on sale) on the starting price.

on the start price and matched-set fixed effects), and the expected (normalized) price conditional on sale (by regressing the sale price on the start price and matched-set fixed effects, using only successful sales). This yields, for each category, the slope of the average sales curve for items in the category and the slope of the price curve conditional on sale, with both probability of sale and price being a function of the start price.

The results are presented in Figure 8 and Table 11. The x-axis shows the effect of start price on the probability of sale, so a value of -0.5 means that an increase in the start price from 0.5 to 0.8 as a fraction of the item's value reduces the probability of sale by 0.15. The y-axis shows the effect of start price on the expected price conditional on sale; a value of 0.1 means that an increase in the normalized start price from 0.5 to 0.8 increases the expected price conditional on sale by 3 percent of the item's value. Each point in Figure 8 shows the two effects of the start price for a particular eBay product category.

Certain features are consistent across all categories. A higher start price always reduces the probability of sale, and (with the exception of DVDs where the effect is near-zero) increases the average price of successful sales. Yet, the magnitude of the effects varies quite dramatically across categories. For example, one can imagine a researcher running a careful field experiment on eBay by listing DVDs (or, more likely, specific types of DVDs), randomly varying their start prices, finding a large effect on the quantity sold, but very little effect on price. This researcher may have no reason to believe that DVDs are special, and therefore conclude that start prices do not affect sale prices, which may be consistent with some theories and less consistent with others. Yet, as Figure 8 suggests, such conclusions would be misleading,

Table 11—Category Heterogeneity in the Effect of Auction Starting Price

				Dep. variable is sale indicator		Dep. variable is sale price (if sold)	
	Matched sets	Listings	Sales	Coeff.	SE	Coeff.	SE
Clothing, shoes, accessories	2,505	24,351	7,692	−0.771	(0.030)	0.340	(0.046)
Jewelry and watches	2,036	54,397	10,951	−0.586	(0.022)	0.344	(0.034)
Home and garden	1,257	51,181	15,656	−0.518	(0.041)	0.424	(0.049)
Health, beauty	1,148	38,367	19,536	−0.565	(0.060)	0.226	(0.049)
Cell phones, PDAs	961	45,519	22,131	−0.619	(0.039)	0.149	(0.021)
Computers, networking	928	17,134	10,000	−0.543	(0.056)	0.183	(0.022)
Electronics	836	29,076	19,705	−0.677	(0.040)	0.107	(0.022)
Sporting goods	631	25,120	10,052	−0.660	(0.057)	0.196	(0.036)
Collectibles	609	9,113	4,008	−0.575	(0.072)	0.208	(0.074)
Video games	605	12,885	9,076	−0.573	(0.055)	0.086	(0.020)
Sports mem, cards, and fan shop	556	7,187	1,653	−0.634	(0.047)	0.510	(0.120)
Everything else	329	6,498	3,130	−0.651	(0.063)	0.306	(0.097)
Cameras, photo	534	23,565	12,243	−0.854	(0.032)	0.259	(0.030)
Toys and hobbies	475	7,693	4,462	−0.610	(0.034)	0.138	(0.034)
Coins and paper money	373	8,964	5,063	−0.564	(0.111)	0.264	(0.125)
Business and industrial	352	7,088	2,765	−0.778	(0.067)	0.309	(0.041)
DVDs and movies	329	6,388	4,844	−0.689	(0.076)	0.015	(0.052)
Books	249	1,695	713	−0.530	(0.138)	0.178	(0.056)
Crafts	165	4,814	2,173	−0.939	(0.091)	0.316	(0.070)
Tickets	162	597	216	−0.469	(0.090)	0.098	(0.117)
Pet supplies	150	5,290	3,127	−0.440	(0.071)	0.091	(0.030)
Musical instruments	121	2,667	982	−0.526	(0.116)	0.171	(0.026)
Entertainment memorabilia	117	3,357	1,224	−0.263	(0.210)	0.582	(0.302)
Pooled				−0.641	(0.017)	0.205	(0.012)

Notes: The table illustrates the heterogeneity in the effects across categories, using regressions that are similar to those reported in Table 6. We report the effect of auction starting price on the probability of sale and transaction price (conditional on sale) for different product categories. For each category, we run a simplified linear regression of the probability of sale on the (normalized) starting price p/v, and (separately) a regression of the transaction price (conditional on sale) on the same starting price variable. We only use categories with at least 100 matched sets in the baseline sample (these account for 97 percent of the matched sets in the baseline sample).

as the DVDs category is quite an outlier, and the price effects are significantly larger in all other product categories.

Of course, once one sees the results presented in this way, the differences across product categories become quite natural. Roughly, one can think of categories with a small dp/ds effect or a large (more negative) dq/ds effect as categories with relatively flat (i.e. elastic) residual demand curves for individual items, as opposed to relatively steep (inelastic) residual demand. So Figure 8 tells us that products listed in seemingly commodity categories such as DVDs, electronics, video and coins fall into the former elastic category, whereas products listed in potentially more differentiated categories such as clothing, jewelry, sports memorabilia and home fall into the inelastic category. While a full exploration is beyond the scope of the present paper, Figure 8 suggests the possibility of using our approach to obtain meaningful comparisons of price sensitivity and competition across retail product categories.

IV. Conclusion

In this paper we consider a simple empirical strategy for using large-scale internet data to study consumer behavior and pricing strategies: identifying large numbers of episodes where sellers offered nearly identical product listings with targeted variation in pricing or auction design. The motivation for the approach is the ease and ubiquity of retail experimentation on the internet. While our data construction pools pricing variation that might have heterogeneous causes, we are able to use the scale of the data to demonstrate that the results are robust to narrower matching criteria that help address potential concerns about endogeneity or selection biases.

We used the approach to consider a series of applications: estimating the degree of price dispersion across equivalent auctions, the relationship between auction prices and equivalent posted prices, the (average) shape of auction demand, the effect of buy-it-now prices, and the extent to which consumers internalize shipping fees. We expect that the same or similar approaches can be applied in a range of internet retail, advertising or labor markets. It can also be applied retrospectively to understand changes in markets over time, as in Einav et al. (2013).

One interesting question that we have not addressed in this paper is how much sellers who actively experiment learn from what they are doing. Some of the patterns we have documented—for instance that sellers generally tend to avoid intermediate start prices, or low but positive shipping fees—are consistent with the idea that sellers have over time accumulated knowledge about strategies that do not work well. In other cases, sellers face nonobvious trade-offs—for instance between a lower quantity and a higher price—where the optimal decision depends on seller costs that we do not observe. We have found that sellers do not converge in their listing behavior for a given item; instead, they persistently experiment by varying their sale parameters. Perhaps this is because online markets are constantly evolving, and sellers' optimal strategies, about which sellers try to learn, change over time. This observation suggests that a successful theory of active experimentation in online marketplaces would be one in which sellers remained somewhat unsure over time about exactly what strategy is best. Understanding how online retailers become more effective, and the process through which this occurs, is something we hope to explore in further work.

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