

Auctions versus Posted Prices in Online Markets*

Liran Einav, Chiara Farronato, Jonathan Levin and Neel Sundaresan†

January 2016

Abstract. Auctions were very popular in the early days of internet commerce, but today online sellers mostly use posted prices. We model the choice between auctions and posted prices as a trade-off between competitive price discovery and convenience. Evidence from eBay fits the theory: auctions are favored by less experienced sellers and for idiosyncratic products, and auction listings sell at a discount but with higher probability relative to comparable posted price listings. We then show that the decline in auctions was not driven by changes in the type of sellers and items. Instead, seller incentives changed. We estimate the demand facing individual sellers at different points in time, and document falling sale probabilities and a fall in the relative demand for auctions. Both favor posted prices; our estimates suggest the latter is more important for explaining the shift away from auctions. We provide supporting evidence from a survey of eBay sellers, and discuss why sellers might use a mix of auctions and posted prices in order to price discriminate.

*We are grateful to Pat Bajari, Nathan Hendren, Preston McAfee, Justin Rao, David Reiley, four anonymous referees, and the Editor (Phil Reny) for helpful comments. We appreciate support from the National Science Foundation, the Stanford Institute for Economic Policy Research, the Toulouse Network on Information Technology, and the Alfred P. Sloan Foundation. The data for this study were obtained through a contract between Einav, Farronato, and Levin and eBay Research. Neel Sundaresan was an employee of eBay at the time this research was done.

†Department of Economics, Stanford, and NBER (Einav and Levin); Harvard Business School (Farronato); Microsoft (Sundaresan). Email: leinav@stanford.edu, cfarronato@hbs.edu, jdlevin@stanford.edu, and nsundare@gmail.com.

1 Introduction

One of the classic questions in economic theory concerns the best way to make a sale. Should a seller post a price, run an auction, or try to haggle with buyers? How does this depend on the good being sold, the prospective demand and the market environment? If a seller faces buyers with private information about their willingness-to-pay, and there are no further transaction costs, an auction is optimal (Myerson, 1981; Riley and Samuelson, 1981; Harris and Townsend, 1981). An auction aggregates information and helps the seller identify the appropriate buyer and price. However auctions can have high transaction costs. They take time and require communication with multiple buyers. If buyers appear gradually, are impatient, or are few in number, price posting may be preferable (e.g. Wang, 1993; Zeigler and Lazear, 2003). Casual empiricism aligns nicely with these trade-offs. Auctions are used for art, wine, and sales of large or rarely traded assets. Posted prices are used for more standardized goods. They became the norm in retail markets after being introduced by department stores in the 1840s to make shopping more convenient for buyers (Surowiecki, 2011).

In the early days of the internet, many observers speculated that technology would shift retail markets in the direction of more dynamic pricing mechanisms. The *Economist* (2000) wrote that the internet had introduced “the possibility of a permanent worldwide bazaar in which no prices are ever fixed for long, all information is instantly available, and buyers and sellers spend their lives haggling to try to get the best deals” (see also Hall, 2002). By 2001, eBay had become a dominant platform for consumer auctions, and was the third-ranked website in terms of time spent by consumers.¹ Its growth was enabled by the development of proxy bidding that allowed buyers to submit a maximum bid and have the computer respond to opponent bids up to this maximum. This lowered transaction costs by allowing bidders to participate in a dynamic auction without paying constant attention.

Since this time, online commerce has grown enormously but internet auctions have not. Today most online commerce takes place at posted retail prices. Figure 1 shows the evolution on eBay: the share of listings and transaction volume attributable to auction sales has fallen

¹Source: <http://blog.compete.com/2007/10/01/top-ranked-web-sites-popularity-2001/>.

well below fifty percent.² Figure 2 shows a similar pattern, this time for Google searches involving the terms “online auctions” and “online prices.” Nonetheless, the continuing use of auctions along with posted prices makes the internet, and eBay, a natural laboratory for studying how sellers choose between auctions and posted prices, how the results compare, and how the incentive to use auctions might have changed over time. The goal of this paper is to address these questions.

We combine a simple model with rich data from eBay. The data include all listings from 2003, when auctions were dominant, to 2009, when posted prices had overtaken auctions. We use this data to shed light on which items tend to be sold by auction, which sellers favor auctions, and how a seller’s behavior changes as he or she becomes more experienced. Following Elfenbein et al. (2012, 2015) and Einav et al. (2015), we also take advantage of a ubiquitous feature of eBay’s platform, namely that sellers frequently list the same item multiple times, either simultaneously or over time, while varying their sale format or other pricing parameters. We construct a large dataset of matched listings during the 2003 to 2009 period, focusing on sellers who listed the same item by auction and by posted price. There are many such cases, which enables an “apples-to-apples” comparison of auctions and posted prices.

The key trade-off introduced above is that auctions enable price discovery and buyer competition, but are less convenient for buyers. In Section 2, we propose a model of this trade-off to help us interpret patterns in the data. The model is parsimonious. It has just a few parameters, which capture how reduced uncertainty about an item’s value, greater retail competition, and greater demand for convenience all favor posted prices. After describing the setting and data, we document in Section 4 that the use of auctions on eBay corresponds broadly with the theory. Auctions are used by smaller and less experienced sellers, for used goods, and for goods that are more idiosyncratic. Auction listings are also more likely to sell than matched posted price listings, but at lower prices, a prediction that comes naturally

²Figure 1 uses data from the US eBay platform, eBay.com. As shown in Appendix D, the eBay platforms in other countries across the world, with the exception of India, have experienced similar trends. Note that Figure 1 also shows a very sharp drop in the share of auction listings in September 2008, due to a change in eBay policy that allowed thirty-day posted price listings to roll over from one month to the next (“good-till-canceled”). The figure omits less prevalent sales mechanisms such as “hybrid” auctions that allow a preemptive posted price purchase, or “best offer” listings that allow a buyer to negotiate down from the posted price.

from the model.

We then turn to the question of why auctions became less popular over time. One immediate hypothesis is that there were changes in the composition of internet sellers, or of items being sold online. We show in Section 5.1 that on eBay this does not appear to explain much of the move to posted prices. Instead, the shift to price posting has occurred *within* natural groupings of sellers and products. A second possibility is a change in consumer preferences for convenience. Fifteen years ago, internet auctions were a form of online entertainment. Today, YouTube, Facebook, and other online diversions may have made bidding in auctions less fun by comparison. Finally, the price discovery benefits of auctions may have declined because of increased retail competition, on eBay and more generally with the rise of Amazon and improvements in internet search.

Our model captures the latter effects as increases in distinct parameters — the “hassle cost” of auctions λ and the “best alternative” for buyers u . It suggests that either mechanism might explain why sellers would be motivated to shift to posted prices. We provide direct evidence on the changing incentives for sellers in Section 5.2 by documenting the growth of a large “auction discount.” In 2003, auction prices were on average within five percent of matched posted price sales. By 2009, the discount had grown to over sixteen percent. The drop was not due to sellers lowering their auction reserve prices. In fact, reserve prices generally increased relative to matched posted prices. Instead, the growing auction discount suggests a fall in the demand for auction listings relative to an analogous posted price listing.

We develop this idea further in Section 6. We use variation in posted prices and auction start prices within sets of matched listings to estimate the combinations of sale probability and sale price that can be achieved with different sale formats. The estimates allow us to derive “listing-level” demand curves. Comparing the estimated listing-level demand curves from 2003 and 2009 leads to a striking observation. Listing-level demand fell sharply for both formats, but much more for auctions. We connect the demand estimates to the model, and by calibrating the model parameters infer how changes in competition and buyer preference for posted prices shifted seller incentives. We find that increased competition did push sellers toward posted prices, but played a less important role than the secular fall in auction demand. This is particularly true in categories such as Collectibles, Jewelry and Clothing

that feature relatively differentiated products. In commodity categories such as Electronics and Computers, the increase in competition plays a bigger role in explaining the shift toward price posting.

The final section of the paper provides some broader context and additional evidence. We discuss the role that changes in eBay policies, such as its search algorithm and listing fees, might have played in the transition to posted prices. We also look in more detail at buyer behavior. We show that compositional changes in the set of buyers do not appear to have driven the reduced demand for auction listings. But we also show that at any given time, there is significant heterogeneity in the pool of buyers. Frequent buyers tend to focus more on auctions, and they get better bargains when they are bidding. This suggests that customer segmentation could be one reason why sellers have continued to use auctions for items that are not particularly idiosyncratic or unusual. From this perspective, the rationale for auctions is less about price discovery and closer to the use of couponing or other strategies that target price-sensitive buyers. Finally, we provide some supporting evidence for our basic story by reporting on a survey we conducted of long-time eBay sellers.

Our paper relates to theoretical work on auctions and posted prices, and to research on online auctions. The theory papers include Wang (1993), Lu and McAfee (1996), Kultti (1999), and Ziegler and Lazear (2003). Ziegler and Lazear focus on the use of posted prices in retail markets and their perspective is close in spirit to ours. They propose a model in which sellers can vary in impatience to sell, and buyers arrive gradually. They show that posted prices are desirable if the seller is impatient, if buyers arrive slowly, or if buyers have attractive outside options. Our model similarly captures the idea that better outside options for buyers, for instance due to increased retail competition, push sellers toward price posting. There is also a small literature on “buy-it-now” auctions (e.g. Budish and Takeyama, 2001), which we do not study here but analyzed in Einav et al. (2015). This mechanism allows buyers to preempt an auction by purchasing at a posted price, and provides a way to segment impatient high-value buyers from price-sensitive ones, an idea we discuss in Section 7.1.

There is also a large literature studying online auctions (Bajari and Hortacsu, 2004, is an early survey), and several papers that specifically compare online auctions and posted prices. Zeithammer and Liu (2006) and Hammond (2010, 2013) both note the coexistence of

auctions and posted prices on eBay, and explain it based on seller heterogeneity. Zeithammer and Liu (2006) argue that posting an effective price requires gathering information, which will be worth the investment only for sellers with larger inventory. Using data from sales of Canon digital cameras on eBay in September and October 2005, they provide evidence that sellers with more inventory favor posted prices. Hammond (2010) shows a similar pattern in sales of compact discs on eBay. Hammond (2013) develops the analysis further by estimating a model of sale format choice using data on eBay compact disc sales. A key idea is that sellers with high opportunity costs of selling prefer posted prices (something that is also true in our model), and Hammond finds that variation in seller opportunity costs can explain the coexistence of auctions and posted prices in his CD sales data.

Bauner (2011) studies the use of auctions and price posting using eBay sales of Major League Baseball tickets. He finds that not only seller costs but heterogeneity across buyers, broadly divided into “fixed price lovers” and “neutrals,” helps to explain the coexistence of auction and fixed price sales. Our discussion of buyer heterogeneity and price discrimination in Section 7.1 echoes this idea. Sweeting (2012) also provides evidence on auction and posted price sales in a separate study of Major League Baseball ticket re-sale. Sweeting’s paper focuses on dynamic price adjustment, but he observes that auction prices are typically below posted price transaction levels. Finally, Ariely and Simonson (2003) and Malmendier and Lee (2011) analyze auction prices relative to posted prices in an earlier time period and document some cases where auction prices have been anomalously high.

2 A Model: Price Discovery versus Convenience

We start by modeling a seller’s choice of sales mechanism. The model is designed to emphasize the trade-off between price discovery and convenience. The model is extremely parsimonious, but it allows us to show how buyer preferences, or changes in competition or information, can affect the optimal choice of sales mechanism. We also discuss some extensions of the model later in the paper.

A seller has a single item to sell, and a cost c of making the sale. We assume there are two or more buyers, each with the same value v for the item, and a common fixed

reservation utility u . We assume that v is drawn from a log-concave distribution F , where the distribution (but not the realization) is known to the seller.³ The seller can choose between posting a price or running a second-price auction. If the item is sold via auction, there is a hassle cost that reduces the buyer valuation from v to a lower amount $v - \lambda$, where λ is assumed to be identical across buyers and known to the seller.

The seller’s problem is to choose a sales mechanism, and either a posted price or a reserve price. Suppose the seller opts for a posted price p . The item will sell if $v - u \geq p$, or with probability $Q_F(p) = 1 - F(p + u)$. So the expected profit is $\pi_F(p) = (p - c)Q_F(p)$. If instead the seller runs an auction, and sets a reserve price r , the item will sell if $v - u - \lambda \geq r$, or with probability $Q_A(r) = 1 - F(p + u + \lambda)$. If the item does sell, the auction price will be $v - u - \lambda$, so the expected price conditional on sale is $p_A(r) = \mathbb{E}[v - u - \lambda \mid v - u - \lambda \geq r]$. The seller’s expected profit is therefore $\pi_A(r) = (p_A(r) - c)Q_A(r)$.

Figure 3 illustrates the difference between the two sale mechanisms. The black line shows the posted price demand curve, i.e. for any price p , the probability of sale is $Q_F(p)$. The gray line shows the implied “auction demand curve.” That is, each possible reserve price r is converted to its implied sale probability $Q_A(r)$ and the expected price conditional on sale $p_A(r)$. The demand curves are drawn assuming that consumer values are distributed uniformly on $[0, 1]$, with $u = 0$ and $\lambda = 0.2$. The dashed gray line shows the probability of sale associated with different reserve prices, that is, the auction sale probability $Q_A(r)$ for each reserve price r .

An immediate observation is that the posted price demand curve is steeper than the auction demand curve.⁴ This is intuitive: the auction uniformly reduces the willingness to pay of all buyers including those with the highest value, but it also creates competition that increases the final price above the reserve price. The second effect is largest for low reserve prices (or high sale probability). Both effects are visible in the picture if we consider the auction sale curve. The vertical distance between the posted price demand curve and the

³In Appendix A, we discuss a more general version of the model in which there are $n \geq 1$ bidders, and the value of bidder i is given by $v_i = v + w_i$, where v is common across bidders and w_1, \dots, w_n are independent across bidders. Under appropriate distributional assumptions, all of the comparative statics discussed in this section continue to hold in this more general model.

⁴More generally, assuming F is log-concave, then so long as $\lambda \leq \mathbb{E}[v] - \underline{v}$, where \underline{v} is the lowest possible value of v , the fixed price demand curve will start above the auction demand curve and cross it exactly once to end below it.

auction sale curve is the hassle cost λ , while the distance between the auction sale curve and auction demand curve represents the effect of competition – the expected amount by which the auction price will rise above the reserve price.

Now consider the seller’s choice of sale format. We will not take the view that every seller chooses the optimal sales strategy for every listing. Indeed our empirical approach will be premised on the idea that sellers engage in considerable experimentation. Nonetheless, it is useful to consider the profit-maximizing incentives. A profit-maximizing seller will want to choose a point on the upper envelope of the demand curves: using a fixed price if she aims to sell at a high price, and an auction if she aims to sell with high probability. For a fixed price listing, the optimal price p^* maximizes $\pi_F(p) = (p - c)[1 - F(p + u)]$, and satisfies the first order condition: $p^* = c + \frac{1 - F(p^* + u)}{f(p^* + u)}$. For an auction, the optimal reserve price is $r^* = c$. Overall, the seller does best to use a posted price if and only if $\pi_F(p^*) \geq \pi_A(r^*)$.

The model gives rise to several comparative statics predictions. (1) All else equal, a higher level of c pushes the seller toward a posted price. For the example shown in Figure 3, an auction is optimal for $c \lesssim 0.317$ while a posted price is preferable for $c \gtrsim 0.317$. (2) All else equal, a higher level of u (i.e. lower buyer value relative to the next best alternative) also pushes the seller toward a posted price. For instance, if we fix $c = 0.3$ in the example of Figure 3, a posted price is optimal if and only if $u \geq 0.017$. (3) Finally, a higher level of λ pushes the seller toward a posted price by directly making auctions less attractive.⁵

Another prediction of the model is that (under some additional restrictions on λ) conditional on using a posted price, a seller will optimally choose a higher p and lower $Q_F(p)$, than if she sells by auction, in which case using the optimal reserve price $r^* = c$ implies a probability of sale equal to $Q_A(c)$ and expected price $p_A(c)$. Below we will see that this general pattern holds in the data: if we look at sellers who have tried using posted prices and auctions to sell a given item, their sale rate is higher with auctions but their expected price is lower. These observations suggest some simple tests of the model, and a way to disentangle possible explanations for the shift from auctions to posted prices over time.

⁵Reduced uncertainty about buyer values will also make posted prices more attractive. Specifically, if the seller has access to a signal z that is informative about v , this will increase the expected profit from posted price, but have no effect on the expected auction profit. In a related but somewhat different model, Wang (1993) also has shown that a reduction in the “dispersion” of F will favor price posting.

3 Data and Setting

Our analysis focuses on eBay, which started in 1995 purely as an online auction site. Initially eBay was known for used and idiosyncratic items – famously, an early item sold was a broken laser pointer – and for diverse small-time sellers (Lucking-Reiley, 2000). It has evolved into a vast marketplace that includes large retailers such as Buy.com and Toys“R”Us, and has over 80 billion dollars in annual transactions. In the summer of 2002, eBay began allowing sellers to list items at posted prices using the “Buy it Now” (BIN) format,⁶ and transactions have shifted steadily toward this format, as shown in Figure 1.

Two features make eBay an interesting environment to study pricing mechanisms. The first is the coexistence of auctions and posted prices, which allows us to look at which sellers choose to run auctions and for what types of goods, and to compare the performance of auctions and posted prices in a controlled fashion. The second is the transition toward price posting, which allows us to ask what features of the economic environment might lead sellers to change sale formats. We will start with the cross-sectional analysis, before looking at the transition from auctions to posted prices.

Our analysis makes use of two datasets. The first consists of all listings on eBay.com (eBay’s US platform) except auto and real estate listings. Autos and real estate have a different institutional structure. The second is a large sample of “matched listings”, that is situations where a seller lists the same item multiple times, either simultaneously or sequentially. We use matched listings to compare auction and posted price outcomes holding the seller and the item fixed. Elfenbein et al. (2012) introduced matched listings to study charity auctions, and we used them in Einav et al. (2015) to study shipping fees, price dispersion, reserve prices, and hybrid auctions.

To construct the matched listings sample, we start with all listings posted in 2003, 2005, 2007, and 2009 by a random 50% sample of eBay sellers.⁷ We group these into matched sets, where a match means the listings have a common seller, a common ten-word item description and were posted in the same calendar year. We drop a small number of sets (0.8% or less

⁶The hybrid BIN auction format had been introduced earlier. We return to this format briefly in Section 7, and see also Einav et al (2015).

⁷The 50% sample is used to keep the size of the data manageable.

in each of the years) where the average posted price is above \$10,000, or where there is an outlier sale at a price more than five times the average. Because our goal is to compare auctions and posted prices, we drop listings with less common formats, such as hybrid “buy it now” auctions or “best offer” listings. We then select the matched sets that include at least four listings by auction and four by posted price, at least ten listings overall, and at least one auction and one posted price sale. This leaves at least 20,000 matched sets and 1,000,000 listings for each year.

The matched listings data is large-scale but not a random sample of eBay listings. It excludes listings that are truly “one of a kind” (we will see below that these are mostly auctions). It also excludes sellers who use only auctions or only posted prices. Indeed, given our focus on the choice of sale mechanism, it might seem odd to focus on sellers who use both formats. However, an overwhelming feature of the data is that sellers very commonly do use both auctions and posted prices, and persist in doing so even if they come to favor one format most of the time. Below we will discuss why in certain cases it might be profit-maximizing to use both formats, but our general view is that online sellers engage in a great deal of experimentation, and there are few costs of doing this, so it is not surprising that they use multiple sale formats for a given product.⁸

The underlying assumption in using matched listings is that once we fix the seller, the item and the time window, variation in sale format will be unrelated to market demand. A potential concern is that sellers may switch between formats over the course of a product’s life cycle, or in response to less predictable changes in demand. One way to address this is to focus on listings posted in a short time window, so that demand conditions are stable. The drawback is that this restricts the size of matched sets. In the main paper, we use the matching definition above, but in Appendix C we repeat the analysis using a shorter three-month window to match listings. Appendix C also repeats the analysis for six additional specifications in which we focus in different ways on seller-item pairs for which demand over time or the mix of sale formats was relatively stable.

Finally, our main outcome variables are whether a listing sold, and at what price. Posted

⁸Appendix Table B1 provides a comparison of the matched listing sample with all eBay listings and with various intermediate samples.

price listings often last for up to 30 days, and can allow for the sale of multiple units, something that became common in the later years of the sample. The typical auction lasts a week, and auctions are always for a single unit. For comparability, we define an auction listing to be successful if it resulted in a sale, and a posted price listing to be successful if it sold at least one unit within the first week.⁹ We also define for each matched set of listings a *reference value* equal to the item’s average price across all fixed price listings in the set. Then to facilitate price comparisons across heterogeneous products, we define for each successful listing a normalized sale price equal to the sale price divided by the item’s reference value. We also define the normalized start price for each auction as the start price divided by the reference value. So an item that lists on average for \$100 and is offered by auction with a start price of \$50 has a normalized start price of 0.5. If the item subsequently sells for \$95, its normalized sale price is 0.95.

4 Internet Auctions and Posted Prices

We start by using listings from a single year (2009) to show that sellers favor auctions for items that are used or unique, or when the seller has less eBay experience. The prevalence of used and unique goods helps explain why auctions are common in some product categories but less so in others. We then show that when a seller uses both auctions and posted prices to sell a given item, the auction listings are more likely to sell, but at a lower price. This holds across essentially every product category, and aligns with the theory we described above.

4.1 Who Sells What by Auction?

Auctions are attractive when it is difficult for the seller to know the appropriate price: either because the item is idiosyncratic, or because demand is uncertain, or because the seller has relatively little experience. Auctions also may be attractive if the seller has little interest in keeping the item or trying a second time to sell it. Because eBay’s platform is so large and

⁹Due to the way the data is archived, we do not observe the exact timing of sales of multi-unit listings that eventually have multiple sales. We therefore use the distribution of time until sale for single-unit posted-price listings to convert the overall sale rate of multi-unit listings to sale rate within a week. The conversion assumption is that the distribution of first sale times, conditional on sale, is the same for multi-unit and single-unit posted-price listings.

diverse, and because of the prevalence of matched listings, we can assess these predictions in a relatively controlled way.

The data clearly show a greater prevalence of auctions for items that are more idiosyncratic. One can define idiosyncratic items in various ways. One is to distinguish used and new goods. To the extent that it is harder to find comparable prices, or there is more uncertainty about buyer valuations, we expect auctions to be more common for used goods. To look at this, we identify all auction and posted price listings in 2009 that were labeled as either “used” or “new” (i.e. the word “used” or “new” appears in the item’s 10-word listing title). Of the used item listings, 79% were offered by auction, compared to 44% auctions for the listings which include the word “new” in the listing title.

Another way to identify idiosyncratic items is to distinguish between items that are part of a matched set (i.e. the seller offered the product for sale in multiple listings) versus listings that are unique in the sense that the seller did not offer another listing with the same title. Around 73% of listings in 2009 have a matched or duplicate listing, but there are many millions of unique listings. Generally, matched listings are products that the seller is sourcing or has multiple units in inventory, whereas unique or truly idiosyncratic items (e.g. a lock of Justin Bieber’s hair) would have no match. In 2009, about 75% of the unique listings were auction listings, compared to 57% of the matched listings.¹⁰

Product characteristics help to explain why auctions are more or less prominent across broad product categories. Figure 4 shows that across eBay’s product categories, the categories that have a higher fraction of “new” or duplicate listings (and hence less idiosyncrasy) have significantly more posted price listings. For instance, auctions are commonly used for collectibles and clothing, but much less prevalent for electronics or computers. A similar pattern also shows up for earlier years.

Seller experience is another important determinant of sale format. To categorize sellers, we rely on eBay’s internal classification which is based on past eBay transaction volume. We compare experienced (“business”) sellers and inexperienced (“occasional”) sellers. There

¹⁰Note that these numbers make auctions look more prevalent than would appear to an eBay buyer. The reason is that fixed price listings generally remain active for at least 30 days, whereas the most common auction length is 7 days. So a consumer who randomly sampled an active listing would see a much smaller fraction of auction listings compared to posted prices.

are also two groups of sellers with intermediate experience. Business sellers are much more likely to use posted prices. Their listings are 65% posted price, compared to only 13% for occasional sellers. Sellers also gravitate toward posted prices as they gain experience. To see this, we consider all sellers who entered the market between 2004 and 2008, and were active for at least two years. For this group of sellers, the second-year listings were about three percentage points more likely to be posted price than their first-year listings, controlling for the overall growth of posted prices over time.¹¹

4.2 Comparing Matched Auctions and Posted Prices

In our model, a seller who uses an auction should sell with higher probability but at a lower price than if she uses a posted price (assuming the posted price and auction start price are set optimally). This pattern – higher auction success rates but lower prices – is a general feature on eBay. Looking at the complete data for 2009, 42 percent of auction listings sold compared to 25 percent of posted price listings. And the average auction sale price was \$40 compared to \$67 for posted price sales. Of course, the items being sold with these formats are not the same, as we have just seen. This motivates our use of matched listings to compare sale probabilities and prices.

We start by comparing the probability of sale when a specific seller sells a specific item by auction and posted price. We use the following regression approach. Let i index sets of matched listings, and j index listings within a set. Let A_{ij} be an indicator equal to one if the listing is an auction, and q_{ij} be an indicator equal to one if the listing results in a sale. We compare success rates using a linear probability model with seller-item fixed effects:

$$q_{ij} = \alpha_i + \beta A_{ij} + \varepsilon_{ij}. \tag{1}$$

In this specification, α_i is the average sale probability for posted price listings of item i , and β is the extra sale probability for auction listings.

¹¹This result comes from a regression in which the dependent variable is the share of posted-price listings for a seller in his second year on eBay minus the share in his first year. The right-hand-side is the corresponding difference on eBay overall over the same two years. The number we report is the constant term. As discussed below, there is little evidence of additional cohort-specific patterns after the second year.

We similarly can compare transaction prices of successful auction and posted price listings. Letting p_{ij} denote the transaction price (posted price or final auction price), we estimate the following regression model on successful sales:

$$\log p_{ij} = a_i + bA_{ij} + e_{ij}. \quad (2)$$

Here, the coefficient b can be interpreted as the price premium (conditional on sale) for an auction listing relative to a fixed price listing of the same item by the same seller. Equivalently, the expected (log) auction price conditional on sale for item i is $a_i + b$, where a_i is the average (log) price of the posted price transactions of item i .

Estimating these regressions on the 2009 sample shows that auction listings are more likely to be successful than their matched posted price listings ($\beta = 0.115$, s.e. 0.0005) but conditional on success, auction prices are lower. The auction discount is substantial ($b = -0.165$, s.e. 0.0005). Neither estimate is driven by a particular class of products. We illustrate this point in Figure 5. In Figure 5(a), we plot the average posted price success rate (the average α_i) for each category against the average auction success rate in the category. The category averages place equal weight on items in the category. Figure 5(b) is an analogous plot of average sale price.¹² Auction success rates are higher in every category except jewelry, often by a wide margin. Auction prices are below matched posted prices in every category.

In comparing matched listings, it is potentially useful to distinguish two scenarios. The first occurs when a seller runs an auction while contemporaneously offering the same item by posted price. The second occurs when a seller uses both formats but at different times. When listings are contemporaneous, eBay's search algorithm tends to separate matched listings, so buyers may not make direct comparisons. But if they do, one might expect the auction price to be lower because of the ability to substitute to the posted price. In this sense, the sequential scenario arguably fits more cleanly with our theoretical model, where the outside option (u) is exogenous. In the Appendix, we replicate the analysis separately for these two situations. The difference in success rates is similar in the two subsamples,

¹²The second panel shows prices in levels rather than logs, so it is generated from a price regression specified in levels. The figure looks similar for a log specification.

while the estimated auction discount is larger for auctions with a contemporaneous posted price (18.2% versus 14.4%). Appendix Table B3 and Appendix Figure B1 provide full details on these alternative specifications.

5 The Decline of Internet Auctions

We now turn to the decline of auctions illustrated in Figure 1. We show that changes in the set of sellers and items being sold cannot easily explain the decline. Instead it appears that seller incentives have shifted over time. We provide some initial evidence for this by looking at changes in the auction discount.

5.1 Changing Composition of the Market

One natural hypothesis about the decline in auctions is that the marketplace has evolved: from an environment where consumers sold each other unique items such as dolls or collectibles, towards a retail channel for business sellers. There is evidence to support this shift. The share of “idiosyncratic” listings (i.e. those without a matched listing) declined from 32 percent to 25 percent between 2003 and 2009. And even as late as 2005, business sellers accounted for just 16 percent of listings; by 2009 they accounted for 27 percent.

However, these compositional changes do not have much power in explaining the shift toward posted prices. One way to see this is to decompose the overall growth in posted price transaction volume into changes in the share of volume by different types of sellers, changes in the shares of different product categories, and changes that occurred within seller-product classifications. Because 2005 is the first year for which we have the data that allow us to construct the seller classification, we do this for 2005 to 2009, a period which captures the sharpest shift in sales formats.

Define $Z = 21.1\%$ to be the overall share of posted price transaction volume (in dollars) in 2005 and $Z' = 51.6\%$ the corresponding share for 2009. Let s index eBay’s seller classifications (four groups ranging from “occasional” to “business”) and c index eBay’s 33 product categories. Next, let $\sigma_{c,s}$ denote the share of volume in item category c and seller category s in 2005, let $\sigma_c = \sum_s \sigma_{c,s}$ denote the share of volume in item category c , and let $\sigma_{s|c} = \sigma_{c,s}/\sigma_c$

denote the share of volume in seller category s within item category c , also in 2005.

Using σ' s to define the corresponding quantities for 2009:

$$\begin{aligned} Z' - Z &= \sum_{c,s} Z'_{c,s} \sigma'_{c,s} - \sum_{c,s} Z_{c,s} \sigma_{c,s} \\ &= \sum_{c,s} Z_{c,s} \sigma_{s|c} (\sigma'_c - \sigma_c) + \sum_{c,s} Z_{c,s} (\sigma'_{s|c} - \sigma_{s|c}) \sigma'_c + \sum_{c,s} (Z'_{c,s} - Z_{c,s}) \sigma'_{c,s}. \end{aligned} \tag{3}$$

The first term captures the shift toward posted prices due to a change in the composition of products (e.g., from collectibles to electronics). The second term captures the shift due to changes in the sellers within product categories. The final term is the average change within seller-product groupings. Almost all of the shift is attributable to the final component. Of the overall 30.5 percentage point increase in posted price transaction volume, the final term is responsible for 25.7 percentage points.¹³ Changes in product composition account for the vast majority of the remainder (4.6 percentage points out of 4.8), and the increase in business sellers has almost no effect. This conclusion remains essentially identical when we break down each product category further into listings that do and do not have a matched listing. This additional decomposition does not help explain the change in listing format.

Another way to look at compositional changes is also informative. Suppose that early sellers were primarily consumers offering idiosyncratic items, while later arrivals tended to be professionals offering retail items. Then later cohorts of sellers might be more likely to use posted prices. To examine this, we group sellers based on the year during which they first sold an item on eBay (all sellers who joined prior to 2002 are grouped together). Figure 6 then plots for each cohort the fraction of their revenues that were posted price, and how this fraction has evolved over time. The figure shows the “first year” effect noted earlier, with the newest sellers favoring auctions more than the platform average. However, apart from this modest new cohort effect, different cohorts of sellers behave in remarkably similar fashion at any given point in time, with all cohorts evolving together toward posted prices.

¹³The prevalence of posted prices rose in almost every seller-product category cell. Of the $4 \cdot 33 = 132$ cells, the posted price share has increased in 131 of them.

5.2 The Increasing Auction Discount

The shift from auctions to posted prices seems to have occurred for every type of seller and every category of product. This suggests looking at whether, for a given seller offering a given item, the incentive to use auctions has decreased. To explore this, we ask whether the performance of auction listings relative to matched posted price listings has declined over time. In particular, we re-estimate regressions (1) and (2) separately for each year. Recall that the first regression identifies the average difference in success probabilities for matched auction and posted price listings. The second regression identifies the average price difference between matched auction and posted price sales.

Figure 7(a) displays, for each year, the success rate of auction and posted prices. The black line plots the average sale probability for a posted price listing, i.e. the average of the estimated α_i 's for each year. The grey line plots the corresponding sale probability for auction listings, computed as the fixed price sale probability for that year plus the estimated β . Two features stand out. The average sale probability for both formats has declined substantially. For posted prices, the average sale rate in our sample fell from 40.3% to 25% between 2003 and 2009. However, the difference across formats (the estimated β), has not changed much. It starts at about 8% in 2003, declines a bit, and then increases to 11% in 2009.

Figure 7(b) displays, for each year, the estimated price differential for matched listings (the b coefficients).¹⁴ The auction discount increased dramatically over time. In 2003, sellers offering a given item by auction and posted price received 4.7% less for their auction sales. In 2009, the difference had grown to 16.5%.¹⁵ The average price for posted price sales remained very similar over time in our sample, despite turnover in the set of items and sellers.¹⁶ The average log posted price was 3.1 in 2003 and 3.0 in 2009.

¹⁴The regression results underlying Figure 7 are available in Appendix Table B2.

¹⁵Similar to above, we also can consider the auction discount for listings with and without a contemporaneous posted price. For auctions with concurrent posted price listings, the auction discount has increased from 11.3% in 2003 to 18.2% in 2009, while for auctions with no concurrent posted price listing the discount has increased from 2.2% to 14.4%. So similar to above, the discount is bigger if there is a contemporaneous posted price, but the increase in the discount does not depend much on exactly how we set up the posted price comparison.

¹⁶That is, the average (across items) of the a_i 's. To construct this average we use all items in the sample (which were all sold at least once in each format, given our sample restrictions), and weight each item by the number of sales in each format. We use the same average in Figure 7(a).

These results together suggest two important changes over time: a general fall in the success rate of item listings, and a fall in the relative demand for auctions that has reduced auction prices relative to comparable posted prices. Several pieces of evidence add additional context. The first is that the growing auction discount was not driven by sellers using lower auction start prices over time. In fact, during our sample period, sellers shifted toward slightly *higher* reserve prices, so the increase in the auction discount resulted from a fall in auction sale prices conditional on reserve prices. We also can see further evidence of a drop in auction demand by looking at the number of bidders participating in successful auctions. In 2003, successful auctions had an average of 3.98 unique bidders, and 33% of successful auctions had only a single bidder. By 2009, the average number of bidders had fallen to 3.19 and the share of successful auctions with a single bidder had increased to 45%. We provide details on these points in Appendix Figures B2, B3 and B4.

6 Explaining the Decline of Auctions

The growing auction discount provides a fairly strong indication that seller incentives have shifted. At the same time, this simple measure does not cleanly separate shifts in the demand a seller faces — due to changes in buyer preferences, or in competition — from shifts in pricing behavior. In this section, we use variation in sellers’ pricing behavior to estimate the trade-off sellers face between probability of sale and expected price for both posted price and auction listings. These estimates can be interpreted as residual, or “listing-level” demand curves. We use the estimates at various points in time to map back to the parameters in the theoretical model that determine sellers’ incentives to use auction or posted price listings.

6.1 Estimates of Listing-Level Residual Demand

To estimate listing-level demand, we exploit the variation in auction start prices and posted prices within sets of matched listings. The variation in auction start prices is very large. The average standard deviation in auction start prices within a matched set of listings is 25% of the item’s reference value, as reported in Table 1. The variation in posted prices is not as dramatic. Nevertheless, the average standard deviation in posted prices within a matched

set of listings is still over 10% of the item’s reference value.

We consider the case of auction demand first. We start with all auction listings in our matched listings data, and estimate separately for each year the probability of sale as a function of the auction start price:

$$q_{ij} = \alpha_i + g(s_{ij}^n) + \varepsilon_{ij}. \quad (4)$$

In this specification, i indexes sets of matched listings, j indexes listings within a set, and q_{ij} is an indicator variable equal to one if the auction results in a sale. The key pricing variable is the normalized start price, s_{ij}^n . It is equal to the start price s_{ij} divided by the reference value for item i . The normalization allows for a comparison of items of different value. We specify the function $g(\cdot)$ flexibly by allowing separate dummy variables for different levels of the normalized start price.¹⁷ In this regression and those that follow, we weight each matched set of listings by its total number of listings.

We estimate a parallel regression for the final auction price. Here we restrict attention to successful auctions and estimate for each year:

$$p_{ij}^n = a_i + h(s_{ij}^n) + e_{ij}. \quad (5)$$

The normalized price p_{ij}^n is the final auction price divided by the item’s reference value. Again, $h(\cdot)$ is estimated flexibly by allowing separate dummy variables for each level of the normalized start price.

The last step is to combine the regression estimates and trace out an auction demand curve for each year. For each value of the normalized start price s^n , we consider the locus $\bar{q}(s^n) = \bar{\alpha} + \hat{g}(s^n)$, $\bar{p}^n(s^n) = \bar{a} + \hat{h}(s^n)$, where $\bar{\alpha}$ and \bar{a} are the average fixed effects.¹⁸ This construction yields, for each possible start price, the probability of sale and the *expected* sale price (if there is a sale). Note that focusing on expected auction prices, we put aside the possibility that sellers might prefer posted prices in order to avoid price variability; this idea

¹⁷Specifically, we categorize the (normalized) start price to the following bins: [0-0.3], (0.3-0.4], (0.4-0.5], (0.5-0.6], (0.6-0.7], (0.7-0.8], (0.8-0.9], (0.9-1], (1-1.1], (1.1-1.2], and >1.2.

¹⁸Here we define $\bar{\alpha}$ as the weighted average of the fixed effects α_i , weighting each matched set i by its total number of listings. We use the same weighting in constructing \bar{a} .

is discussed by Chen et al. (2013).

We also estimate listing-level demand for posted price listings, again separately for each year. This exercise is conceptually more straightforward. We estimate the fixed effects linear probability model:

$$q_{ij} = k_i + m(p_{ij}^n) + \eta_{ij}. \quad (6)$$

Here q_{ij} is an indicator equal to one if the listing results in a sale, and p_{ij}^n is the normalized price of the listing (equal to the listing price divided by the item’s reference value). To estimate $m(\cdot)$ we specify separate dummy variables for different levels of the normalized price.¹⁹ Note that with this flexible specification, the variation in posted prices within matched sets of listings limits the range over which we can obtain a demand estimate.

Figure 8 presents the estimated demand curves using the 2003 and 2009 samples.²⁰ One prediction of the theory is apparent. In both years, the posted price demand curve is steeper than the auction demand curve. Their relative positions, however, look quite different in 2003 and 2009. In 2003, the estimated auction demand lies mostly above the posted price demand. A seller facing these residual demand curves would be better off using an auction, unless her marginal cost was extremely high. In 2009, the auction demand lies below the posted price demand for a wide range of prices. For a seller facing these residual demand curves, the optimal sale format would depend on marginal cost.

The estimates in Figure 8 involve averaging over a range of heterogeneous items. It is informative to repeat the exercise focusing on more narrowly defined groups. To do this, we used the characteristics described earlier to rank the eBay product categories from “most idiosyncratic” to “least idiosyncratic”.²¹ We then select the five most idiosyncratic and

¹⁹The pricing variation for posted-price listings is not as rich as it is for the auction listing. The specific (normalized) price bins we use are [0-0.7], (0.7-0.8], (0.8-0.85], (0.85-0.9], (0.9-0.95], (0.95-1.05], (1.05-1.1], and >1.1.

²⁰The underlying regression results are available in Appendix Table B4 and Figure B5.

²¹To construct the ranking, we used a large random sample of 2009 listings. For each category, we constructed the following variables: share of items that are classified in the eBay catalog (which is a database of products that includes unique product codes, such as ISBN for books, or CNET for digital cameras), share of sales from multi-unit listings, share of listings with the word “new” in the title, and share of duplicate listings. We then used principal components to assign each category a one-dimensional score, with a high score corresponding to “less idiosyncratic” and a low score corresponding to “more idiosyncratic.” Appendix Table B5 provides more details. One point of caution is that although this classification seems quite natural, the items from the idiosyncratic categories that make it into our matched listings sample are still retail items, in the sense that the seller is trying to sell multiple units. Hence we do not include the truly one-of-a-kind

five least idiosyncratic categories from the largest fifteen categories. This gives us a set of idiosyncratic categories (Collectibles, Fan Shop, Toys, Jewelry, and Clothing), and a set of commodity categories (Electronics, Computers, DVDs, Health, and Phones).

Figure 9 presents separate demand estimates for each year and group of categories.²² The estimates for the idiosyncratic categories show that the average listing-level demand for auctions dominated posted prices in 2003. By 2009, however, the auction demand curve had shifted considerably, making posted prices more attractive across a fairly wide price range. In contrast, the average demand estimates for the commodity categories suggest that posted prices were attractive even in 2003. By 2009, posted prices had become even more attractive, but only because both demand curves shifted inward by approximately the same amount. We return to the interpretation of these shifts below.

6.2 Identifying Seller Incentives

The estimates in Figure 8 show a clear shift in the relative demand for auctions over time. They also can be viewed as the empirical analogues of the theoretical demand curves in Figure 3. In this section, we tighten the connection. We use the demand estimates to calibrate the key parameters of the model. While the model is obviously too parsimonious to capture the heterogeneity of the many thousands of sellers and items in the data, the exercise is nonetheless useful to place some structure on how and why seller incentives have shifted over time. We do this both on average across all categories and for the idiosyncratic and commodity categories defined above.

The theoretical model derived listing demand curves from three parameters: the distribution of consumer valuations $F(\cdot)$, the utility from the next best alternative u , and the auction disutility λ . Each might have changed over time. Roughly, one might think of changes in the reservation utility u as capturing intensified competition, perhaps due to consumers being able to search more easily for alternative products. In contrast, changes in the auction disutility λ are a potential proxy for increased online entertainment options that may have made auction bidding less fun or exciting in comparison.

items that might come to mind in thinking about an idiosyncratic category such as Collectibles.

²²The underlying regression results are available in Appendix Tables B6(a), B6(b), and B6(c).

We begin by estimating λ . We already observed that in the theoretical model λ could be identified as the vertical distance between the fixed price demand curve and the auction sales curve. To see why, recall that given a posted price p , the probability of sale is $1 - F(p + u)$. Similarly, given an auction with start price r , the probability of sale is $1 - F(r + u + \lambda)$. So a given probability of sale q corresponds to a posted price $F^{-1}(1 - q) - u$ and an auction start price $F^{-1}(1 - q) - u - \lambda$. The difference is λ .

Figure 10 plots the estimated posted price demand curves for 2003 and 2009 (identical to Figure 8), along with the estimated auction sale curves from the auction sale regression in equation (4). If the estimates were perfectly consistent with the theoretical model, the posted price demand curve for year t would be an exact upward translation of the auction sale curve. In practice, the shapes are similar but not identical, so to estimate λ_{2003} (corresponding to 2003) and λ_{2009} (corresponding to 2009), we compute the average vertical distance between the curves across the quantity range where we have nonparametric estimates of both curves.²³ We find that $\lambda_{2003} = 0.076$, and $\lambda_{2009} = 0.163$. That is, we estimate that an auction in 2003 involved an inconvenience factor equal to roughly eight percent of an item's typical price (or reference value), and that this inconvenience factor doubled between 2003 and 2009.

Next, we estimate changes in u by looking at how demand has shifted over time. Here, a normalization is required. Because consumer decisions are based on the incremental value $v - u$, it is not possible to separately identify u from the mean of the v distribution. To proceed, we normalize $u_{2003} = 0$. We further assume that $F(\cdot)$ remained constant over time.²⁴ It follows that to achieve sale probability q in year t required a posted price $F^{-1}(1 - q) - u_t$. So the vertical distance between the 2003 and 2009 posted price demand curves is $\Delta u = u_{2009} - u_{2003}$. We therefore estimate Δu by computing the average vertical distance between the estimated demand curves. This yields an estimate of $\Delta u = 0.144$. That is, between 2003 and 2009, the consumer reservation utility increased by around 14% of the reference value

²³The results we report use an unweighted average of the vertical distance between the two curves. We repeated the analysis using two sets of weights (one that weights by the reserve prices of auction listings in the data, and one that uses the empirical distribution of posted prices in the data), and the calibrated values for the parameters remain essentially the same.

²⁴In principle, we only need a known percentile of $F(\cdot)$ to have remained constant, but making the stronger assumption keeps things very simple. Note that if the distribution of consumer valuations remained constant, the posted price demand curves in Figure 10 would be exact translations. In practice they are similar in shape, but not identical.

for an average item.²⁵

The final step is to evaluate how these changes in λ and u might have affected seller incentives. Here we return to the model and use some price theory. For either format $k \in \{A, F\}$, we can think of the seller as choosing to sell with probability q , so

$$\Pi_k(\lambda, u) = \max_q q [p_k(q; \lambda, u) - c]. \quad (7)$$

We can then apply the envelope theorem to look at small changes in λ or u . For $x \in \{\lambda, u\}$, we have

$$\frac{\partial \Pi_k}{\partial x} = q_k^* \frac{\partial p_k(q_k^*; \lambda, u)}{\partial x}, \quad (8)$$

where q_k^* is the profit-maximizing probability of sale under format k .

In the posted price case, $p_F(q; \lambda, u) = F^{-1}(1 - q) - u$ is the posted price a seller must charge to sell with probability q . It follows that

$$\frac{\partial \Pi_F}{\partial u} = -q_F^* \quad \text{and} \quad \frac{\partial \Pi_F}{\partial \lambda} = 0. \quad (9)$$

Intuitively, a small change of du will not affect the optimal probability of sale, but will force the seller to lower the price by du to offset the reduction in residual buyer value.

In the auction case, to sell with probability q requires a reserve price $r = F^{-1}(1 - q) - u - \lambda$. This leads to an expected price $p_A(q; \lambda, u) = \mathbb{E}[v \mid v \geq F^{-1}(1 - q)] - u - \lambda$. Therefore we have $\partial \Pi_A / \partial \lambda = -q_A^*$ and similarly $\partial \Pi_A / \partial u = -q_A^*$, where q_A^* is the optimal sale probability for an auction seller.

We are interested in the *difference* in posted price and auction profits. We have shown that

$$\frac{\partial (\Pi_F - \Pi_A)}{\partial \lambda} = q_A^* \quad \text{and} \quad \frac{\partial (\Pi_F - \Pi_A)}{\partial u} = q_A^* - q_F^*. \quad (10)$$

The derivation indicates that a change in λ , which shifts only the auction demand curve, will have a bigger effect than an equivalent change in u , which shifts both demand curves.

²⁵Note that the analysis of each year is based on a different set of sellers and items, so in order to compare demand and outcomes across different years, we implicitly assume that overall pricing patterns on the internet remained unchanged (e.g., we assume that markups online did not decline), so that the average posted-price listings serve as a reasonable online price index.

On the other hand, we have estimated a larger absolute change in u .

To sort out these competing effects, we approximate the effect of $\Delta\lambda$ on $\Pi_F - \Pi_A$, by $q_A^* \cdot \Delta\lambda$, and the effect of Δu by $(q_A^* - q_F^*) \cdot \Delta u$. This requires information on q_A^* and q_F^* . In 2003, the average sale probability in our data was 0.40 for posted price sales and 0.48 for auctions, so for this exercise we assume $q_F^* = 0.40$ and $q_A^* = 0.48$.

Table 2 shows the resulting calculation for the effects of u and λ on seller incentives. The calculation suggests that the increase in λ had more than three times the effect on the posted price profit differential as did the increase in u . If we set q_F^* and q_A^* using the 2009 sale probabilities, we obtain a somewhat smaller multiple, just under two. But either way the increase in λ seems considerably more important.

It is also informative to focus on particular product categories, as we did in the prior section. When we restrict attention to only the most idiosyncratic product categories, we estimate that $\lambda_{2003} = 0.06$ and $\lambda_{2009} = 0.186$. So $\Delta\lambda = 0.126$, while $\Delta u = 0.109$. As a result, by far the most important factor in these categories in explaining the move toward posted prices was a fall in the relative demand for auctions. The increase in λ accounts for well over 80% of the total change in relative profits.

We obtain somewhat different quantitative conclusions for the commodity categories. There we estimate $\lambda_{2003} = 0.186$ and $\lambda_{2009} = 0.235$. So $\Delta\lambda = 0.048$, while $\Delta u = 0.153$. As noted above, there appears to be a significant auction discount in these categories as early as 2003. As shown in Table 2, the implication is that the increase in λ and u had roughly similar effects on the profit differential between posted prices and auctions. To understand why the effects are equivalent despite the increase in u being much larger, recall that λ affects only the auction demand curve, whereas the increase in u reduces the profitability of both sale formats.

6.3 Additional Evidence on Buyers

Our analysis has highlighted the role of changing (residual) demand in explaining the shift toward posted price listings. In this section, we ask whether the change was due to shifts in the composition of buyers. We first show, parallel to our earlier analysis of sellers, that there is considerable heterogeneity in the cross-section of buyers. However, and also parallel to our

seller findings, the time-series changes in demand appear to have taken place within cohorts of buyers rather than through changes in the composition of buyers over time. Below, we point out that the cross-sectional heterogeneity in consumers can help to explain why sellers might want to offer both types of sales mechanisms as a way to target different types of buyers.

As in our earlier classification of sellers, we divide buyers based on their purchases in a given year. We label buyers who purchase more than 100 items a year as “professional” and those who buy less than 5 as “occasional”, and include an intermediate category as well. Professional buyers are more likely to buy at auction. In 2003, the auction expenditure share of these buyers was 95%, compared to 80% for occasional buyers. The corresponding statistics for 2009 were 69% and 38%. Using the successful sales in the matched listings sample, we find that the buyer is 5.4% more likely to be a professional buyer if the item was listed for sale by auction.²⁶

An additional and striking feature of the data is that more active buyers get better deals. We already have documented the auction discount, so by doing more purchasing at auction, professional buyers are more likely to experience discounts. Experienced buyers also pay less conditional on purchasing at auction. To do this, we use the 2009 matched listings data. In this sample, we find that professional buyers obtained on average a 20% auction discount relative to the matched posted price, compared to only 12% for the occasional buyers.²⁷

Despite these cross-sectional differences, however, the shift away from auctions over time cannot be explained by an increase in occasional relative to professional buyers. The fractions of occasional and professional buyers on eBay have been relatively stable over time. The professional buyers account for just over 1% of the buyers, and the occasional buyers for around 60%. In fact, the purchasing share of professional buyers increased over the period we study. Professional buyers accounted for 14% of transaction volume in 2003 and 20% in 2009. Instead, the shift toward posted prices has been within buyer groups, when buyers are stratified by purchasing intensity.

²⁶This is based on a linear probability regression (not shown), in which we use all the posted-price and auction sales and regress an indicator for professional buyer on an auction dummy variable and seller-item fixed effects.

²⁷This estimate is based on regressing (log) price on seller-item fixed effects, an auction dummy and a categorical variable for buyer’s types interacted with the auction dummy (not shown).

The decline of auctions also cannot be explained by differences between early cohorts of online shoppers and later cohorts. Figure 11 shows the purchasing propensities of different buyer cohorts, analogous to our earlier depiction of sellers. As can be seen in the Figure, buyers in their first year are more likely than average buyers on the site to buy using a posted price, but after the first year, different cohorts look very similar, and all cohorts have trended together toward posted price purchasing. Our interpretation, therefore, is that the documented shift in item-level demand curves is likely to come from changes in online attitudes and competition, rather than from changes in the composition of buyers.

7 Alternative Hypotheses and Survey Evidence

7.1 Alternative Hypotheses

We have provided a variety of evidence about how and why internet auctions declined over the last decade. In this Section, we briefly discuss three factors that did not play a major role in our analysis, but that potentially might have some explanatory power. The first is changes in the eBay platform that might have favored posted price listings. The second is the possibility that the basic empirical pattern can be explained by gradual seller learning. The third, which does not directly explain the fall in auction listings, but might help to explain their continued use, is the idea that sellers might use auctions and posted prices in combination as a form of price discrimination.

Changes in the eBay platform. Our analysis emphasized changes in the marketplace incentives facing sellers. There also have been some changes in eBay’s platform that may have favored posted prices, especially beginning in 2008. In February 2008, eBay changed its search ranking algorithm. Rather than putting the soonest-to-end listing at the top – a natural strategy for auctions with a fixed ending time, but less natural for posted price listings – it implemented a relevance ranking. Then in September 2008, eBay allowed 30 day posted price listings to be “rolled over” with automatic payment of the monthly listing fee. The mechanical effects of that change help explain the sharp concurrent rise in active posted price listings that can be seen in Figure 1. However, given that posted prices already had

been on the rise for several years, it probably makes more sense to think of these platform changes as a response to changes in the market, rather than the impetus for evolution of sales format.

In addition to its search algorithm, eBay also has changed its fees on multiple occasions over the last decade. Many of these changes have not had clear implications for the choice of sales format, and their net effect is not entirely obvious. To take just one example, eBay in September 2008 lowered its posted price listing fee and raised the commission rate for successful sales. Posted price listings increased, despite the fact that in expectation total fees were slightly higher.²⁸ More generally, it seems difficult to tell a story in which the steady decline of auctions in Figure 1 is driven by a series of occasional, discrete changes in the fee structure, only some of which have favored posted prices.

Gradual seller learning. Until the middle of 2002, eBay sellers did not have the option to use posted price listings, although they could use a hybrid format that allowed buyers to preempt an auction by purchasing at the “buy it now” price. One hypothesis we have heard is that once posted prices were introduced, they were from the start the better mechanism, but it took a long time for sellers to realize this and for posted prices to diffuse in the market.

Several pieces of evidence go against this hypothesis. First, posted prices are hardly an unfamiliar technology, so even if there is some stickiness in buyer and seller behavior, a decade of learning seems like a very long time. Second, our estimates of auction prices and demand indicate that in 2003, auctions were in fact a very attractive sale format. In particular, auctions offered a profitable way for sellers to increase sales probability in return for accepting a modest price discount.

Price discrimination strategies. In the previous section, we pointed out that more active buyers on eBay are more likely to buy at auction compared to occasional buyers. In principle, this type of buyer heterogeneity might help to explain why sellers might want to offer both sale formats as a way to cater to different types of buyers. We illustrate this in a very simple extension of the model.

²⁸The effects here are confounded because sellers also gained the opportunity to roll over their listings. However, the fee changes were differential across categories, and the increase in posted price listings is not closely related to the differential changes in the fees.

Imagine that there are two types of buyers: “deal shoppers” (denoted as type D) and “convenience buyers” (denoted as type C). They have the same intrinsic value v for a given item, drawn from $F(\cdot)$, but different (λ, u) . Assume that the convenience shoppers have a high λ_C so they are not interested in auctions, and a relatively low u_C that increases their willingness to pay. On the other hand, deal shoppers have a low λ_D and, because they are searching for deals, a relatively high u_D . Then, provided that $u_D - u_C$ is sufficiently large, and there are enough convenience shoppers, a seller who lists by posted price will sell to the convenience shoppers but to few (if any) deal shoppers. If she adds additional auction listings, she may be able to sell to the deal shoppers, without cannibalizing her existing market.²⁹

One point to note is that allowing for buyer heterogeneity as in this example might suggest a modification of our calibration exercise, because at least in this example auction and posted price demand would come from different types of buyers, so the lower auction sales curve could reflect the lower willingness-to-pay (higher u) of the deal shoppers as well as their λ . Trying to construct richer econometric models of e-commerce that incorporate different forms of heterogeneity across buyers, sellers, and items, and might help rationalize different types of price discrimination would be a worthwhile goal for future research. A recent paper by Coey et al. (2015) makes a promising start in this direction by positing that buyers have different deadlines for purchasing.

7.2 Evidence from a Survey of eBay Sellers

As a way to complement our empirical evidence, we also conducted a small-scale survey of sellers who have been active on eBay over much of the observation period. We obtained from eBay contact information for fifty sellers who had expressed explicit consent to be approached and possibly respond to occasional eBay queries. We contacted these sellers in May 2014

²⁹In a more general version of this model, we might consider a more continuous distribution of types. In that case, one would have to take a stand on the extent to which buyers arbitrage between sale formats when both are offered at the same time. We do not focus on such a model because based on our estimates in Section 4.1 it is not clear that arbitrage between sale formats for a given seller/item is playing a very major role on the eBay marketplace (or else we would have expected to see very different pricing results for contemporaneous vs. non-contemporaneous auction and posted-price sales). One interesting feature of these models is that they also can rationalize the use of the hybrid auctions used by some sellers on eBay.

and offered a financial incentive of \$50 to answer our survey. Fifteen sellers responded. Of these, 13 were selling on eBay at least since 2003, one started selling in 2006, and one started more recently. We discuss the responses here. Details of the survey procedure and a record of the (de-identified) responses are provided in Appendix E.

The survey responses match many of the patterns reported in the paper. At the time of the survey, eight respondents were using only posted prices, six were using both posted prices and auctions, and only one reported using auctions only. Twelve of the fifteen sellers responded “Agree” or “Strongly Agree” to the claim that competition on eBay is fiercer today than ten years ago. Similarly, thirteen of fifteen sellers agreed that competition across internet retail platforms had increased – indeed, eight of the sellers reported that they sell today on multiple platforms, while only three of the sellers did so ten years ago.

More directly on the demand for auctions, the sellers generally agreed that the relative demand for auctions has declined on eBay. To assess this, we asked sellers if they agreed with the claims that eBay buyers prefer auctions over posted prices today and 10 years ago. When asked about buyer preferences ten years ago, eleven of the sellers agreed that buyers preferred auctions (two were neutral and two disagreed). When asked about buyer preferences today, only five agreed that buyers prefer auctions (five were neutral and five disagreed). We also asked the sellers more specifically about why demand might have changed over time. Many responses mentioned that today’s buyers want speed and convenience and don’t enjoy auctions as much; a few also mentioned the importance of protecting their profit margin. Some selected quotes are revealing: “buyers just want to buy at a good price and be done”; “customers don’t want to wait for the auction to end, they want immediate gratification”; “I think the newness of the ‘auction’ has worn off. People now just want items immediately at a good price.”³⁰

Of course, there is a limit to the information contained in a small number of subjective and not necessarily representative survey responses. Nevertheless, we were encouraged that the answers provided by the sellers were in line with our empirical results, and our interpretation of the empirical patterns.

³⁰The last seller also commented on the information now available to sellers: “Being able to see completed items on eBay gives you an idea of what they [buyers] will bring so as long as your price is in the average that’s what they want.”

8 Conclusion

The internet provides a rich laboratory for thinking about trade-offs between different selling mechanisms. In this paper, we argued that the choice between auctions and posted prices can be viewed as a trade-off between the competitive price discovery offered by an auction versus the convenience of a posted price. We provided supporting evidence using rich data from eBay, and used a simple model of the trade-off to help explain the dramatic shift — on eBay but also reflecting a broader trend in internet retail — from auctions to price posting. Perhaps surprisingly, the shift is not well-explained by changes in the composition of buyers, sellers, or items. Instead, it can be attributed primarily to a decline in the relative demand for auctions, operating within item categories and cohorts of buyers. We used the model to investigate whether the decline in auction demand was driven by increased retail competition or by a change in preferences toward convenience shopping. A simple calibration exercise suggests that the latter accounts for the majority of the decline in auctions, especially for more idiosyncratic item categories.

As emphasized throughout the paper, we purposely adopted a very parsimonious approach to modeling and estimation. An important feature of internet commerce, and eBay in particular, is the remarkable heterogeneity of sellers and breadth of goods for sale. We showed at the start that auctions are more appealing for certain goods and sellers, and one can easily imagine that the specific incentives to use an auction depend on the seller and product. Our goal in this paper was not to provide a story that fits every seller and product, but rather to propose a simple theory and model that could shed light on the broad patterns and trends. Trying to construct richer econometric models of e-commerce that either focus on specific products, or try to incorporate the requisite heterogeneity across buyers, sellers, and items would be a worthwhile exercise, and would complement the evidence provided here.

Our analysis focuses on eBay during the period of 2003 to 2009. While eBay is a very large marketplace and interesting in its own right, a natural question is whether some of our findings are specific to time and place. We view the general trade-off between auction price discovery and competition, and posted price convenience, as quite general. The evolution

of eBay’s marketplace is less typical, but it is not unique in online commerce. The online lending platform Prosper.com initially used an auction process to set interest rates on loans, but switched in December 2010 to posted rates. Prosper’s CEO explained the decision by arguing that posted rates were more efficient and that auctions were “too complicated” (Gonsalves, 2010). The online labor market TaskRabbit also initially emphasized an auction process for setting job payments, before shifting more recently to posted hourly wages (see e.g. Cullen and Farronato, 2015). The design and study of pricing mechanisms in online markets is likely to be a fruitful area of research for many years.

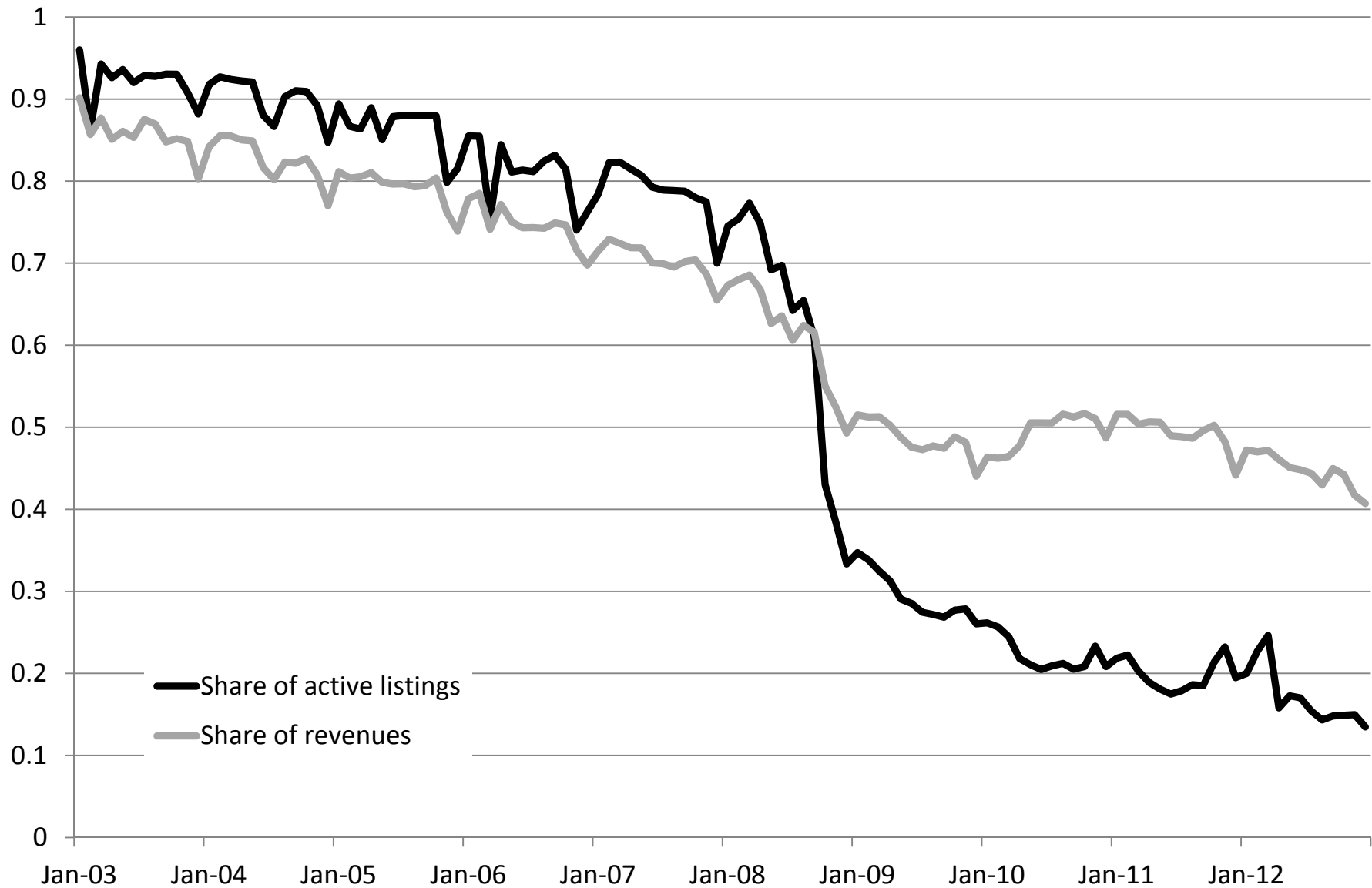
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Figure 1: Auction Share on eBay over Time



For each month, the figure shows the average daily share of active eBay listings (black) and transaction revenues (gray) based on comparing pure auction listings to all pure auction and posted price listings. Less common formats, such as hybrid auctions or “best offer,” are not included. The sharp drop in Fall 2008 coincides with a decision in September 2008 to allow “good till canceled” posted price listings (see Section 7).

Figure 2: Google Search Volume for Online Auctions and Online Prices

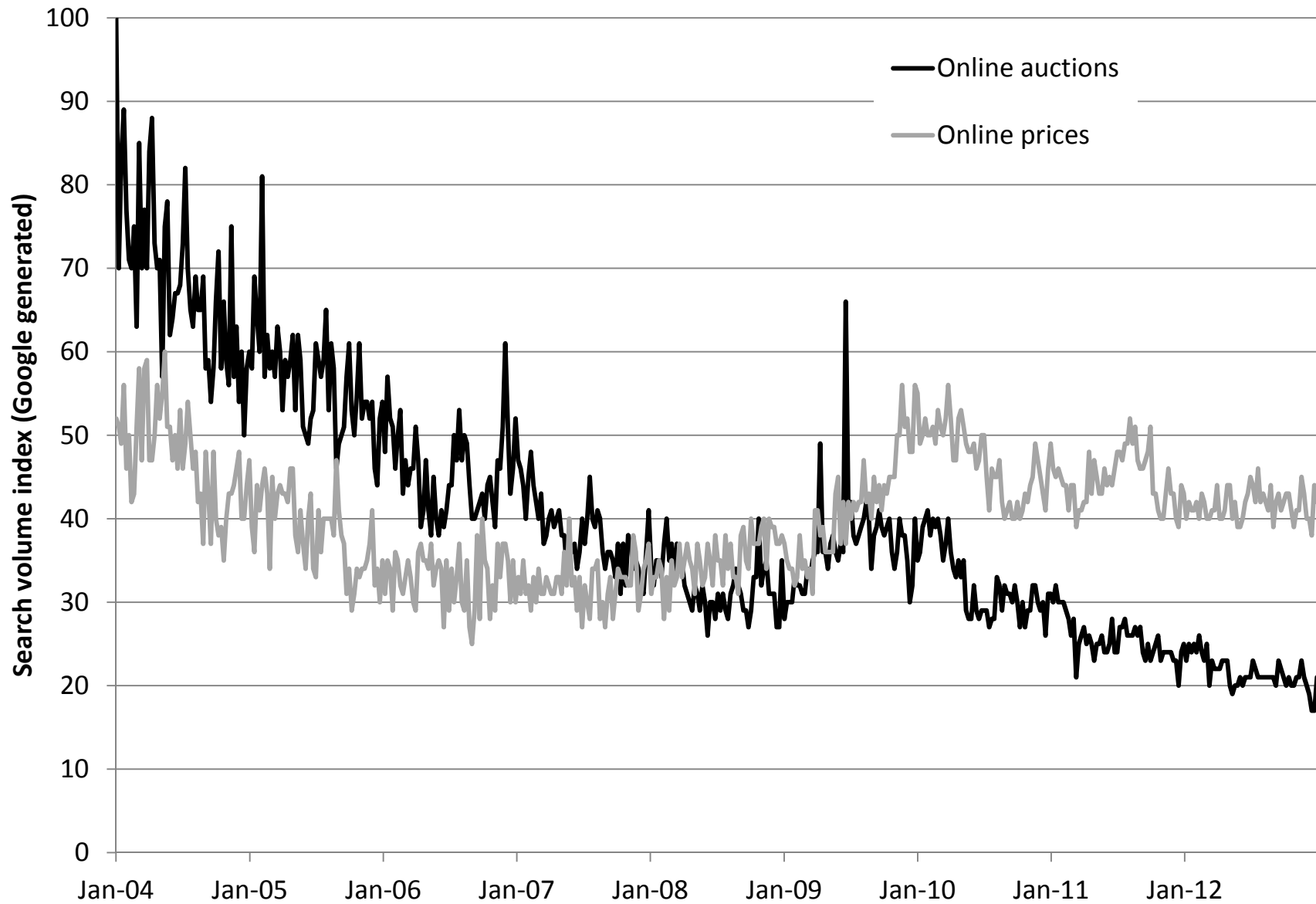


Figure presents results from "Google Trends" for search terms "online auctions" and "online prices." The y-axis is a Google generated index for the weekly volume of Google searches for each of the two search terms, which should make the weekly volume figures comparable over time and across the two search terms.

Figure 3: Theory – The Auction and Posted-Price Demand Curves

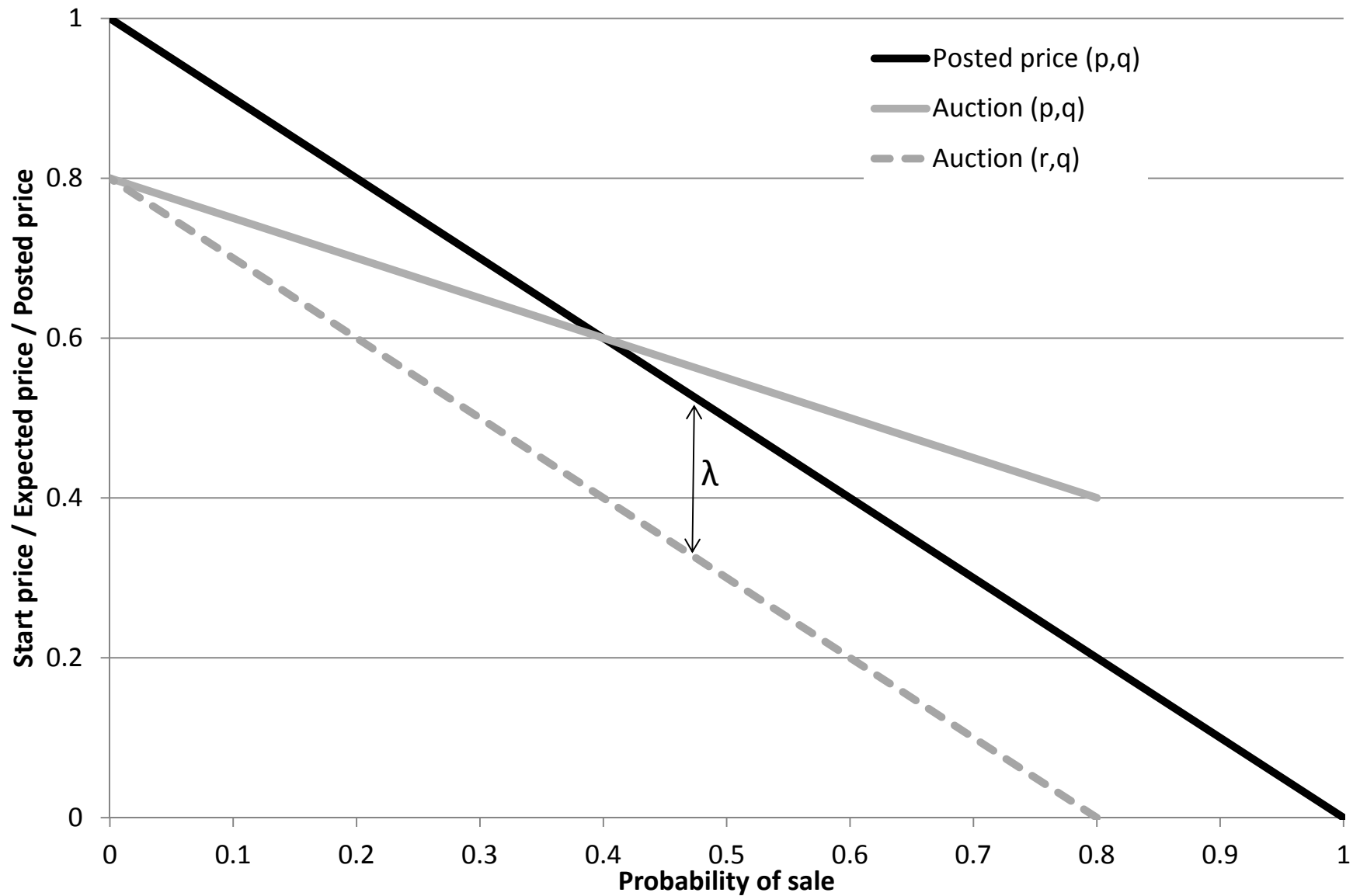


Figure is based on the model of Section 2, assuming that values are drawn from a uniform distribution on $[0,1]$, with $u=0$ and $\lambda=0.2$. The black solid line is the posted-price demand curve. The dashed gray line is the auction sale curve, which shows the probability of sale as a function of the auction start price. The solid gray line is the “auction demand curve,” which plots the probability of sale from a given start price against the expected sale price from that start price.

Figure 4(a): Posted Prices are more Prevalent for “Less Idiosyncratic” Items

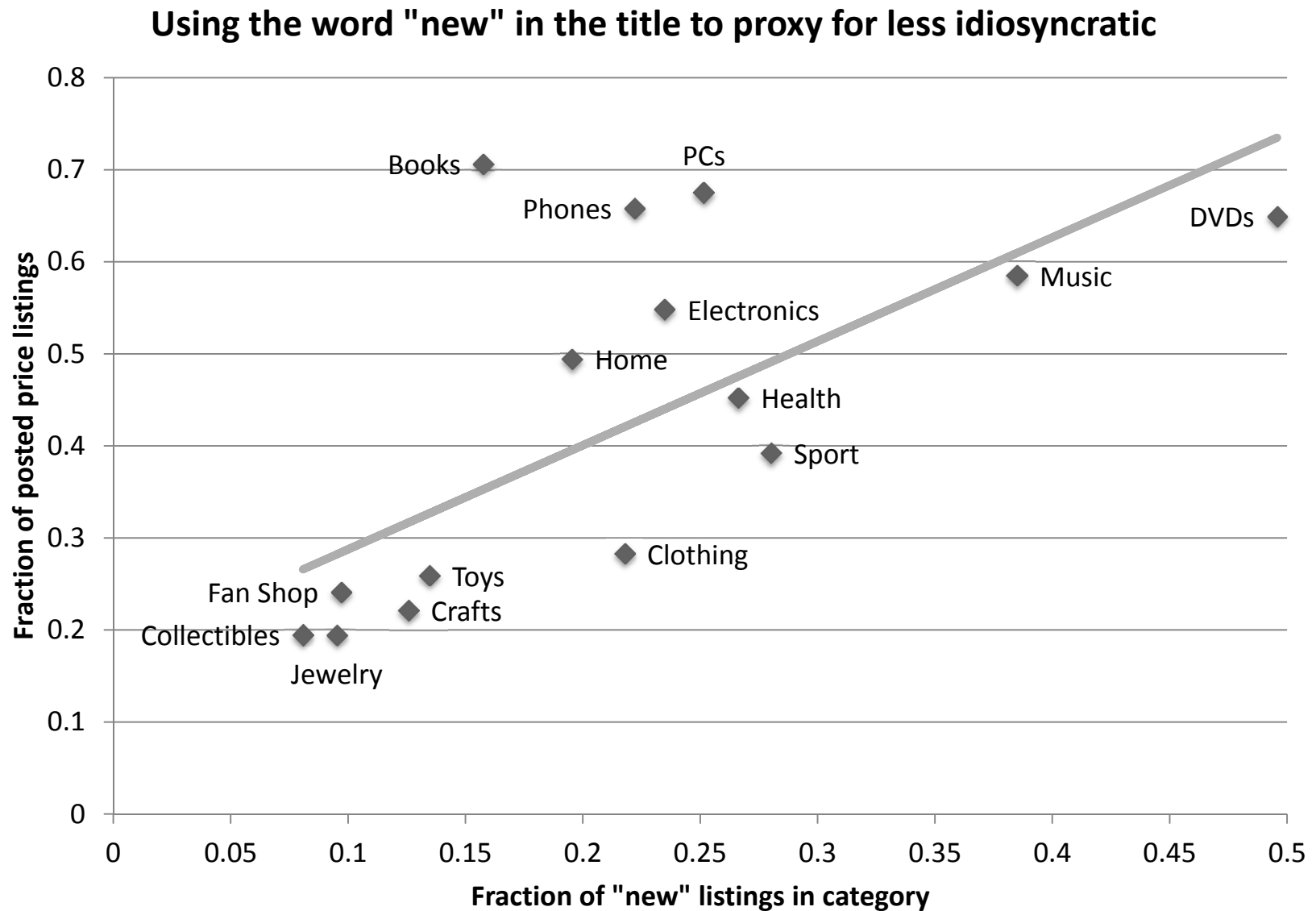


Figure presents the share of posted price listings in the largest 15 item categories, plotted against the share of category listings that have the word "new" in the listing title, along with a (listing-weighted) regression line. The figure is based on all eBay listings in 2009 that were either posted price or pure auction listings.

Figure 4(b): Posted Prices are more Prevalent for “Less Idiosyncratic” Items

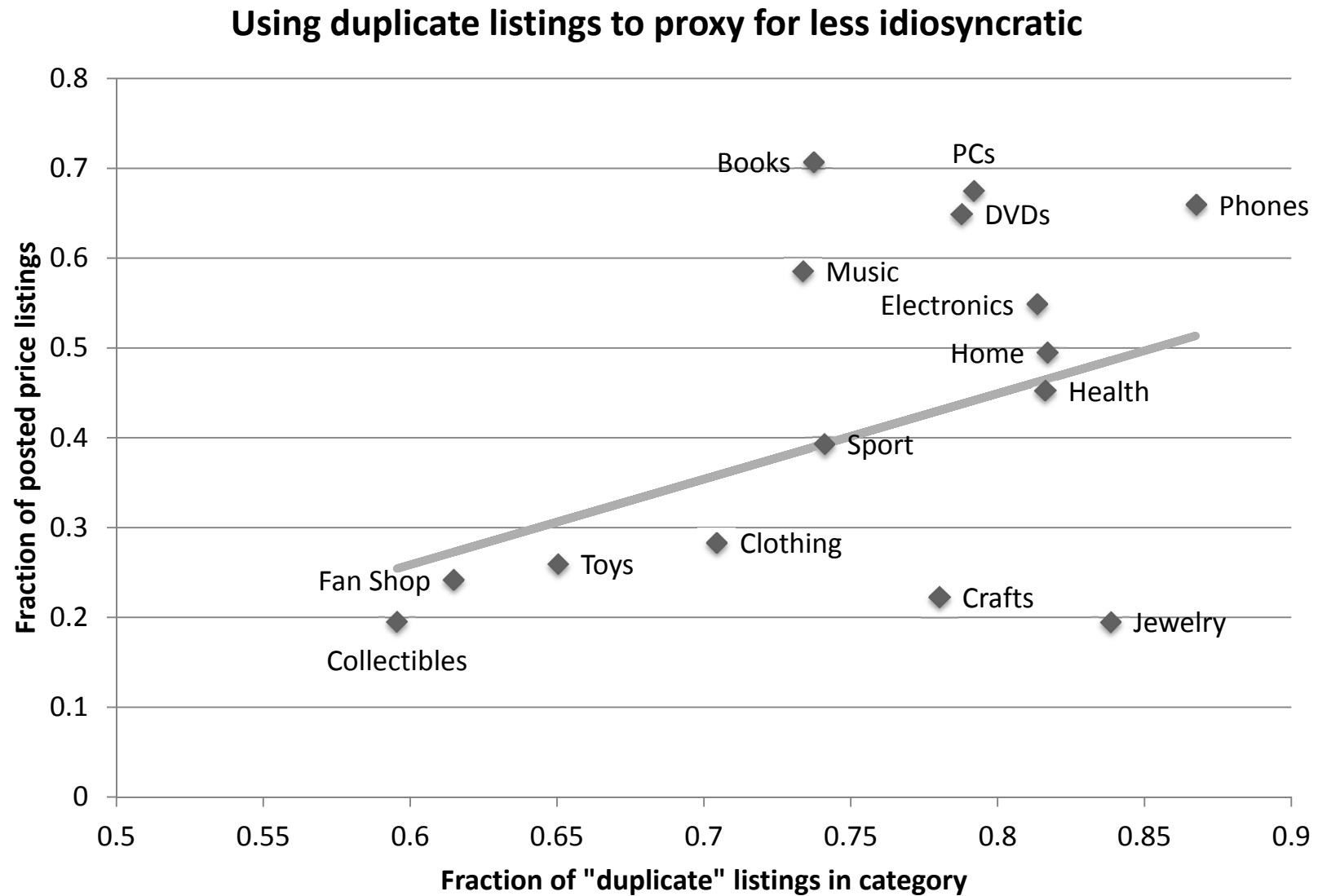


Figure presents the share of posted price listings in the largest 15 categories, plotted against the share of category listings that have at least one “duplicate” (i.e. another listing by the same seller with the same title), and a (listing-weighted) regression line. The figure is based on all eBay listings in 2009 that were either posted price or pure auction listings.

Figure 5(a): Sale Rate of Posted Price and Auction Listings, by Category

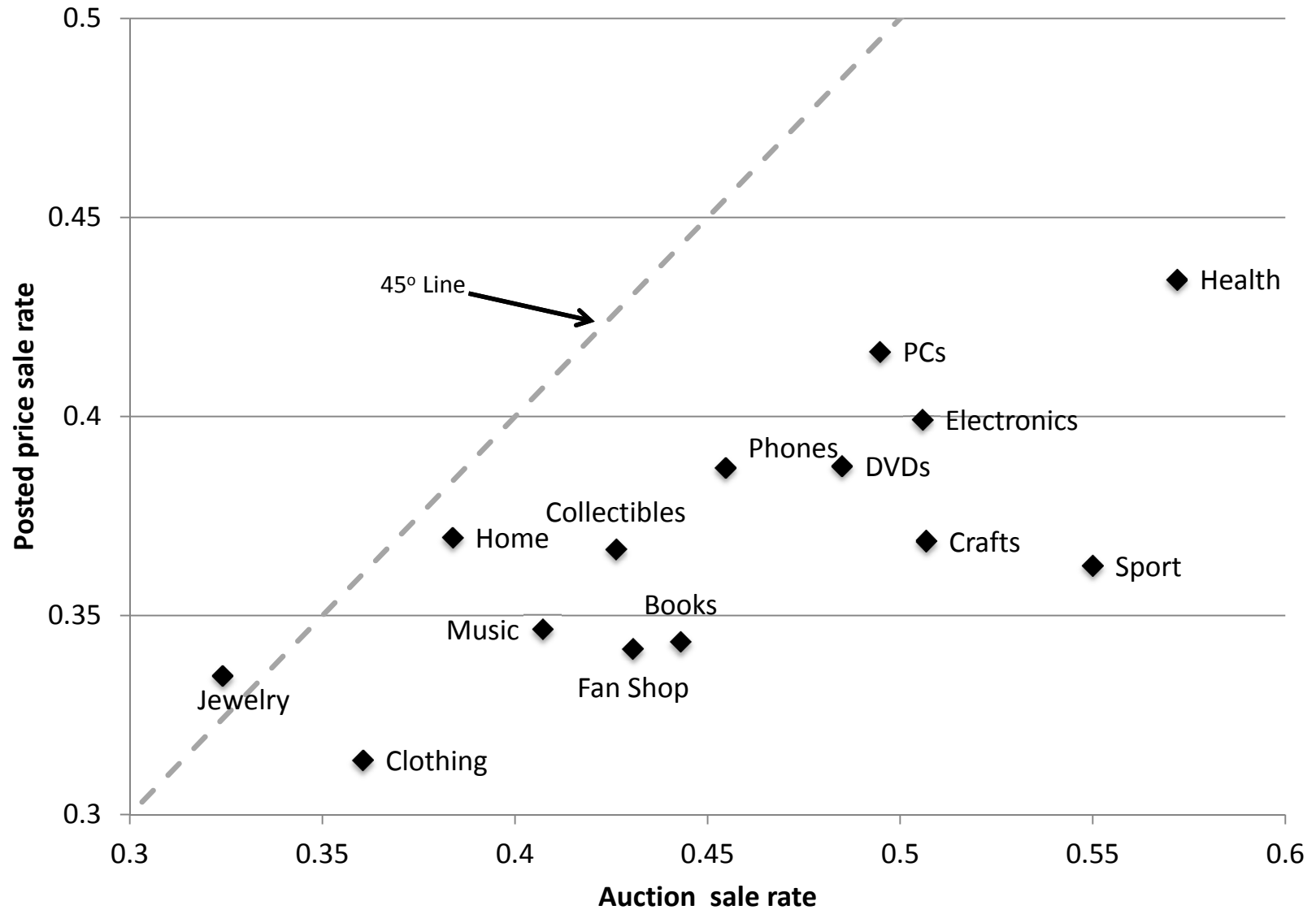


Figure is based on the 2009 matched listings sample described in Section 3 and reports the average sale rate in each category, by listing format. For each item in the sample, we compute the sale rate in each listing format, and then average (unweighted) across all items within each category.

Figure 5(b): Average Sale Price of Posted Price and Auction Listings, by Category

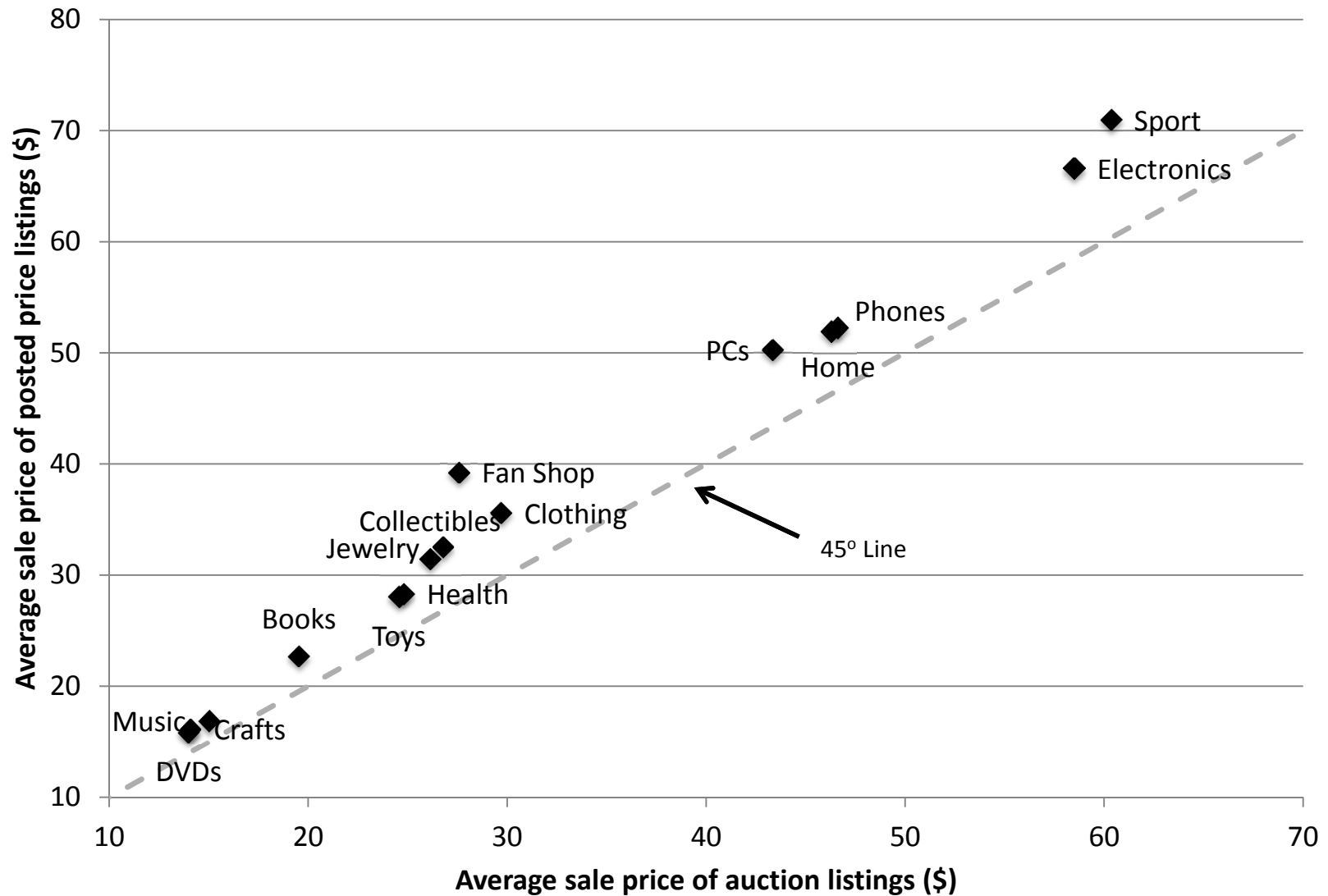


Figure is based on the 2009 matched listings sample described in Section 3 and reports the average sale price in each category, by listing format. For each item (matched set) in the sample, we compute the average sale price in each listing format, and then average (unweighted) across all items within each category.

Figure 6: Posted Price Use, by Seller Cohort

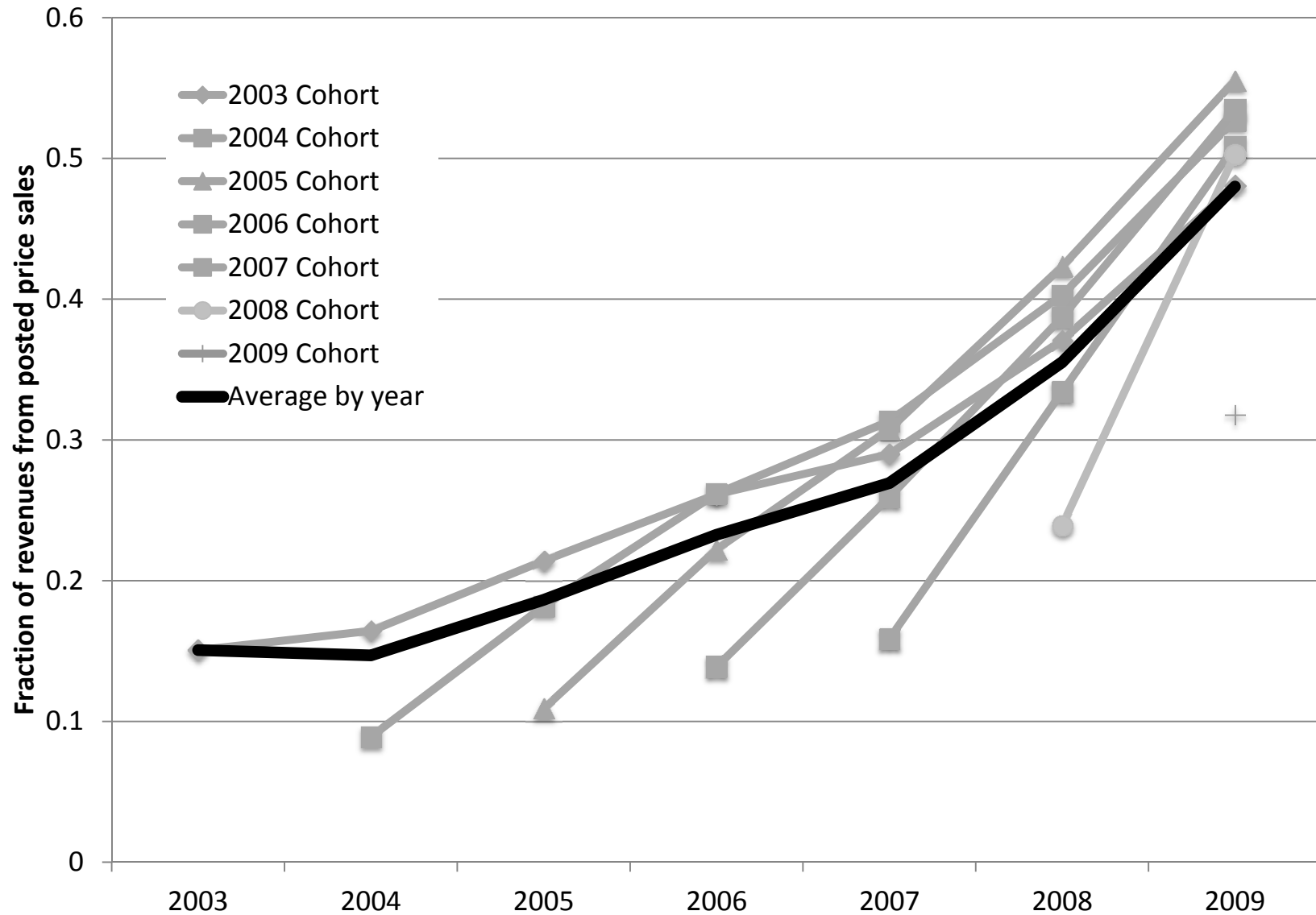


Figure presents the evolution of the annual fraction of eBay sellers' revenue from posted price listings (out of revenues from posted price and "pure" auction listings), separately for each cohort of sellers. A seller is assigned to a cohort based on the calendar year in which the seller's first ever sale was made on eBay. The thick black line presents the overall platform average for each year.

Figure 7(a): Trends in Sale Rate Based on Matched Listings

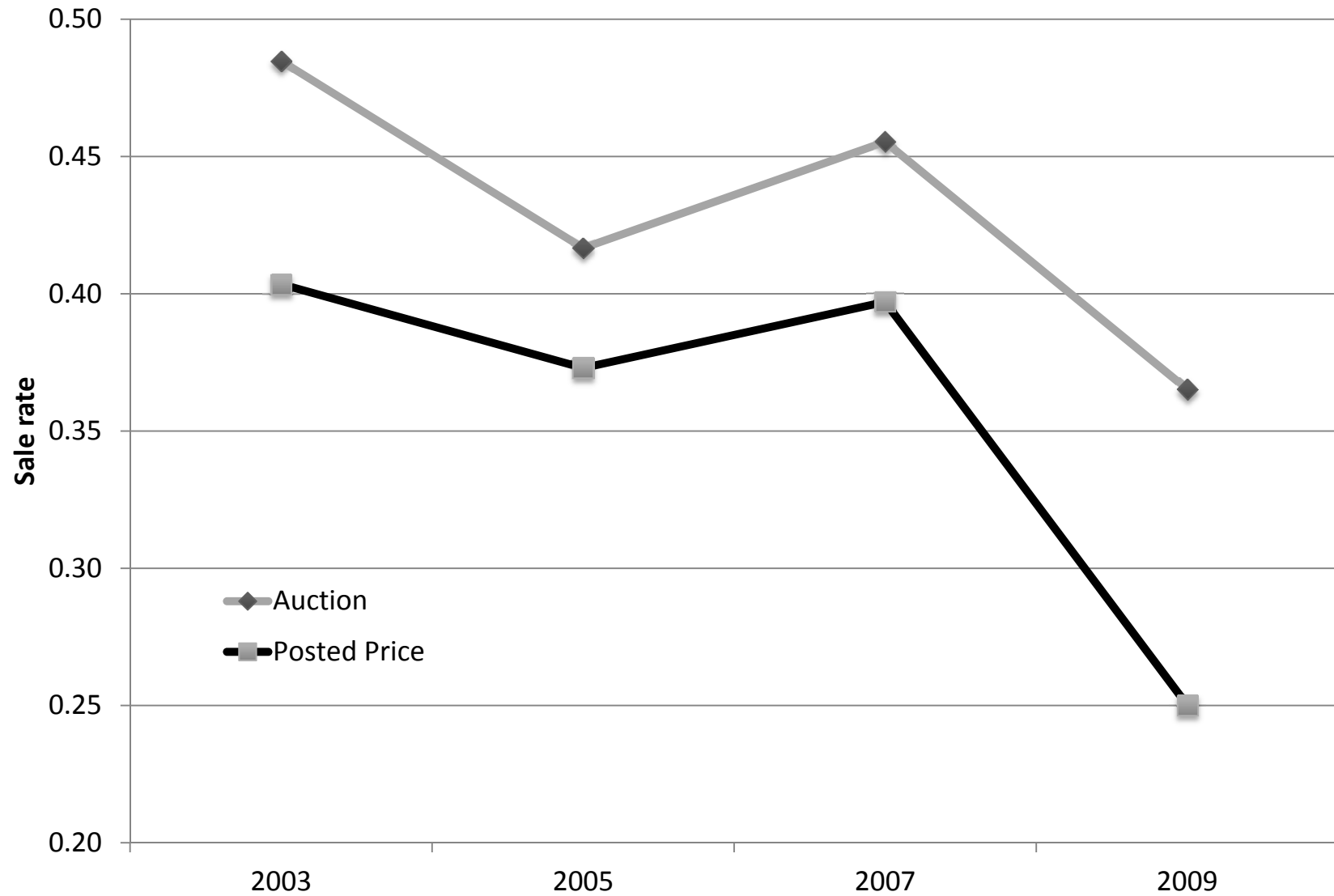


Figure is based on the matched listings sample described in Section 3. The lines represent the predicted value from a linear probability regression of a sale indicator on an indicator that is equal to one for an auction listing and on seller-item fixed effects. The regression is estimated for each year separately.

Figure 7(b): Trends in The "Auction Discount" Based on Matched Listings

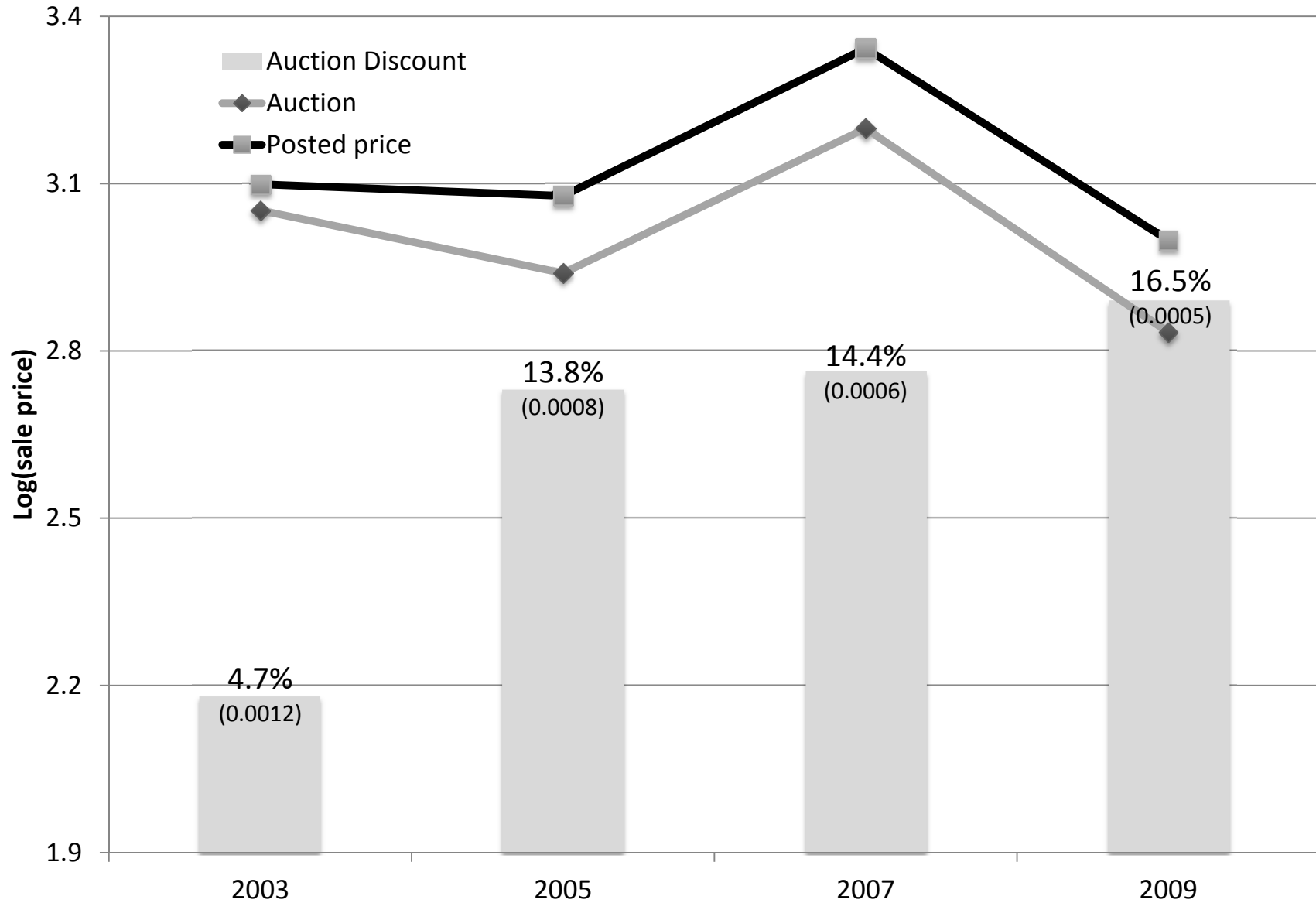


Figure is based on the matched listings sample described in Section 3. The lines represent the predicted value from a regression of (log) sale price on an indicator that is equal to one for an auction listing and on seller-item fixed effects. The regression is estimated for each year separately. The bars represent the estimated coefficient on the auction indicator (which is the same as the vertical difference between the two lines). Robust standard errors are in parenthesis.

Figure 8(a): Auction and Posted Price Demand Curves in 2003

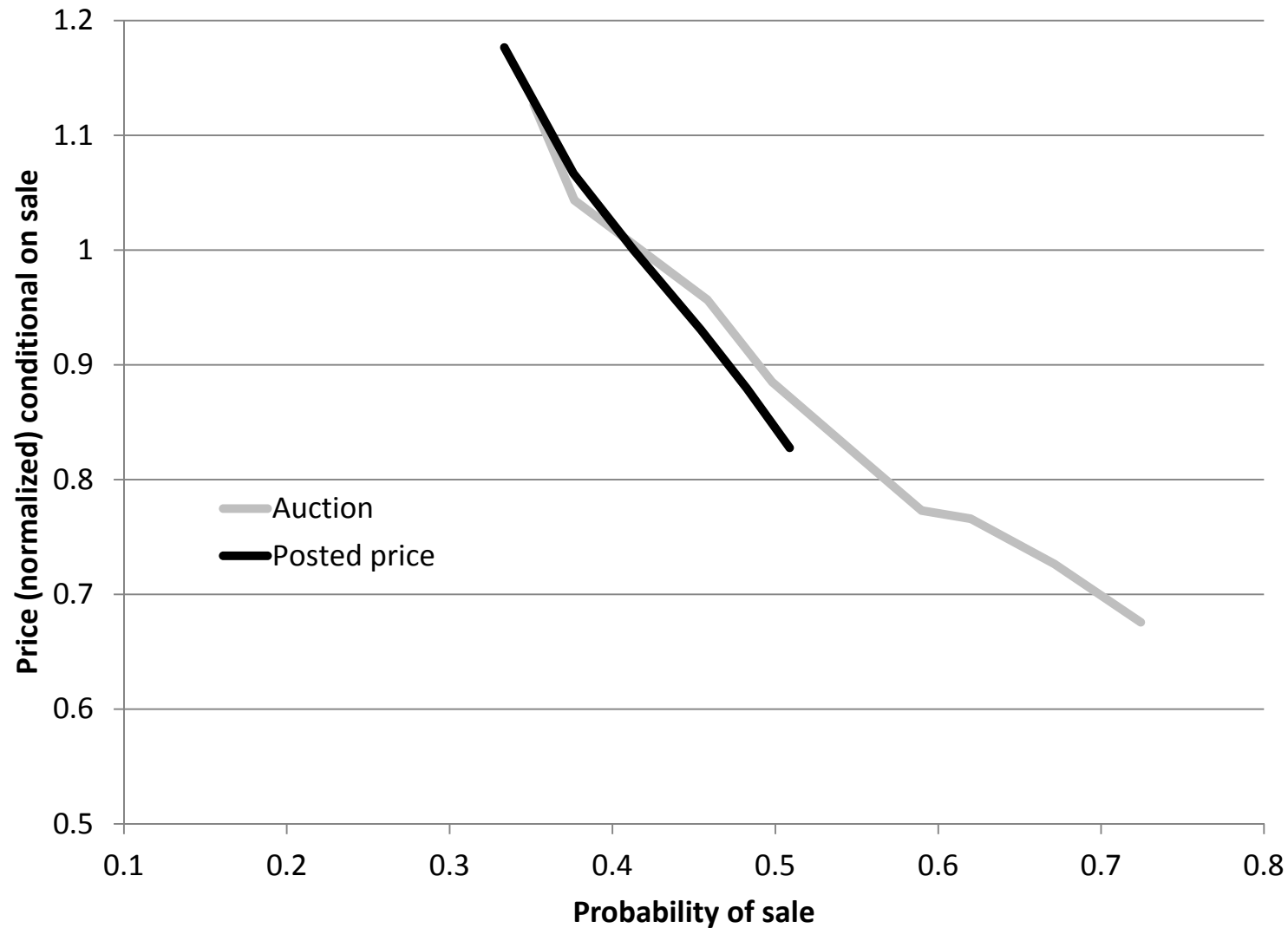


Figure is based on the 2003 matched listings sample described in Section 3. The posted price demand curve is based on estimating a linear probability model of a sale indicator on the posted price and seller-item fixed effects. The auction demand curve is based on estimating a similar sale equation (sale indicator on start price and seller-item fixed effects) and a separate price equation (normalized sale price on start price and seller-item fixed effects), and combining the estimates to construct an auction demand curve as described in the text, and shown in Figure 3.

Figure 8(b): Auction and Posted Price Demand Curves in 2009

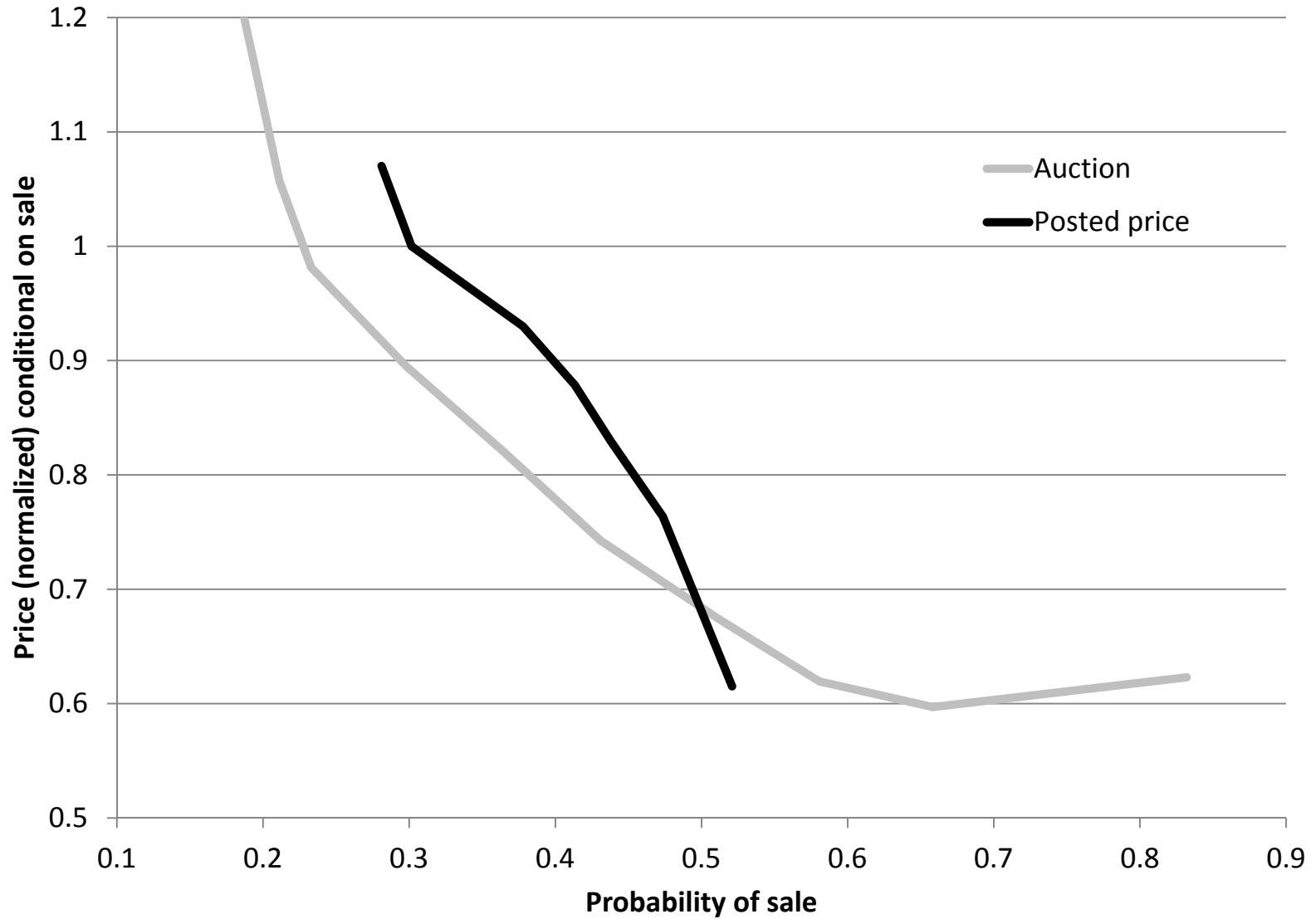


Figure is based on the 2009 matched listings sample, and is otherwise identical to Figure 8(a).

Figure 9(a): Listing-Level Demand Curves for Idiosyncratic Categories

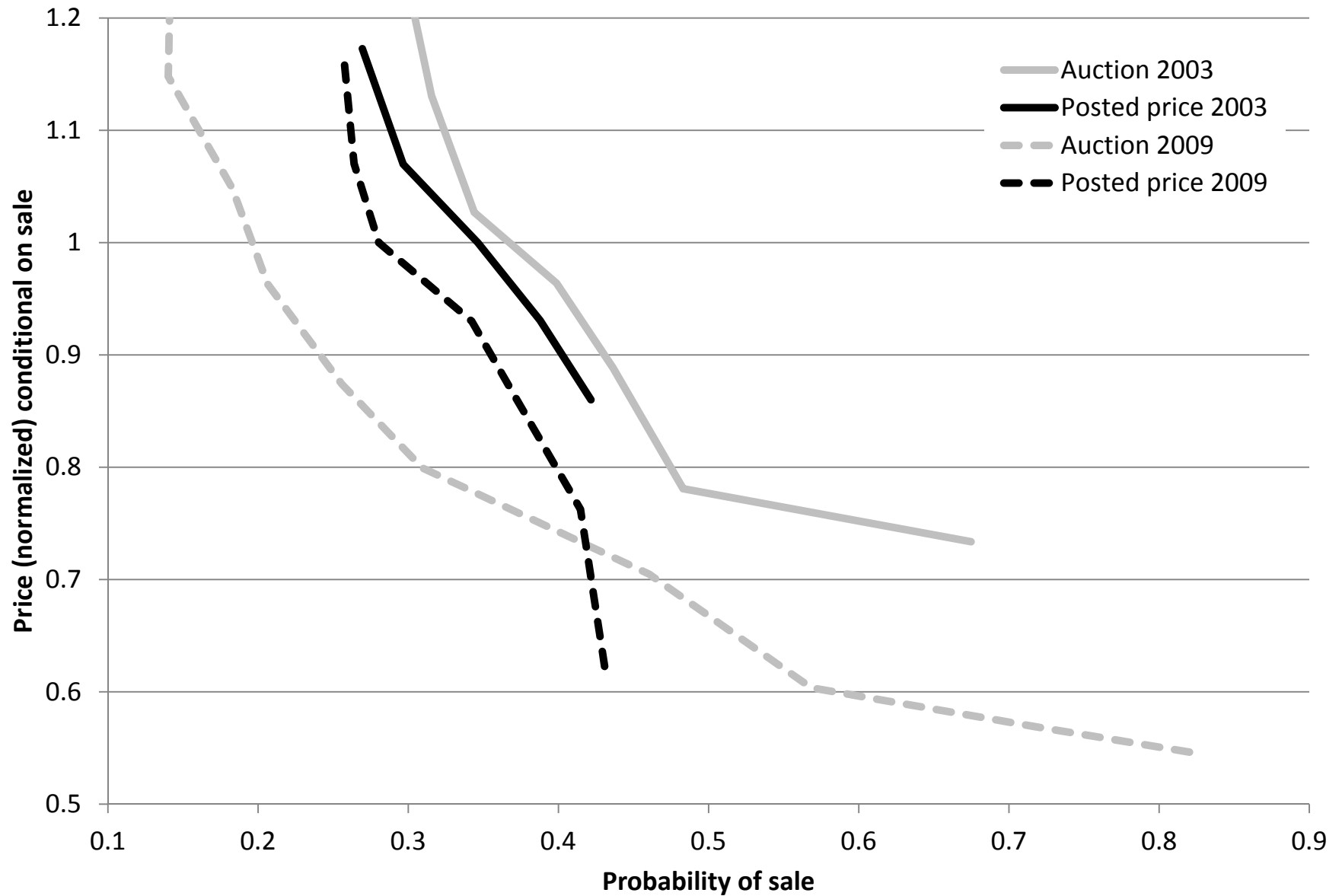


Figure is based on the 2003 and 2009 matched listings samples described, restricting estimation to five idiosyncratic categories: Collectibles, Fan Shop, Toys, Jewelry, and Clothing. It is otherwise identical to Figure 8(a) and Figure 8(b) combined.

Figure 9(b): Listing-Level Demand Curves for Commodity Categories

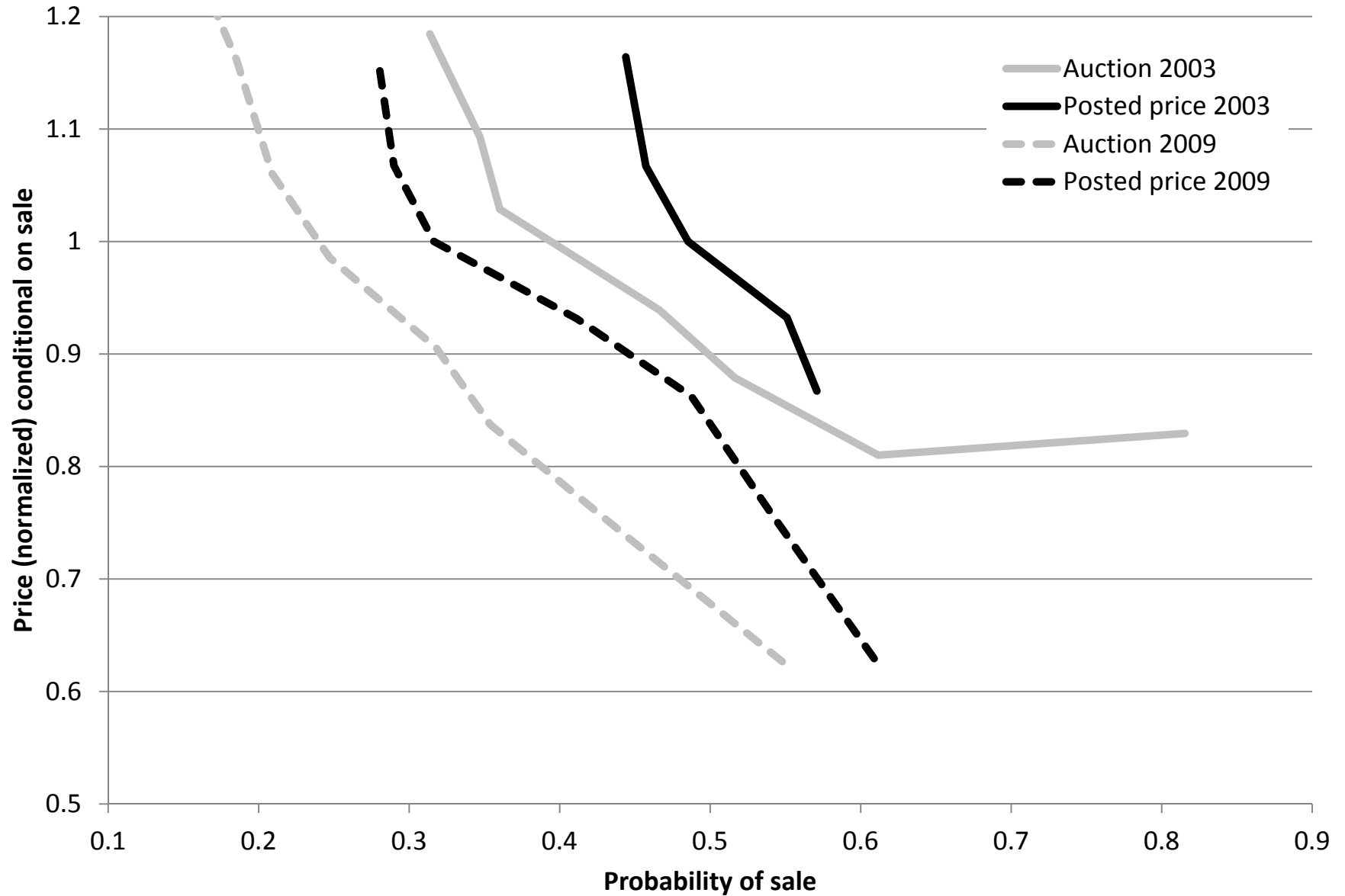


Figure is based on the 2003 and 2009 matched listings samples, restricting estimation to five commodity categories: Electronics, Computers, DVDs, Health, and Phones. It is otherwise identical to Figure 8(a) and Figure 8(b) combined.

Figure 10: Calibrating λ and u from Posted-Price and Auction Sale Curves

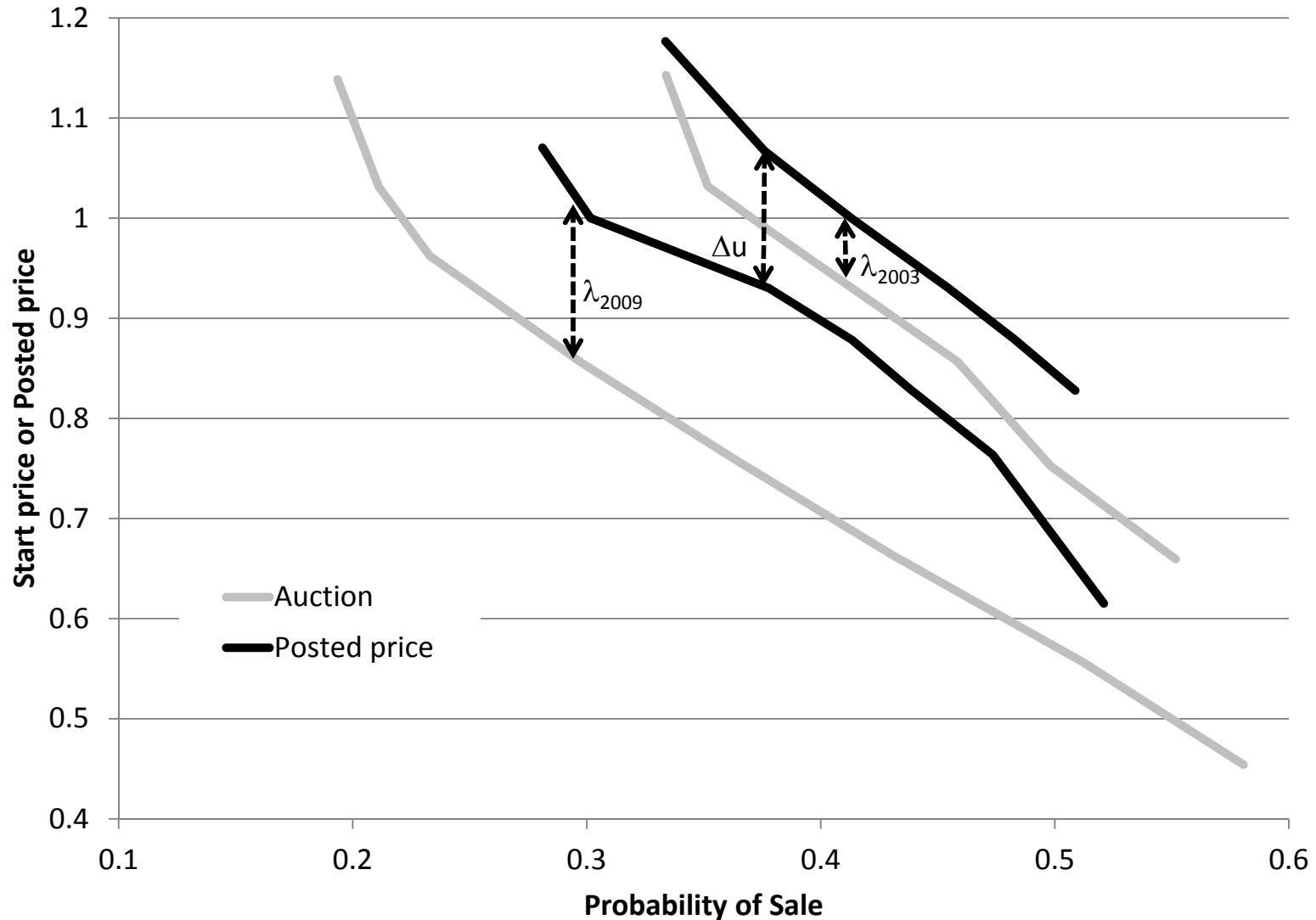


Figure illustrates the way by which we calibrate the values of λ and u , and presents the empirical analog to the theoretical Figure 5. The black lines are the estimated posted price demand curves in 2003 and 2009 (also shown in Figures 8(a) and 8(b)). The gray lines are the auction sale curves (that is, our estimates – based on estimating equation (4) – of the effect of start price on the probability of sale for auction listings). The vertical distance between the two graphs is an estimate of λ , and the vertical distance between the two posted price demand curves is Δu .

Figure 11: Posted Price Use, by Buyer Cohort

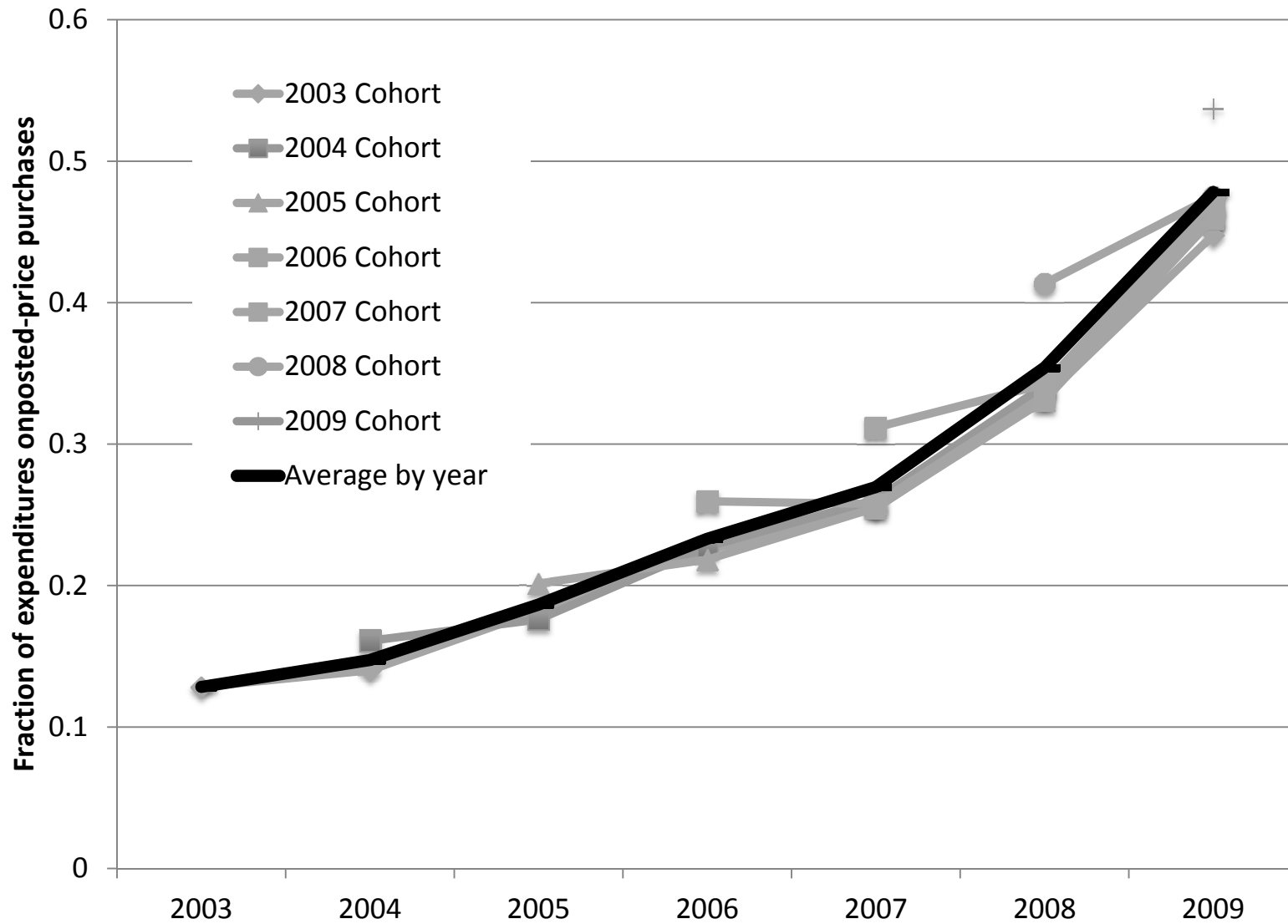


Figure presents the evolution of the annual fraction of buyers' expenditure on posted price purchases (out of expenditures on posted price and "pure" auction purchases), separately for each cohort of buyers. A buyer is assigned to a cohort based on the calendar year in which the buyer's first ever purchase was made. The thick black line presents the overall platform average for each year.

Table 1: Summary of Matched Listings Sample

	2003			2009		
	23,057 items and 1,168,033 listings of which 64% are auction listings			83,685 items and 5,924,448 listings of which 71% are auction listings		
	Mean	25th pctile	75th pctile	Mean	25th pctile	75th pctile
Number of listings	50.7	18	50	70.8	19	68
Auction listings	32.5	8	29	50.0	9	45
Posted-price listings	18.2	6	19	20.8	6	18
Share of auction listings	0.56	0.38	0.74	0.61	0.43	0.81
Avg. sale rate for auctions	0.51	0.22	0.80	0.44	0.16	0.73
Avg. sale rate for posted prices	0.44	0.20	0.67	0.37	0.17	0.50
Diff. in sale rate	0.07	-0.10	0.23	0.08	-0.12	0.25
Avg. sale price (normalized) for auctions	0.96	0.83	1.04	0.86	0.75	0.98
Avg. sale price (normalized) for posted prices	0.97	0.97	1.00	0.98	0.97	1.00
Diff. in sale price	-0.01	-0.15	0.08	-0.13	-0.24	0.00
Item reference value (avg. posted price)	40.3	8.2	32	42.7	10.0	40.0
Std. dev. of (normalized) auction start prices	0.25	0.14	0.34	0.19	0.09	0.27
Std. dev. of (normalized) posted prices	0.10	0.00	0.15	0.08	0.02	0.11

Table presents summary statistics for the 2003 and 2009 matched listings samples. The unit of observation is a matched set of listings, i.e. a set of listings that have identical seller, listing title, and calendar year. Notes: (1) The share of auction listings is higher in 2009 because a larger number of the posted price listings are multi-unit listings. (2) The posted price sale rate is the share of listings with a sale within seven days. (3) The difference in sale rate and sale price are auction minus posted price.

Table 2: Calibration Results

	All categories	Idiosyncratic	Commodity
<u>Panel A. Calibrated values</u>			
λ_{2003}	0.08	0.06	0.19
u_{2003}	----- Normalized to zero -----		
λ_{2009}	0.16	0.19	0.23
u_{2009}	0.14	0.11	0.15
<u>Panel B. Success rates (q*)</u>			
Posted price success (2003)	0.40	0.34	0.49
Auction Success (2003)	0.48	0.38	0.56
Posted price success (2009)	0.25	0.25	0.29
Auction Success (2009)	0.37	0.31	0.41
<u>Panel C. Relative effects of λ and u</u>			
Change in λ	0.09	0.13	0.05
Change in u	0.14	0.11	0.15
Relative importance of λ vs. u (2003 quantities)	3.60	10.22	2.52
Relative importance of λ vs. u (2009 quantities)	1.92	6.11	1.12

The top panel presents estimates of u and λ from the estimated demand curves in 2003 and 2009. The middle panel shows success rates estimated from the linear probability regression in Section 4.2. The bottom panel derives the relative profit effects due to the calibrated increase in u and λ , as explained in Section 6.2. Specifically, we compute the increase in posted price profit minus auction profit due to λ and also due to u and report the ratio in the Table.