The Seller's Listing Strategy in Online Auctions: Evidence from eBay

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Abstract

The paper empirically studies why the sellers of identical commodities adopt different listing formats in online auctions, and the consequences thereof. We postulate that the sellers adopt different listing formats because of the differences in their experience and size of inventory. We first use these two characteristics to endogeneize the seller's choice between three listing formats: fixed-price posting, buy-it-now (BIN) auction, and pure auction. We then estimate the differences in sales rate, transaction price, and sale duration between the three formats. We find that the fixed-price format results in the highest transaction price and the lowest sale rate. The pure and BIN auctions have similar sales rate and transaction price, but the latter has the shortest sale duration among all three. These results strongly suggest that there is a tradeoff between price and sale probability for the seller's choice between an auction (including pure and BIN) and a fixed-price listing, and that both risk and time preference considerations are important in adopting BIN.

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1 Introduction

The development of the Internet has made online auctions one of the most important forms of C2C transactions. The fast development of such auctions has also made this into a full-scale research area.[1] The research for online auctions has mainly focused on the bidder's behavior under various transaction rules.[2] Research on the seller's behavior, either theoretical or empirical, is relatively scarce. Even less studied is the seller's strategic choice between various transaction formats available to them.

There are basically two styles by which the sellers can list their items in the online auction sites: The auction style listing and the fixed-price style listing. The former contains two major formats to conduct an auction. In the first, the seller lists an item with or without a reserve price, and the highest bidder (at the end of auction) wins the item. We will call this the "pure auction" format. In the second, the seller also posts a buy-it-now (BIN) price, and the buyers are allowed not only to place competitive bids, but also to buy out the item immediately by agreeing to pay the BIN price. In this paper we will call this the "BIN auction" format. It is important to note that the BIN option is temporary in eBay auctions: Once a bidder places a bid before any bidder exercises BIN, the BIN option will disappear, and the auction will then become a pure auction. Since the transaction price for the pure and BIN auctions is partially determined by the bidders, and is uncertain *ex ante*, we will also call them the "open-price" style formats.

The other listing style, the fixed-price style, works in an obvious way: The seller simply

[1] As far as we know, there have already been five surveys of online auctions in less than a decade. See Bajari and Hortaçsu (2004), Ockelfels et al. (2006), Pinker et al. (2003), Hasker and Sickles (2010) and Haruvy and Popkowski Leszczyc (2009). There has also been an early partial survey by Lucking-Reiley (2000).

[2] For example, see Roth and Ockelfels (2002) and Ockenfels and Roth (2006) on sniping, and Budish and Takeyama (2001), Hidvegi et al. (2006), Reynolds and Wooders (2009) and Chen et al. (forthcoming) on bidding strategy under buy-it-now. Though not a bidder's strategy per se, readers interested in shill bidding can see Chakraborty and Kosmopoulou (2004) and Engelberg and Williams (2009).

posts a price, and any buyer who is willing to pay that price can obtain it as long as it is still available. All three listing formats (the pure auction, the BIN auction, and the fixed-price listing) occupy a substantial proportion in eBay listings. (Hasker and Sickles, 2010.)[3,4]

In this paper, we empirically investigate the following issues: Given the array of selling formats available to them, how do the sellers choose one over the others, and what are the consequences of the choice? Is there a certain tradeoff between adopting these formats, so that the seller's choice is essentially a balance of the tradeoff? We suggest answers to these questions by analyzing data from the eBay auctions of Apple iPods. We focus on three types of online listing format mentioned above: the pure auction, the auction with buy-it-now, and the fixed-price listing. Similar to Hammond (2010), we hypothesize, and confirm with our data, that the main determinant of the sellers' choice between a fixed-price format and the open-price format (the pure and BIN auctions) is the size of their inventory. We therefore use the size of the seller's inventory to endogenize their decision of whether to list items in the fixed-price format.[5] Regarding the adoption of BIN, current theory suggests that one of the main reasons for a seller to post BIN in an auction is to reduce risk.[6] Therefore, we

[3] The readers are cautioned of the use of terminology in our paper. Since eBay facilitates a fixed-price purchase with a BIN in which the buyers are not allowed to place bids, what we call the "fixed-price" listing in this paper is called a BIN auction in some other papers (e.g., Hasker and Sickles, 2010). Moreover, eBay now does not allow a seller to list an item as a BIN auction and at the same time set a starting bid equal to the BIN price (which essentially makes it into a fixed-price listing). But at the time we collected our data, it was still possible to do this. Therefore, in our data we have checked the auctions with BIN to see whether their starting bids were equal to the BIN prices, and, if yes, categorize them as a fixed-price listing.

[4] There is also a variation of BIN auction, the auction with best-offer, in which the seller posts a BIN price, and the potential buyers can negotiate the terms in a formalized procedure designed by eBay. There are, however, still few items for which best-offer option is available. Moreover, the offers of both sides during negotiation are not observable to the third party. Therefore, we do not include best-offer auctions in our study.

[5] We emphasize that using inventory to endogenize the seller's choice of the fixed-price listing is not our innovation. Hammond (2010), citing the results in Harris and Raviv (1981) as the theoretical foundation, is the first to use inventory to endogenize the adoption of posted price in the empirical study (with data of CDs). Our data confirm his result (with iPods data) in this regard. However, he only compares the pure auction and the fixed-price listing.

[6] See Hidvegi et al. (2006), Mathews and Katzman (2006), Reynolds and Wooders (2009), and Chen et al. (forthcoming).

hypothesize (and confirm with data) that the main determinant of a seller's decision to adopt BIN auction is his experience (see Section 3 for details), and we use the seller's experience as the instrumental variable to endogenize the adoption of BIN.

In order to investigate the outcomes of adopting different listing formats, we run three main regressions, each for sales rate, transaction price, and sale duration. We find that the fixed-price style listing has a lower sales rate, but a higher transaction price if there is a sale, when compared the (BIN and pure) auction style listing. Within the auction style, the BIN and pure auctions have about the same sales rate and transaction price. This result therefore implies that there exists a tradeoff of sales rate and transaction between the auction (open-price) and fixed-price styles of listing. The existence of this tradeoff between the pure auction and fixed-price listing has already been identified in several empirical works (e.g. Hammond, 2010 and Einav et al., 2012), and our result only provides another confirmation of this relation by also including the BIN auctions in our data. More important is our finding that, within the auction-style listing, although pure and BIN auctions have a similar sales rate and transaction prices, the latter have a substantially shorter sale duration; that is, the BIN auction takes a substantially shorter time to reach a transaction than the pure auction.[7] This not only explains why a seller is willing to take the trouble to figure out the correct BIN price and pay the additional cost of posting a BIN,[8] but, more importantly, confirms another strand of theoretical literature which explains BIN in terms of its function in satisfying time-impatience for the sellers (Mathews, 2004 and Chen et al., 2013).

[7] There are two types of duration for an auction. The "posted duration" is the duration (in terms of number of days) that the seller sets when he lists an item. The "sale duration" is the actual number of days that an item takes to be sold (if there is a transaction).

[8] The sellers not only incur mental cost in computing the BIN price but, during the time of our data's study period, are also subject to fees of posting BIN in eBay.

2 Literature Review

The literature on the seller's choice of online auction format has been scarce. An early paper by Wang (1993), which is not specifically related to online transactions, compares a monopolist's choice between fixed-price listing and pure auction in terms of the dispersion of the bidders' valuations. If the seller has one unit of the commodity to sell, he shows that pure auction outperforms fixed-price listing when the bidders' valuations are more dispersed. Harris and Raviv (1981) consider the case in which the monopolist can have many items, but faces the possibility of capacity constraint in the sense that potential demand can exceed the monopolist's capacity.[9] They show that a modified version of the Vickrey auction (fixed-price listing) is optimal when potential demand is greater (smaller) than its capacity. Etzion et al. (2006) consider a monopolistic online seller who offers identical items using both posted price and auction (i.e., fixed-price and pure auctions in our paper) simultaneously. They build up a dynamic model in which buyers arrive stochastically. The monopolist sets auction duration, quantity of items in auction, and the posted price to maximize revenue per unit of time. It is shown that this dual-channel selling strategy can segment buyers, with the auction used to capture buyers who are priced out in the fixed-price format. Their simulation shows that sometimes the dual-channel selling can substantially outperform a lone fixed-price venue. Bose and Daripa (2009) consider a traditional store owner who can pay an online auction access fee to also sell his commodities simultaneously. They show that the optimal mechanism involves a fixed price at the store plus an online auction in which only high-valuation buyers participate. They also show that this optimal mechanism corresponds exactly to the eBay-type BIN auction.

We are aware of only five related empirical works. Vakrat and Seidmann (1999) compare

[9] In their paper, capacity constraint means that the production cost is infinite when output exceeds a threshold.

prices in the online auctions and the corresponding catalog prices for identical goods,[10] and find that the transaction in the auction price is 25% lower than the catalog price. They explain the difference by the monitoring, delay, and search costs that online auctions bidders have to incur. However, their comparison is between online and catalog prices, not the prices between two formats in the same online auction site. Anderson et al. (2008) use eBay auction data of Palm Vx PDAs to investigate the seller's motivation for using BIN, together with its consequence. They show that the BIN option is more likely to be adopted by sellers with higher ratings and fewer units. Moreover, the fixed-price format is more likely to be adopted for used items. They also find that auctions with BIN do not result in higher prices, although in the subsample where BIN options are offered, those in which the bidders win with BIN result in higher prices. Their model is mainly concerned with the seller's adoption of BIN, rather than with distinguishing the three formats considered in our paper. They also do not consider the endogeneity problem of the sellers' choices. Finally, it is important to note that in their paper, the BIN auctions include all auctions having the BIN options, which are essentially the fixed-price listing plus the BIN auctions considered in our paper.

Einav et al. (2012) use a comprehensive dataset from eBay listings in the past ten years to show that the proportion of pure auction listings in eBay has substantially declined over time, while that of the fixed-price listings has greatly increased. They also suggest that this is mainly caused by the shift of the buyer's preference toward the posted-price format. Bauner (2011) uses auction data of baseball tickets in eBay to show that, in addition to opportunity costs, buyers' heterogeneity is also an important factor in explaining the simultaneous existence of auctions and fixed-price sales.

In a highly related paper, Hammond (2010) uses auction data of compact discs to compare

[10] Specifically, they compare online auction prices on SurplusAuction with prices on its catalog-based site Egghead.com. They also compare auction prices at the online auction site OnSale with search results of prices on the web using a shopping agent.

fixed-price listing and pure auctions, and finds that the former results in a higher price but lower sales. He also finds that the sellers with large inventories are more likely to adopt the fixed-price format. Our paper differentiates from his in that, in addition to pure auction and fixed-price listing, we also consider the BIN auction. Moreover, although he considers identical objects, his sample includes not only both new and used CDs in differing condition, but also those from two different auction sites (eBay and Half.com), and therefore the data are not homogeneous. As a result, he has to control for the CD characteristics in the regressions. Also note that even CDs with the same physical condition might not be identical, as CDs with different performers can have different demand.

It should be emphasized that this paper is concerned with the seller's choice of auction formats for *identical* objects. Therefore, we collected data with completely identical items, and sought explanations which depend not on product characteristics,[11] but rather on the seller's characteristics. This differentiates our study from Anderson et al. (2008), who also consider how product characteristics affect choice of auction format. Moreover, we consider the situation in which the sellers choose auction formats within the same venue. This differentiates our study from those in which the sellers post fixed prices in real stores and list items in online auctions simultaneously (e.g., Etzion et al., 2006 and Bose and Daripa, 2009). Finally, and most importantly, as far as we are aware, our paper is the first to compare the BIN auction along with the other two formats.

3 Theoretical Underpinning

The theoretical literature has shown that the BIN option serves two possible purposes in the auctions. The first is to reduce transaction risk for both the sellers and the bidders.

[11] As can be seen from Table 1 in Hasker and Sickles (2010), there exists a substantial difference in auction formats adopted by different categories of products.

For example, Hidvegi et al. (2006) have shown that an appropriately chosen BIN price can improve the utility of the seller when either the bidder or the seller is risk averse. In a more restricted model, Chen et al. (forthcoming) show that BIN necessarily improves the seller's utility unless *both* the bidders and the seller are risk neutral. Both papers are concerned with the Yahoo! permanent BIN model. Mathews and Katzman (2006) and Reynold and Wooders (2009) prove similar results for the eBay temporary BIN model. Based on this theory, we hypothesize that the less experienced sellers, who feel more uncertain of the outcomes of their listings, are more in need to adopt BIN in order to reduce risk. Therefore, we expect a reverse relationship between a seller's experience and his propensity to post a BIN. Since the adoption of BIN is an endogenous decision of the seller, if the above relationship is valid, we can use the seller's experience to endogenize his adoption of BIN.

The second purpose for adoption of BIN that had been discussed in the theoretical literature is that it can be used to satisfy the seller's time impatience. For example, Mathews (2004) showed that unless the seller's time-discount rate is unity, BIN in eBay can improve the seller's utility. The reason for this is quite intuitive. The seller, being time-impatient, offers the bidders the chance to purchase the item at a fixed BIN price without competition, and therefore the possibility to complete the transaction earlier than through the lengthy bidding process. Using this time-impatience framework, Chen et. al. (2013) characterized the seller's optimal choice between the three listing formats as a function of his degree of time-impatience. It was shown that the fixed-price listing and the pure auction are both special cases of a BIN auction. In their model of the BIN auction, the sellers choose the values of BIN prices and reserve price to maximize expected revenue. If the optimal BIN price is so high that no bidder will exercise it, the BIN auction reduces to a pure auction. Furthermore, if the optimal reserve price equals the optimal BIN price, it is essentially a fixed-price format. In other words, the fixed-price listing, the BIN auction and the pure auction are each a solution of the same optimization problem. It is shown that the sellers who are perfectly patient (those whose discount rate is equal to 1) optimally adopt the pure auction; those who are more patient adopt the BIN auction; and those who are impatient (who discount the future heavily) adopt the fixed-price listing.

If the explanation of BIN in the framework of Chen et al. (2013) is correct, we would expect to observe two empirical regularities. First, since BIN serves the need of the time-impatient seller, we should observe that for items that reach transactions, the BIN auction will have a shorter sales duration than the other two formats, given identical posted duration. Second, since a seller with a larger inventory of the same items in a given period will be under more pressure to sell the items quickly, they will be less patient than a seller who has a smaller inventory. Therefore, we would expect a seller with a larger inventory to be more likely to adopt the format preferred by the most impatient sellers, the fixed-price listing. Again, since the adoption of fixed-price listing is also an endogenous decision of the sellers, we will use the size of inventory as an instrumental variable to endogenize their adoption of the fixed-price format. This hypothesis is consistent with Hammond (2010), who also used the size of inventory to endogenize the seller's adoption of the fixed-price format (against the adoption of the pure auction). His reasoning, however, was based on the theory of Harris and Raviv (1981), who showed that for a multi-item monopolist facing capacity constraint, fixed-price listing (auction) is a better selling format when capacity exceeds (falls short of) potential demand. Therefore, Hammond (2010) hypothesized that a seller with more inventory is more likely to adopt a fixed-price format, as his capacity is more likely to exceed demands.

Since risk-aversion and time-impatience are very different in nature, it is difficult to build up a simple theoretical model that can capture both concerns simultaneously. Therefore, in this paper we will not attempt a full theoretical modelling to formally derive its empirical implications. Rather, we only take stock of the empirical regularities that are implied by the two strands of theoretical literature, and test them with the data we have collected.

4 Data Description

The data were from eBay auctions of iPod Nano between November 1 and December 31 of 2007, and every auction was observed from its start to its end. Each observation contained information in three categories: transaction information, price information, and other information. Transaction information included whether the item resulted in a sale and, if yes, in what way it was sold. The price information included starting bid, BIN price posted by the seller, whether there was a secret reserve price, and the transaction price if there was a sale. Other information included auction formats, auction characteristics (starting and ending time, sale and posted durations, number of bids, methods of payment, shipping and handling charge, etc.), product characteristics (generation and capacity of iPods, whether the item was new, etc.), and seller characteristics (account names, time as eBay members, reputation, amount of feedback, etc.).

As is explained in the Introduction, our aim is to investigate why sellers of identical commodities use different auction formats, together with the differences in the auction results. For this purpose, we selected from the whole sample those auctions that were as similar as possible. Specifically, we only included in our data the third generation 4G memory iPods that were new, and excluded auctions with secret reserve prices and those for which certain information was missing in the data-collection process. Eventually we had 1187 auctions.

One of the difficulties for empirical studies of eBay BIN auctions is that the BIN auctions disappear as soon as a bidder places a bid. Therefore, if the investigator collects data of only auction outcomes (rather than the whole process), then there is ambiguity of whether an auction which ends with a competitive bids had been listed as a pure or BIN auction in the beginning. Because of this consideration, we collect data for every auction from its start to its end, and can therefore clearly distinguish between a BIN and a pure auction.

Table 1 reports the basic information of the listing formats and their transaction results. We can see that the majority of the auctions were pure auctions (929 in a total of 1187). There were 178 fixed-price listings and only 80 BIN auctions. Among the 1187 listings, 1085 resulted in a sale (sale rate 91.41%), and the average transaction price was $147.48. Among the items which were sold, 912 were sold with competitive bids,[12] 147 were sold with fixed price, and 26 were sold with BIN.

If we look into more details of the transaction results for each of the three listing formats, we can see that there exists substantial difference. Pure auction had the highest sales rate of 94.83%, but the lowest transaction price ($145.6). Fixed-price listing resulted in the highest transaction price, at about $157, but took the longest time to reach a sale (about 4.5 days). We also note that although BIN auction did not perform best in either sale rate or transaction price, it took the shortest time to reach a sale (about 2.7 days). All these seem to suggest that there exists a certain tradeoff between the three listing formats regarding sales rate, transaction price, and sale duration.

Table 2 reports the summary statistics of auction characteristics. The BIN auctions had a much higher starting bid (average $122.6) than the pure auctions (average $28). We can also see that the BIN prices were about the same for the BIN and fixed-price listings.[13] The pure and BIN auctions had about the same posted durations (slightly over 3 days), and were substantially shorter than that for the fixed-price listing (5.6 days). Quantity is the quantity of available items in a single listing given by the seller. This number is closely related to

[12] Pure auctions and fixed-price auctions must end with the formats they start with, but BIN auctions can end with a bidder winning either with competitive bid or BIN.

[13] As explained in footnote 3, eBay facilitates a fixed-price listing by allowing the seller to post a BIN price only, which serves as the posted price.

the seller's size of inventory. As can be seen from the table, the fixed-price listing had a substantially higher quantity than the other two listing formats.

Table 3 summarizes the characteristics of the sellers. The average number of days the seller had been an eBay member was the largest for fixed-price listings (1640 days), followed by pure auctions (1534 days) and BIN auctions (1469 days). The differences between these numbers were not significant, suggesting that the time a seller had been an eBay member is not an important determinant of the auction format adoption decision. We use the percentage of the amount of positive feedback to total feedback, which we call "positive ratio", as a measure of the seller's reputation. The average positive ratios for the three formats are 0.977, 0.991 and 0.996, respectively. Finally, we construct two variables that are of central importance to our empirical model: the seller's experience and inventory size. Experience score is defined to be the sum of positive and negative feedback that a seller has received.[14] The size of inventory for a seller is the total number of iPods in a seller's possession (sold or unsold) during our study period. We will explain in detail how the size of inventory is defined, and why a seller's experience score and size of inventory are important for our empirical study, in Section 5. As can be seen from Table 3, both variables exhibit substantial difference across the three formats.

All in all, there also exist significant differences in auction characteristics and seller characteristics across the three listing formats.

5 Empirical Model

In this section we formally build up an empirical model to investigate the causes and consequences of adopting different listing formats for the sellers. We ask two questions: First,

[14] For example, if a seller has 6 positive and 3 negative instances of feedback, then his total amount of feedback (and therefore his experience score) is 9.

what motivates a seller's decision to adopt a particular listing format from among the three? Second, what are the consequences of adopting a particular listing format, as compared with the other two? We first use the whole sample to estimate the following trade regression:

$$\begin{aligned} TRADE_i^* &= \beta_0 + \beta_1 \cdot BIN_i + \beta_2 \cdot FP_i + \beta_3 \cdot X_i + \varepsilon_i, \\ TRADE_i &= 1\{TRADE_i^* > 0\}. \end{aligned} \tag{1}$$

The left-hand side of (1) is an estimate of whether listing i results in a sale; BIN_i and FP_i are two dummy variables for whether listing i is a BIN auction ($BIN_i = 1$ if yes, and 0 otherwise) or a fixed-price listing ($FP_i = 1$ if yes; otherwise it equals 0); and ε_i is the error term.

The vector X_i contains variables that influence the transaction probability of the item. They include the starting bid ($STARTBID$), the positive ratio ($POSFB$), and posted duration ($DURATION\_PO$).[15] The level of starting bid determines how many potential bidders will actually place bids and, in its extreme case, whether anyone will bid at all. The higher its value, the more likely that the item remains unsold. Therefore, we expect that there is a negative relationship between the starting bid and the transaction probability. The positive ratio is a measure of the seller's reputation, which has been shown in an enormous amount of literature to have a positive effect on transaction probability.[16] The posted duration should also have a positive relation with transaction probability, as the longer an item is listed, the more likely that bidders willing to bid and buy will arrive.

Since the adoption of listing format is the endogeneous choice of the sellers, which might very well depend on the factors that are correlated with transaction probability and price, we need to find instrumental variables which affect the choice, but not the likelihood and price of transactions. We follow Hammond (2010) in using a seller's size of inventory as an

[15] All the dependent and independent variables, together with their summary statistics, are listed in Table 4.

[16] See surveys of the literature in Bajari and Hortaçsu (2004) and Haruvy and Popkowski Leszczyc (2009). A recent contribution of reputation in online auctions is Livingston (2005).

instrumental variable to endogenize his adoption of the fixed-price format. Our theoretical foundation, however, is different. While Hammond's reasoning is based on the theory of Harris and Raviv (1981) that the adoption of fixed-price listing versus pure auction is influenced by the relative size of capacity and potential demand, our reasoning is based on the theory in Chen et al. (2013), who showed that, among the three listing formats, the fixed-price listing is preferred by the most impatient among the sellers. Therefore, a seller with large inventory, facing more pressure to sell the items rapidly, will be less impatient, and is therefore more likely to adopt the fixed-price format.

A seller's precise size of inventory, however, is very difficult to gauge from the listing webpages. There was no explanation of how the size of inventory was computed in Hammond (2010). In our paper, it is defined in the following way. When a seller had only listed once during the period of our study, then the size of inventory of the seller is defined as the available quantity (which is the variable *Quantity* in Table 2) shown on the seller's listing webpage. If there were at least two listings by the same seller, then we checked if every pair of neighboring listings overlapped in time. If there was overlap, then we assume that the seller had acquired additional items to list before the previous listing ended, and inventory is the sum of available quantities in both listings. If there was no overlap, we assume that the seller simply relisted the items that were unsold in the previous listings, with replenishment if the number of available items in the subsequent listing was more than what remained in the previous listing. Therefore, the size of inventory is the quantity in the previous listing plus the difference of quantities in the two neighboring listings, plus the number of items sold in the previous listing. Finally, if a seller had more than 10 available items in a listing, then we assume that the seller had items so plentiful that there was even no need to adjust for the number of available items in the next listing, and he simply relisted them with the same quantity. In this case the size of inventory is defined to be the maximal quantity of all the seller's listings in our study period.[17]

We therefore run the following regression:

$$FP_i^* = \gamma_0 + \gamma_1 \cdot INVENTORY_i + \gamma_2 \cdot X_i + v_i,$$
$$FP_i = 1\{FP_i^* > 0\}, \tag{2}$$

where $INVENTORY_i$ is the inventory size of listing i's seller, and v_i the error term.[18]

As is explained in Section 3, a main function of BIN is to reduce transaction risk for the seller. A less experienced seller, who feels more uncertain about the transaction outcomes of his listings, will be in more need of the BIN option to reduce risk, and is more likely to adopt the BIN format. We therefore use the experience of a seller as an instrumental variable to endogenize his adoption of the BIN format. Although an obvious proxy of the seller's experience is the number of days he has joined eBay as a member, it is an imperfect measure, as a seller might have joined but remained inactive for a long period of time. Another possible measure is the reputation score (which is the total amount of positive feedback instances minus that of negative feedback instances received by the seller) of the seller. This is not a perfect measure either, as experience is more related to the number of transactions a seller has been through, rather than the number of transactions his buyers are satisfied with. We therefore use the total amount of feedbacks a seller has received (regardless of positive or negative) as the measure of the seller's experience, which in turn is used as the instrumental variable for the seller's decision of whether to adopt the BIN format in listing an item. A question arises as to whether it will be the case that our definition of experience is highly correlated with a seller's reputation and, since reputation affects

[17] We are fully aware that inventory size thus defined is flawed because of data limitations. However, by manual check we found that few listings required complicated calculation. Most sellers listed only once and, if more than once, mostly less than 10. There are 432 sellers in our data. Among them, 298 have a size of inventory equal to 1, and only 25 have an inventory larger than 10.

[18] Zeithammer and Liu (2006) have theoretically shown that heterogeneity of inventory affects the listing preference of the sellers. In our data, all items are identical. Therefore, there is no need to consider inventory heterogeneity. In fact, Hammond (2010) has shown in his data of CDs that heterogeneity does not affect the seller's choice between pure auction and fixed-price listing.

transaction probability, experience is also correlated with transaction probability, making it not a good instrumental variable. This is not the case: In our sample the correlation between reputation and experience is only 0.05. We therefore run the following regression:

$$\begin{aligned} BIN_i^* &= \theta_0 + \theta_1 \cdot EXPER_i + \theta_2 \cdot X_i + u_i, \\ BIN_i &= 1\{BIN_i^* > 0\}, \end{aligned} \tag{3}$$

where u_i is the error term.

Equations (1), (2) and (3) form a simultaneous recursive mixed-process model and, conditioned on the value of X_i, we assume that the error terms follow a joint normal distribution:

$$\begin{bmatrix} \varepsilon_i \\ u_i \\ v_i \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho_{\varepsilon u} & \rho_{\varepsilon v} \\ & 1 & \rho_{uv} \\ & & 1 \end{bmatrix} \right).$$

We use a maximum likelihood method to estimate the value of β's, θ's, γ's and $\rho_{\varepsilon u}$, $\rho_{\varepsilon v}$, ρ_{uv}.

As we are also interested the transaction prices and sale durations for each of the three formats, and as transaction price and sale duration are observable only for items that are sold, we must correct for the sample selection bias in our estimation of the price and sale duration equations. This is therefore a sample selection model in which two explanatory variables are endogenous. (Wooldridge, 2002, p.567.) After substituting the instrumental variables $EXPER$ and $INVENTORY$ into the trade equation, (1) becomes

$$\begin{aligned} TRADE_i^* &= \kappa_0 + \kappa_1 \cdot INVENTORY_i + \kappa_2 \cdot EXPER_i + \kappa_3 \cdot X_i + \eta_i, \\ TRADE_i &= 1\left\{TRADE_i^* > 0\right\}. \end{aligned} \tag{4}$$

The regressions for the transaction price and the sale duration are then

$$Log(TP_i) = \delta_0 + \delta_1 \cdot BIN_i + \delta_2 \cdot FP_i + \delta_3 \cdot S_i + \omega_i, \tag{5}$$

$$DURATION_i = \alpha_0 + \alpha_1 \cdot BIN_i + \alpha_2 \cdot FP_i + \alpha_3 \cdot H_i + \mu_i \tag{6}$$

In equation (5), TP_i is the transaction price plus the shipping cost for auction i. This reflects the fact that the total amount that the buyer pays for an item is its transaction price plus its shipping cost. S_i is the vector of variables which influence the transaction price of auction i. It includes the posted duration and the positive ratio for auction i's seller. In equation (6), the vector H_i contains variables which influence sale duration. It includes the starting bid, the posted duration, and the positive ratio of auction i's seller. Note that the starting bid actually serves as the reserve price in an auction. It affects transaction price only through its influence on transaction probability. That is, a starting bid will not affect the optimal bid of the bidders, but only prevents the low-valuation bidders from placing bids. Therefore it affects transaction price only because the average transaction price with starting bid is the average of the censored transaction prices, rather than all possible transaction prices when starting bid is absent. Because of this, we include starting bid in the transaction probability and duration equations, but not in the price equation.

We use equations (2), (3), (4) and (5) to estimate the price equation, and (2), (3), (4) and (6) to estimate the duration equation. Similar to Hammond (2010), we use the conditional (recursive) mixed-process for our estimation.[19]

6 Results

We first test whether our selection of the instrument variables ($INVENTORY$ and $EXPER$) is valid. For the trade equation, we conduct the weak instrumental variable test to verify whether our choice of instrumental variables is appropriate. Using the rank statistic of Kleibergen and Paap (2006), we reject the null hypothesis that the model is underidentified (χ^2 value 16.62, p-value 0.000046). This suggests that our two instrumental variables are highly related to the choice of the listing formats. Furthermore, as can be seen from

[19] See Roodman (2011) for Stata software implementation.

Table 5, the χ^2-value of the endogeneity test is large (78.8) and highly significant (at the 1% significance level). Table 5 also shows that experience negatively influences a seller's tendency to adopt the BIN format (at 1% significance level), and that the size of inventory positively influences a seller's tendency to adop the fixed-price format (at 5% significance level). These results are consistent with the explanation we propose for the seller's adoption of the BIN and fixed-price formats. All in all, the results for the instrumental variable tests support our hypothesis that experience negatively influences the sellers' incentive to adopt the BIN format, while inventory positively influences their incentive to adopt the fixed-price format.[20]

The second column of Table 5 indicates that the BIN and pure auctions have about the same transaction probability, while the fixed-price format results in the lowest sales rate. Therefore, in terms of transaction probability, the fixed-price format performs the worst. However, this disadvantage is compensated for by its transaction price: As can be seen from the results of the price regression in the second column of Table 6, fixed-price listing results in the highest transaction price, while BIN and pure auctions again perform similarly. Moreover, the sale duration regression in the third column shows that, *conditional on identical posted duration*, a pure auction takes the longest time to result in a sale, followed by the BIN auction, while the fixed-price format is the shortest.[21]

[20] In order to test whether inventory mainly influences the adoption of the fixed-price listing and experience mainly the BIN listing, we also run regressions in which both $EXPER$ and $INVENTORY$ are included in the right-hand sides of equations (2) and (3). The regression results for transaction equation are in Table A1 of the appendix, and the results for price and duration regressions are in Table A2. The results are almost identical, except that now inventory also significantly (but negatively) influences the BIN adoption. This can be explained by the fact that fixed-price listing allows for multi-item listing, while BIN auction only allows for single-item listing. (Pure auction allowed for multi-item listing during the time of our study). Therefore, a seller who has many items is forced to list each item separately if he adopts BIN, which is very time-costly. Therefore, we do expect a negative relation between size of inventory and propensity to adopt BIN. This, however, is due not to the seller's strategic consideration, but to eBay's listing rule.

[21] This does not contradict Table 1, which shows that the fixed-price listing has the longest sale duration. The result reported in the regression has controlled for the length of the posted duration. We have more discussion on sale duration later in this section.

The estimates of other variables are also consistent with the intuition. For example, starting bid has a negative effect on transaction probability, and posted duration has a positive effect on sale duration. The last result requires some explanation. The sale duration should be substantially affected by posted duration, as the latter is an upper bound for the former. Our result — that pure auction takes the longest time to result in a sale, followed by the BIN auction, then the fixed-price listing — is actually very intuitive. In a pure auction, the seller needs to run the full length of posted duration in order to determine the winner. Therefore, there is no chance that the transaction is completed before the end of the posted duration. The fixed-price listing, on the contrary, allows the bidder to place a bid (and end the auction) anytime before it reaches its posted duration. The BIN auction is halfway between the other two formats: Although it allows the bidder to buy out and completes the transaction before the end of the posted duration, once any bidder places a bid, BIN disappears and the auction becomes a pure auction. Therefore, there is a certain probability that the auction will run the full length of the posted duration (if some bidder places a bid), and a certain probability that it will end earlier (if some bidder buys out). Our result, which controls for the posted duration, duly reflects the relative expected sale duration for each listing format *when their posted durations are identical.*

The posted duration, however, is partially a decision variable of the sellers, and is not identical.[22] In the fourth column of Table 6, we take away the posted duration control in the sale duration regression, and a different picture emerges. BIN auction now takes the shortest time to reach a sale, followed by the pure auction, and then the fixed-price listing. This means that the sellers in the BIN auctions will set the posted durations in a way that, relative to the other formats, their items are the earliest to be sold. This can be seen from the fact that although the pure auction takes a longer time to result in a sale (column 3 of

[22] We say "partially" because eBay allows listing of only 1, 3, 5, 7, or 10 days.

Table 6) than the BIN auction when they have identical posted duration, the sellers in the former actually post longer duration than those of the latter. On the other hand, the sellers in the fixed-price format, given that they set the highest prices, will list the items longer than the other formats in order to facilitate finding a high-valuation buyer. This reasoning is also confirmed by the data: As can be seen from Table 2, the fixed-price listing has the longest posted duration.

The picture which emerges is that for the three kinds of transaction results (price, sale rate, and sale duration) we are concerned with, the open-price format (pure and BIN auctions) has a higher sales rate but lower transaction price, as compared to the fixed-price format. Furthermore, although the pure and BIN auctions are similar in both counts, the latter takes a shorter time to reach a transaction. Our results strongly suggest that there exists a tradeoff of transaction rate and price between the open-price and fixed-price listing styles. The sellers' choice between the two styles simply reflects their difference in characteristics and their preference over the price-sale rate tradeoff. When the seller's experience and the size of inventory are controlled for, the sellers who care more about transaction price will prefer the fixed-price style format, although this at the same time implies that the sale probability is the lower. On the other hand, the sellers who care more about sale probability will opt for the auction (open-price) style format.

Within the open-price style format, however, the BIN auction performs better than the pure auction: While they have a similar sale rate and transaction price, the former takes a shorter time to reach a transaction. This explains why the seller will take the additional trouble (computing the correct BIN price is mentally costly) and incurs the cost (there was a fee for posting BIN in eBay during the time of our study) to post a BIN. This result therefore also supports the theoretical explanation of the function of BIN in term of time-impatience (Mathews, 2004 and Chen et al., 2013), in which the seller posts BIN to force the highestvaluation bidders to buy out early (and with the price the seller sets) to avoid a full-length auction.

7 Conclusion and Discussion

Using eBay auction data of iPods, we empirically investigate the reasons behind the seller's strategic choice of listing formats for identical commodities. Our results confirm the hypothesis that more experienced sellers, being more sure of transaction results, are less likely to post the BIN option to reduce risk, and that the sellers who have greater inventory size are more likely to adopt the fixed-price listing. We also investigate the differences in transaction results between different listing formats. Our results suggest that there has not been an "optimal" listing format which performs better than the others, and their choice appears to be a tradeoff between transaction price and transaction probability. Specifically, the choice between the fixed-price and open-price (auction) styles listing reflects the seller's preference over transaction rate and price. Within the open-price style, BIN auction has a similar transaction rate and price as the pure auction, but takes a shorter time to complete a transaction. This confirms the function of BIN to satisfy the need of time-impatient sellers. Our results therefore suggest that, consistent with theory, both risk and time-impatience considerations contribute to the adoption of the BIN option.

A possible concern with our results is that it might be the case that the diversity of formats adopted by the sellers is simply the result that the *same* seller, having several identical items to sell, allocates the items to different formats for reasons unidentified in this paper. This is not the case: In our data, more than 94% of the sellers, regardless of the number of items they list, adopt a single format.

Our data use identical items for study, which enables us to concentrate on a few simple variables that affect price and transaction probability. It also enables us to identify the seller's characteristics, rather than those of the commodity, that influence the format-adoption decision. However, this also raises the question of how general our results are. For this purpose, research with a much larger database comprising a much wider range of commodities, and using much more complicated econometric techniques, is called for. As such, our investigation should be viewed as a preliminary attempt at answering the complicated question of how the sellers frame their strategies in online auctions.

On the other hand, as can be seen from Table 1 in Hasker and Sickles (2010), there exists a substantial difference in listing formats between different categories of commodities. A promising research venue will be to investigate whether otherwise identical sellers adopt different listing formats for different categories of commodities and, if yes, the reason behind this decision.

Table 1: Data Description and Summary Statistics of Auction Results

Listing Format	All	Pure Auction	BIN Auction	Fixed-Price Listing
Number of items sold with competitive bids	912	881	31	-
Number of items sold with BIN	26	-	26	-
Number of items sold under fixed price	147	-	-	147
Number of items resulting in a sale	1085	881	57	147
Number of items not sold	102	48	23	31
Total number of observations	1187	929	80	178
Sales rate	91.41%	94.83%	71.25%	82.58%
Average transaction price (all sold items)	\$147.477	\$145.606	\$151.885	\$156.982
	(15.143)	(14.997)	(11.538)	(13.274)
items sold with competitive bids	\$145.740	\$145.606	\$149.563	-
	(14.917)	(14.997)	(12.018)	
items sold with BIN	\$154.653	-	\$154.653	-
	(10.500)		(10.500)	
items sold with fixed price	\$156.982	-	-	\$156.982
	(13.274)			(13.274)
Average total price (transaction price plus shipping cost)	\$160.317	\$158.823	\$160.464	\$169.214
	(49.922)	(54.867)	(14.464)	(13.605)
items sold with competitive bids	\$158.851	\$158.823	\$159.650	-
	(54.009)	(54.867)	(16.462)	
items sold with BIN	\$161.434	-	\$161.434	-
	(11.902)		(11.902)	
items sold with fixed price	\$169.214	-	-	\$169.214
	(13.605)			(13.605)
Average sale duration (all sold items)	3.293	3.126	2.719	4.517
	(2.425)	(2.333)	(1.634)	(2.834)
items sold with competitive bids	3.120	3.126	2.935	-
	(2.314)	(2.333)	(1.672)	
items sold with BIN	2.462	-	2.462	-
	(1.581)		(1.581)	
items sold with fixed price	4.517	-	-	4.517
	(2.834)			(2.834)

Notes: Standard errors are in parentheses.

Table 2: Summary Statistics of Auction Characteristics

Listing Format	All	Pure Auction	BIN Auction	Fixed-Price Listing
Auction Characteristics				
Starting Bid (*whole sample*)	$35.248	$27.729	$122.570	-
	(54.624)	(48.370)	(46.907)	
items sold with competitive bid	$27.428	$24.912	$98.929	-
	(47.324)	(45.080)	(54.103)	
items sold with BIN	$130.267	-	$130.267	-
	(42.042)		(42.042)	
items unsold	$100.910	$79.432	$145.734	-
	(68.303)	(72.582)	(21.966)	
BIN Price (*whole sample*)	$159.099	-	$160.017	$158.686
	(12.724)		(12.678)	(12.759)
items sold with competitive bid	$161.820	-	$161.820	-
	(16.877)		(16.877)	
items sold with BIN	$157.037	-	$157.037	-
	(9.970)		(9.970)	
items sold with fixed price	$157.628	-	-	$157.628
	(13.003)			(13.003)
items unsold	$162.534	-	$160.955	$163.706
	(9.317)		(7.735)	(10.304)
Posted Duration (*whole sample*)	3.575	3.215	3.325	5.562
	(2.481)	(2.351)	(1.840)	(2.463)
items sold with competitive bid	3.138	3.145	2.935	-
	(2.327)	(2.347)	(1.672)	
items sold with BIN	4.307	-	4.307	-
	(1.784)		(1.784)	
items sold with fixed price	5.592	-	-	5.592
	(2.539)			(2.539)
items unsold	4.382	4.500	2.739	5.419
	(2.203)	(2.042)	(1.738)	(2.094)
Quantity (*whole sample*)	3.237	1.048	1.000	15.663
	(13.025)	(0.408)	(0.000)	(30.874)
items sold with competitive bid	1.046	1.048	1.000	-
	(0.406)	(0.413)	(0.000)	
items sold with BIN	1.000	-	1.000	-
	(0.000)		(0.000)	
items sold with fixed price	18.755	-	-	18.755
	(33.171)			(33.171)
items unsold	1.029	1.063	1.000	1.000
	(0.221)	(0.320)	(0.000)	(0.000)

Notes: Standard errors are in parentheses.

Table 3: **Summary Statistics of Seller Characteristics**

Listing Format	All	Pure Auction	BIN Auction	Fixed-Price Listing
Seller Characteristics				
Days as eBay Members	1545.341	1533.778	1468.875	1640.056
	(886.042)	(881.577)	(991.264)	(857.201)
The Ratio of Positive Feedback	0.981	0.977	0.991	0.996
	(0.116)	(0.130)	(0.012)	(0.009)
Seller's Inventory Size	18.306	18.342	4.400	24.365
	(26.322)	(25.535)	(3.542)	(33.072)
Seller's Experience	850.089	800.973	411.012	1303.765
	(2088.501)	(2065.189)	(1150.064)	(2443.050)

Notes: Standard errors are in parentheses.

Table 4: Definition of Variables and Descriptive Statistics

Names of Variables	Definitions	Mean	Std. Dev.
$TRADE$	Dummy variable which equals 1 if there is a sale, and is 0 otherwise	0.914	0.280
P	Transaction price	147.477	15.143
TP	The transaction price plus shipping cost	160.317	49.922
$DURATION$	Sale duration, days taken to reach a sale	3.329	2.417
BIN	A dummy variable which equals 1 if the listing uses BIN format, and is 0 otherwise	0.067	0.251
FP	A dummy variable which equals 1 if the listing uses fixed-price format, and is 0 otherwise	0.150	0.357
$STARTBID$	Starting bid set by the seller	53.759	67.113
$POSFB$	Ratio of seller's total amount of positive feedback to the total amount of feedback	0.981	0.116
$DURATION\_PO$	The seller's posted duration	3.575	2.481
$INVENTORY$	The seller's total quantity of items in study period	18.707	27.292
$EXPER$	The sum of a seller's positive and negative feedback	850.089	2088.501
$QUANTITY$	The quantity for a listing set by a seller	3.237	13.025

Table 5: Listing Formats and Sales Rate

Dependent Variables	$TRADE$ (1)	BIN (2)	FP (3)
Independent Variable			
BIN	0.103	-	-
	(0.245)		
FP	-0.564***	-	-
	(0.168)		
$Log(STARTBID)$	-0.139***	0.294***	7.418***
	(0.026)	(0.040)	(0.720)
$POSFB$	0.902***	2.126	9.710
	(0.346)	(2.779)	(6.397)
$DURATION\_PO$	0.013	-0.113***	0.175***
	(0.025)	(0.030)	(0.041)
$CONSTANT$	0.862**	-3.991	-47.589***
	(0.363)	(2.761)	(7.172)
$\rho_{\varepsilon u}$	-0.486***	-	-
	(0.112)		
$\rho_{\varepsilon v}$	0.676***	-	-
	(0.095)		
ρ_{uv}	-0.754***	-	-
	(0.063)		
Instrumental Variables			
$EXPER$	-	-0.0002***	-
		(0.000)	
$INVENTORY$	-	-	0.032**
			(0.015)
Endogeneity Test	78.872***	-	-
Log likelihood	-602.469	-	-
Number of Observations	1187	-	-

Notes: (a) Standard errors are in parentheses.

(b) ***, ** and * denote 1%, 5% and 10% levels of significance, respectively.

Table 6: Results on Price and Duration Regressions

Dependent Variables	$Log(TP)$ (5)	$DURATION$ (6)	$DURATION$ (no control)
Independent Variables			
BIN	0.008	-0.503***	-2.322***
	(0.026)	(0.147)	(0.610)
FP	0.224***	-0.691***	0.662**
	(0.015)	(0.087)	(0.259)
$Log(STARTBID)$	-	-0.001	0.221***
		(0.009)	(0.024)
$POSFB$	-0.009	-0.119	-1.322**
	(0.039)	(0.216)	(0.577)
$DURATION\_PO$	-0.012***	0.938***	-
	(0.002)	(0.011)	
$CONSTANT$	5.089***	0.231	4.437***
	(0.039)	(0.218)	(0.567)
Log likelihood	-194.899	-2080.372	-3259.355
Number of Observations	1187	1187	1187

Notes: (a) Standard errors are in parentheses.

(b) ***, ** and * denote 1%, 5% and 10% levels of significance.

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Appendix (for reference only)

Table A1: Regression Results When Both Instrumental Variables Are Included

Dependent Variables	$TRADE$ (1)	BIN (2)	FP (3)
Independent Variable			
BIN	-0.039	-	-
	(0.278)		
FP	-0.522***	-	-
	(0.173)		
$Log(STARTBID)$	-0.135***	0.310***	7.402***
	(0.027)	(0.046)	(0.744)
$POSFB$	0.915***	1.714	9.874
	(0.347)	(1.575)	(6.639)
$DURATION\_PO$	0.007	-0.123***	0.181***
	(0.026)	(0.032)	(0.041)
$CONSTANT$	0.883**	-3.377**	-47.783***
	(0.364)	(1.582)	(7.467)
$\rho_{\varepsilon u}$	-0.402***	-	-
	(0.135)		
$\rho_{\varepsilon v}$	0.627***	-	-
	(0.105)		
ρ_{uv}	-0.733***	-	-
	(0.067)		
Instrumental Variables			
$EXPER$	-	-0.0001***	8.95e-06
		(0.000)	(0.000)
$INVENTORY$	-	-0.044***	0.044***
		(0.014)	(0.016)
Endogeneity Test	38.295***	-	-
Log likelihood	-594.822	-	-
Number of Observations	1187	-	-

Notes: (a) Standard errors are in parentheses.

(b) ***, ** and * denote 1%, 5% and 10% levels of significance, respectively.

Table A2: The MLE Estimates for Price and Duration

Dependent Variables	$Log(TP)$ (5)	$DURATION$ (6)
Independent Variables		
BIN	-0.015	-0.658***
	(0.027)	(0.163)
FP	0.207***	-0.686***
	(0.015)	(0.087)
$Log(STARTBID)$	-	0.003
		(0.009)
$POSFB$	0.018	-0.108
	(0.039)	(0.216)
$DURATION\_PO$	-0.013***	0.936***
	(0.002)	(0.011)
$CONSTANT$	5.057***	0.236
	(0.039)	(0.218)
Log likelihood	-157.708	-2071.387
Number of Observations	1187	1187

Notes: (a) Standard errors are in parentheses.

(b) ***, ** and * denote 1%, 5% and 10% levels of significance, respectively.