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 auction formats in the online auction, and the consequences thereof. We postulate that the sellers adopt different auction formats because of the differences in their experience and the number of items they have. We first use these two characteristics to endogeneize the seller's choice between three auction formats: fixed-price, buy-it-now (BIN), and pure auctions. We then estimate the differences in sales rate, transaction price, and sale duration between the three formats. We find that the fixed-price auction results in the highest transaction price and the lowest sale rate, while the pure auction is just the opposite, with the BIN auction falling in between. These results strongly suggest that there is a tradeoff between price and sale probability in adopting different formats of auctions.

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1 Introduction

The development of the Internet has made online auction one of the most important forms of C2C transactions. Its fast development has also made it into a full-scale research area.[1] The research on 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 formats by which the sellers can list their items in the online auctions: The auction format and the buy-it-now (BIN) format. In the former, the seller lists an item with or without reserve price, and the highest bidder (at the end of auction) wins the item. We will call this the "pure auction" in this paper. There are two types of auctions under the BIN format. In the first, the seller sets a BIN price (only), and the buyers are not allowed to bid. Within the posted duration of the auction, any buyer can click the buy-it-now button and obtain the item with the BIN price. This is equivalent to a fixed-price format, and in this paper we will call it a "fixed-price auction". Under the second type of BIN format, the bidders are allowed not only to buy out the item with BIN price, but also to place competitive bids. In this paper we will call this the "BIN auction". It is important to note that in the eBay auctions, the BIN option is temporary: Once a bidder places a bid before any bidder buys out the item with BIN price, the BIN option will disappear, and the

[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 Ropkowski 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. (2011) 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).

auction will then become a pure auction.[3, 4]

In this paper, we empirically investigate the following questions: 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 sale format mentioned above: the pure auction, the auction with buy-it-now, and the fixed-price auction. We hypothesize, and confirm with 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 their experience as Internet sellers. More experienced sellers, having greater ability to set the optimal price according to their own and the item's characteristics and the market conditions, are more likely to use the fixed-price format to sell their commodities. We therefore use the seller's experience to endogenize his decision of whether to list his item in fixed-price format.

Regarding the adoption of BIN, current theory suggests that the main reason for a seller to use BIN in an auction is to reduce price risk.[5] Therefore, we hypothesize (and confirm with data) that the main determinant of a seller's decision to adopt BIN auction is his risk

[3] The readers are cautioned of the use of terminology in our paper. Since eBay facilitates a fixed-price purchase with BIN in which the buyers are not allowed to place bids, what we call the "fixed-price" auction in this paper is called a BIN auction in some other papers (e.g., Hasker and Sickles, 2010). Also, although fixed-price format is not an auction per se, we call it a fixed-price "auction" for the sake of convenience in explanation. Finally, eBay now does not allow a seller to list an item as a BIN auction, and at the same time sets a starting bid equal to BIN price (which essentially makes it into a fixed-price auction). 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 whether their starting bids equal to BIN prices and, if yes, categorize them as a fixed-price auctions.

[4] There is also a variation of BIN auction, the best-offer auction, 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] See Hidvegi et al. (2006), Mathews and Katzman (2006), Reynolds and Wooders (2009), and Chen et al. (2011).

consideration. Specifically, a seller who has more listings of iPods can diversify price risk through repeated transactions. As a result, he is less likely to list the objects with BIN. We therefore use the seller's number of listings in our study period to endogenize his decision of whether to post his listing in a BIN auction.

In terms of auction results, we show that among the three formats, the fixed price auction has the lowest transaction probability, while the BIN and pure auctions have about the same sales rate. Furthermore, the fixed-price auction has the highest transaction price if the item results in a sale, followed by the BIN auction, and then pure auction. The results therefore imply that there does not exist a dominant auction format. While fixed-price auction results in the highest transaction price, it has the lowest sale rate. Furthermore, although the pure auction has the highest sale probability, it is at the cost of having the lowest transaction price among all auction formats. The pattern is quite clear: The pure auction and the fixed-price auction are polar opposites to each other in transaction rates and transaction price, with one format having the highest in one transaction result and the lowest in the other, and the other format just the opposite. The BIN auction falls in the middle in both transaction rate and price. Our result is therefore consistent with the findings in the theoretical literature that the function of BIN is to reduce risk (e.g., Hidvegi et al., 2006, Mathews and Katzman, 2006, Reynolds and Wooders, 2009, and Chen at al., 2011).

Note that although the seller's consideration is mainly about the tradeoff between sale probability and price, he also takes other factors into account. Our duration regression shows that, if we control for the duration that the seller posts,[6] then the BIN and fixed-price auctions take about the same time to reach a sale, and are shorter than the pure auction. However, if we do not control for the seller's posted duration, then the fixed-price auction

[6] 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).

has the longest duration, followed by the pure auction, and the BIN auction is the shortest. Therefore, the empirical result is also consistent with the theoretical explanation that one of the functions of BIN is to satisfy the buyer's time-impatience (Mathews, 2004).

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 fixed-price and pure auctions 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 auction when the bidders' valuations are more dispersed. 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 three related empirical works. Vakrat and Seidmann (1999) compare prices in the online auctions and the corresponding catalog prices for identical goods,[7] and find that the auction price is 25% lower than the catalog price. They explain the difference by

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

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 of using BIN, together with its consequence. They show that BIN option is more likely to be adopted by sellers with higher ratings and fewer units.[8] 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 to distinguish the three formats considered in our paper. They also do not consider the endogeneity problem of the sellers' choices. Finally, in a highly related paper, Hammond (2010) uses eBay auction data of compact discs to compare fixed-price and pure auctions, and finds that fixed-price goods sell for a higher price, and that pure auction results in higher sale probability. Consistent with our empirical result, he also finds that the sellers with large inventories are more likely to adopt the fixed-price format. Our paper, however, also investigates the BIN auction, together with the sellers' incentive to adopt it.

It should be emphasized that the paper is concerned with the seller's choice of auction formats for *identical* objects. Therefore, we are seeking explanations which depend not on product characteristics,[9] 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. Finally, 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 simultaneously list items in online auctions

[8] Note that in their paper, BIN auctions include all auctions having the BIN options, which are essentially the fixed-price and BIN auctions considered in our paper.

[9] 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.

(e.g., Etzion et al., 2006 and Bose and Daripa, 2009).

2 Data Description

The data were from eBay auctions of the iPod Nano which started 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 iPod, whether the item was new, etc.), and seller characteristics (account names, time as eBay members, reputation, number of feedbacks, etc.).

As is explained in the Introduction, our aim is to investigate why sellers of identical commodities used 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 which had secret reserve prices and those for which certain information was missing in the data-collecting process. Eventually we had 1187 auctions.[10]

Table 1 reports the basic information of the auction formats and their transaction results.

[10] Hammond (2010) also considers identical objects. However, his sample includes both new and used CDs in differing condition. 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.

We can see that the majority of the auctions were pure auctions (929 in a total of 1187). There were 178 fixed-price auctions and only 80 BIN auctions. Among the 1187 auctions, 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,[11] 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 auction formats, we can see that there exists substantial difference. Pure auction had the highest sale rate of 94.83%, but the lowest transaction price ($140.6). Fixed price auction 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 certain tradeoff between the three auction formats.

Table 2 reports the summary statistics of auction characteristics. The BIN auctions had a much higher starting bid (average $122.6) than the pure auction (average $28). We can also see that the BIN prices were about the same for the BIN and fixed-price auctions. 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 auction (5.6 days).

Table 3 summarizes the characteristics of the sellers. The average number of days the seller had become an eBay member was the largest for fixed-price auction (1640 days), followed by pure auction (1534 days) and BIN auction (1469 days). The differences between these numbers were not significant. This suggests that the time a seller had been an eBay member is not an important determinant of the auction format adoption decision. There was, however, a significant difference between the sellers' reputation. The sellers in the

[11] 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. This is because once a bidder places a bid, BIN disappears and the auction becomes a pure auction.

fixed-price auctions had the highest average reputation (1293), followed by pure auction sellers (793) and BIN auction sellers (407). Finally, the pure auction sellers had the largest average number of items during the period of our study (20), which was not substantially greater than that for the fixed-price auction sellers (16). But the BIN auction sellers had far fewer items than the other two (6). This suggests that the number of listings had a certain relationship with a seller's incentive to adopt BIN.

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

3 Empirical Model

In this section we formally build up an empirical model to investigate the causes and consequences of adopting different auction formats for the sellers. We ask two questions: First, what motivates a seller's decision to adopt a particular auction format from among the three? Second, what are the consequences of adopting a particular auction 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 auction i results in a sale; BIN_i and FP_i are two dummy variables for whether auction i is a BIN auction ($BIN_i = 1$ if yes, and 0 otherwise) or a fixed-price auction ($FP_i = 1$ 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 ($STARTBID$), shipping cost ($SHIPCOST$), the ratio of a seller's total numbers of positive feedbacks to that of total feedbacks ($POSFB$; which we will call the "positive ratio"), and posted duration ($DURATION\_PO$).[12] 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 will expect that there is a negative relationship between the starting bid and the transaction probability, as well as the shipping cost. The positive ratio is a measure of the seller's reputation, which has been shown in an enormous amount of literature to have positive effect on transaction probability.[13] 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 auction 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. In a fixed-price auction, the seller has to set a price at which a transaction must occur. In order to do that, he must be familiar with the market environment (including product characteristics, current demand for his own commodity and the competing close substitutes, and how his reputation affects price, etc.) in order to calculate the optimal fixed price.[14] Therefore, we will expect that the sellers who have more experience in the market are more likely to adopt this 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

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

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

[14] Note that in the BIN auction, the sellers also need to set the optimal BIN price. However, BIN price is only an upper bound for the transaction price of an item. If the seller does not have enough experience to calculate the optimal BIN price, he can simply set a high BIN price in order to avoid a mistake. Therefore, lack of experience does not necessarily preclude a seller from using BIN.

measure is the reputation score (the total positive feedbacks minus negative feedbacks from the buyers) 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 number of feedbacks a seller has received (regardless of good or bad) 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 fixed-price format for an item.[15] Specifically, we run the following regression:

$$\begin{aligned} FP_i^* &= \gamma_0 + \gamma_1 \cdot Log(EXPER_i) + \gamma_2 \cdot X_i + v_i, \\ FP_i &= 1\{FP_i^* > 0\}, \end{aligned} \tag{2}$$

where $Log(EXPER_i)$ is the natural logarithm of seller i's experience, and v_i the error term.

As explained in the Introduction, the theoretical literature has shown that the main reason for the sellers to adopt the BIN auction is to reduce price risk.[16] Given this result, we hypothesize that the more items a seller has posted during our study period, the more able he is to reduce (and diversify) price risk through repeated transactions. Consequently, he faces less price risk, and is less likely to adopt BIN.[17] We therefore use the number of items a seller posted during our study period ($LISTNO$) as the instrumental variable for the seller's decision of whether to adopt the BIN format. Specifically, we run the following regression:

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

where u_i is the error term.

[15] 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 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.

[16] For example, Chen et al. (2011) has shown that BIN benefits the seller if and only if either the seller or the bidder is risk-averse.

[17] Also note that eBay charges sellers who list more than 50 items per month for using BIN.

Equations (1), (2) and (3) form a simultaneous probit 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 estimate model to estimate the value of β's, θ's, γ's and $\rho_{\varepsilon u}$, $\rho_{\varepsilon v}$, ρ_{uv}.

We now come to the price and sale duration equations. As transaction price and sale duration are observable only for items that are sold, we use Heckman's two-stage estimation to correct for the sample selection bias in the two equations. Specifically, after substituting the instrumental variables $EXPER$ and $LISTNO$ into the trade equation, (1) becomes

$$\begin{aligned} TRADE_i^* &= \kappa_0 + \kappa_1 \cdot LISTNO_i + \kappa_2 \cdot log(EXPER) + \kappa_3 \cdot X_i + \eta_i, \\ TRADE_i &= 1\{TRADE_i^* > 0\}. \end{aligned} \tag{4}$$

From the estimation of (4) we can construct Mill's ratio. The regressions for transaction price and sale duration are then

$$\begin{aligned} Log(P_i) = \delta_0 + \delta_1 \cdot BIN_i + \delta_2 \cdot FP_i + \delta_3 \cdot S_i \\ + \delta_4 \cdot Mill's\ ratio + \omega_i, \end{aligned} \tag{5}$$

$$\begin{aligned} DURATION_i = \alpha_0 + \alpha_1 \cdot BIN_i + \alpha_2 \cdot FP_i + \alpha_3 \cdot H_i \\ + \alpha_4 \cdot Mill's\ ratio + \mu_i \end{aligned} \tag{6}$$

In equation (5), S_i is the vector of variables which influence the transaction price of auction i. It includes the shopping cost, 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 starting bid actually serves as an open 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 bids distribution, rather than original bids distribution. Therefore, we include starting bid in the transaction probability and duration equations, but not in the price equation.

4 Results

We first test whether our selection of the instrument variables ($LISTNO$ and $EXPER$) is valid. As can be seen from Table 5, the F-values in the weak instrumental variable test are 4.69 and 8.39 for BIN and FP, and are significant at 5% and 1% statistical levels, respectively. Moreover, the χ^2-value of the endogeneity test is also large and highly significant (at the 1% statistical level). Both results imply that our choice of the two instrumental variables is valid. Table 5 also shows that the number of listings ($LISTNO$) negatively influences the seller's tendency to adopt the BIN format (at 5% significance level), and that the seller's experience has a positive effect on his incentive to adopt the fixed-price format (at 1% significance level). These are also consistent with the explanations we propose for the seller's adoption of the BIN and fixed-price formats.[18] All in all, the results in Table 5 support our hypothesis that the more experienced the sellers are, the more likely they are to adopt the fixed-price format; and that the more items the sellers have, the less likely are they to adopt the BIN format. In other words, experience positively influences the sellers'

[18] In order to make sure that listing number only affects the choice of buy-it-now, and experience affects only the choice of fixed-price format, we also run regressions in which both $LISTNO$ and $EXPER$ enter as dependent variables in (2) and (3). The results are reassuring: $LISTNO$ has no significant influence on FP, and $EXPER$ has no significant influence on BIN. See Table A1 in the Appendix.

incentive to adopt the closed-price auction format, while the number of items negatively influences their tendency to adopt the BIN format.

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 sale 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 auction results in the highest, and pure auction the lowest, transaction price, while BIN auction falls in the middle. The sale duration regression in the third column shows that pure auction takes the longest time to result in a sale, followed by the BIN auction, while the fixed-price auction is the shortest.[19]

The picture which emerges is that for the three kinds of transaction results (price, sale rate, and sale duration) we are concerned with, the pure auction and the fixed-price auction always take the opposite polar positions, while the BIN auction falls in the middle. That is, the pure auction and the fixed-price auction are polar opposite to each other in transaction rates and transaction price, with one format having the highest in one transaction consequence and the lowest in the other, and the other format just the opposite. The BIN auction falls in the middle in both transaction rate and price.

Our results strongly suggest that there exists a tradeoff between the three auction for-

[19] In Table 6, the coefficient for Mill's ratio is not significant in either price or duration equation. This is mainly due to the fact that, in our sample, the transaction rates are very high: 95%, 71% and 83% for pure, BIN, and fixed-price auction, respectively. In Table A2 of the Appendix, we show the results of MLE estimation which considers only endogeneity problem without controlling for sample selection bias. All properties remain similar except that now BIN has the lowest transaction price, which might be because the sale rate for BIN auction is substantially lower than the other two (see Table 1). This shows that, although the Mill's ratios are not significant, it is still necessary to control for the selection bias in order to obtain the unbiased results for each type of auction. Note that although BIN auction has the lowest sale rate in the data, our regression shows that, when controlled for other characteristics, its sale rate is among the highest. This is mainly because (i) the starting bid of the BIN auction is much higher than that of the pure auction ($122.6 vs. $28; see Table 2); and (ii) the positive ratio for the sellers in the fixed-price auction is higher than that of the BIN auction (0.996 vs. 0.991, significant at 1% statistical level).

mats. The sellers' choice of one among the three formats simply reflects their difference in characteristics and their preference over the price-sale rate tradeoff. When the seller's experience and number of listed items are controlled for, the sellers who care more about transaction price will prefer the fixed-price format, although this at the same time implies that the sale probability is the lowest. On the other hand, the sellers who care more about sale probability will opt for the pure auction format. Note that our results also support the theoretical literature that one of the reasons for adopting BIN is out of risk concern: BIN auction falls in the middle in transaction price, sale rate, and sale durations. On a more theoretical level, we can view the sellers as facing a "portfolio selection" problem, in which they choose between the auction formats in order to balance the tradeoff between transaction probability and sale price. The sellers who view price as more important will choose the fixed-price format, while those who care more about sale probability will prefer pure or BIN auctions.

The estimates of other variables are also consistent with the intuition. For example, shipping cost has a negative effect on both transaction price and transaction rate; 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 is 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 auction — 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 of an earlier ending. The fixed-price auction, on the contrary, allows the bidder to place bid (and end the auction) anytime before it reaches its posted duration. The BIN auction is halfway between these two formats: Although it allows the bidder to buy out, once any bidder places a bid, BIN disappears and the auction becomes a pure auction. Therefore, there is 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 auction format when their posted durations are identical.

The posted duration, however, is partially a decision variable of the sellers, and is not identical.[20] 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 auction. This means that the sellers in the BIN auctions will set the posted durations in a way that, relative to the other formats, they are earliest to be sold. On the other hand, the sellers in the fixed-price auctions, given that they set the highest prices, will post the items longer than the other formats in order to facilitate finding a high-valuation buyer. Our result therefore also supports the theoretical explanation of the function of BIN in term of time-impatience (Mathews, 2004), in which the bidders are willing to pay a premium (relative to the pure auction) to buy out the items before any other interested (but not high-valuation) bidder enters and places a bid.

5 Conclusion and Discussion

Using eBay auction data of iPods, we empirically investigate the reasons behind the seller's strategic choice of auction formats for identical commodities. Our results confirm the hypothesis that more experienced sellers are more likely to adopt the fixed-price auctions, and that the sellers who have more items are less likely to adopt the BIN format. We also investigate the differences in transaction results between different auction formats. Our results

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

suggest that there has not been an “optimal” auction format which performs better than the others, and the choice of auction format appears to be a tradeoff between transaction price and transaction probability. Our result also suggests that, consistent with theory, both risk and time-impatience considerations contribute to the adoption of the BIN auction.

A possible concern of 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 post, use 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 on the seller's characteristics, rather than that 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 substantial difference in auction formats between different categories of commodities. A promising research venue will be to investigate whether otherwise identical sellers use different auction formats for different categories of commodities and, if yes, the reason behind this decision.

Table 1: Data Description and Summary Statistics of Auction Results

Auction Format	All	Pure Auction	BIN Auction	Fixed-Price Auction
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	1187	929	80	178
Sales rate	91.41%	94.83%	71.25%	82.58%
Average transaction price (all sold items)	$147.477	$140.606	$151.885	$156.982
items sold with competitive bids	$145.740	$140.606	$149.563	-
items sold with BIN	$154.653	-	$154.653	-
items sold with fixed price	$156.982	-	-	$156.982
Average duration (all sold items)	3.293	3.126	2.719	4.517
items sold with competitive bids	3.120	3.126	2.935	-
items sold with BIN	2.462	-	2.462	-
items sold with fixed price	4.517	-	-	4.517

Table 2: Summary Statistics of Auction Characteristics

Auction Format	All	Pure Auction	BIN Auction	Fixed-Price Auction
Auction Characteristics				
Starting Bid (*whole sample*)	\$35.248	\$27.729	\$122.570	-
items sold with competitive bid	\$27.428	\$24.912	\$98.929	-
items sold with BIN	\$130.267	-	\$130.267	-
items unsold	\$100.910	\$79.432	\$145.734	-
BIN Price (*whole sample*)	\$159.099	-	\$160.017	\$158.686
items sold with competitive bid	\$161.820	-	\$160.820	-
items sold with BIN	\$157.037	-	\$157.037	-
items sold with fixed price	\$157.733	-	-	\$157.733
items unsold	\$162.534	-	\$160.955	\$153.706
Posted Duration (*whole sample*)	3.575	3.215	3.325	5.562
items sold with competitive bid	3.138	3.145	2.935	-
items sold with BIN	3.561	-	3.561	-
items sold with fixed price	5.592	-	-	5.592
items unsold	4.382	4.500	2.739	5.419

Table 3: Summary Statistics of Seller Characteristics

Auction Format	All	Pure Auction	BIN Auction	Fixed-Price Auction
Seller Characteristics				
Days as eBay Members	1545.341	1533.778	1468.875	1640.056
items sold with competitive bid	1527.368	1535.142	1306.452	-
items sold with BIN	1736.539	-	1736.539	-
items sold with fixed price	1573.448	-	-	1573.448
items unsold	1621.176	1508.750	1385.217	1970.323
Reputation Scores	841.615	792.525	407.038	1293.135
items sold with competitive bid	722.034	740.232	204.871	-
items sold with BIN	283.692	-	283.692	-
items sold with fixed price	1428.293	-	-	1428.293
items unsold	1207.520	1752.333	818.966	652.226
Seller's Number of Listings	18.707	20.259	6.075	16.281
items sold with competitive bid	19.613	20.800	4.484	-
items sold with BIN	5.115	-	5.115	-
items sold with fixed price	18.252	-	-	18.252
items unsold	9.069	10.333	9.304	6.935

Table 4: Definition of Variables and Descriptive Statistics

Names of Variables	Definitions	Mean	Standard Error
$TRADE$	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
$DURATION$	Sale duration, days taken to reach a sale	3.329	2.417
BIN	A dummy variable which equals 1 if the auction uses BIN format, and is 0 otherwise	0.067	0.251
FP	A dummy variable which equals 1 if the auction uses fixed-price format, and is 0 otherwise	0.150	0.357
$STARTBID$	Starting bid set by the seller	53.759	67.113
$SHIPCOST$	Shipping cost set by the seller	12.810	46.236
$POSFB$	Ratio of seller's total amount of positive feedbacks to the total amount of feedbacks	0.981	0.116
$DURATION\_PO$	The seller's posted duration	3.575	2.481
$LISTNO$	The total number of listings by a seller in study period	18.707	27.292
$EXPER$	Total amount of a seller's feedbacks	850.089	2088.501

Table 5: Auction Formats and Sales Rate

Dependent Variables	$TRADE$ (1)	BIN (2)	FP (3)
Independent Variable			
BIN	-0.060	-	-
	(0.266)		
FP	-0.725***	-	-
	(0.166)		
$Log(STARTBID)$	-0.131***	0.288***	6.908***
	(0.026)	(0.043)	(0.689)
$Log(SHIPCOST)$	-0.028**	-0.024**	0.026*
	(0.013)	(0.010)	(0.015)
$POSFB$	1.003***	1.336	5.957
	(0.349)	(1.300)	(5.602)
$DURATION\_PO$	0.017	-0.125***	0.157***
	(0.026)	(0.032)	(0.036)
$CONSTANT$	0.817**	-3.083**	-41.578***
	(0.365)	(1.312)	(6.360)
$\rho_{\varepsilon u}$	-0.432***	-	-
	(0.120)		
$\rho_{\varepsilon v}$	0.780***	-	-
	(0.072)		
ρ_{uv}	-0.721***	-	-
	(0.073)		
Instrumental Variables			
$LISTNO$	-	-0.023**	-
		(0.011)	
$Log(EXPER)$	-	-	0.097***
			(0.034)
Weak Instrumental Variable Test	-	4.69**	8.39 ***
Endogeneity Test	252.800***	-	-
Log likelihood	-599.049	-	-
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	$Log(P)$ (5)	$DURATION$ (6)	$DURATION$ (no control)
Independent Variables			
BIN	0.039***	-0.818***	-1.399***
	(0.013)	(0.209)	(0.226)
FP	0.096***	-0.909***	0.469**
	(0.010)	(0.134)	(0.268)
$Log(STARTBID)$	-	0.017	0.288***
		(0.015)	(0.026)
$Log(SHIPCOST)$	-0.003***	-	-
	(0.000)		
$POSFB$	0.001	-0.295*	-2.096**
	(0.023)	(0.178)	(0.838)
$DURATION\_PO$	-0.003**	0.954***	-
	(0.002)	(0.009)	
$MILL's\ RATIO$	-0.047	-0.519	-2.346***
	(0.031)	(0.543)	(0.877)
$CONSTANT$	4.994***	0.472**	5.462***
	(0.026)	(0.237)	(0.878)
Log likelihood	904.532	-1254.020	-2422.250
Number of Observations	1085	1085	1085

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	-0.084	-	-
	(0.280)		
FP	-0.674***	-	-
	(0.171)		
$Log(STARTBID)$	-0.132***	0.291***	6.785***
	(0.027)	(0.044)	(0.693)
$Log(SHIPCOST)$	-0.029**	-0.023**	0.024
	(0.014)	(0.010)	(0.015)
$POSFB$	0.992***	1.824	7.428
	(0.350)	(1.484)	(5.998)
$DURATION\_PO$	0.013	-0.125***	0.163***
	(0.026)	(0.032)	(0.038)
$CONSTANT$	0.845**	-3.473**	-42.507***
	(0.366)	(1.427)	(6.676)
$\rho_{\varepsilon u}$	-0.418***	-	-
	(0.129)		
$\rho_{\varepsilon v}$	0.746***	-	-
	(0.081)		
ρ_{uv}	-0.728***	-	-
	(0.073)		
Instrumental Variables			
$LISTNO$	-	-0.022*	0.009
		(0.011)	(0.008)
$Log(EXPER)$	-	-0.023	0.094***
		(0.036)	(0.036)
Weak Instrumental Variable Test	-	5.85*	9.63 ***
Endogeneity Test	104.753***	-	-
Log likelihood	-597.818	-	-
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	$Log(P)$ (5)	$DURATION$ (6)
Independent Variables		
BIN	-0.133***	-0.892***
	(0.037)	(0.215)
FP	0.106**	-0.971***
	(0.050)	(0.142)
$Log(STARTBID)$	-	0.006
		(0.004)
$Log(SHIPCOST)$	-0.005***	-
	(0.000)	
$POSFB$	0.024	-0.131***
	(0.036)	(0.043)
$DURATION\_PO$	-0.005*	0.954***
	(0.003)	(0.012)
$CONSTANT$	4.978***	0.259***
	(0.036)	(0.068)
Log likelihood	386.399	-1482.315
Number of Observations	1085	1085

Notes: (a) Standard errors are in parentheses.
(b) ***, ** and * denote 1%, 5% and 10% levels of significance, respectively.