Mechanism Choice and the Buy-It-Now Auction: A Structural Model of Competing Buyers and Sellers

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Abstract

In many markets, similar or identical goods are sold using different mechanisms. Little yet is known about what causes this multiplicity of mechanisms and how it affects competition. In this paper, I specify and estimate a structural model of mechanism choice in online markets. I consider both sides of the market: On the demand side, buyers' choices among available listings are equilibrium outcomes of an entry game. On the supply side, sellers make equilibrium decisions when choosing sales mechanisms and prices. I estimate this model using data from sales of baseball tickets on eBay. I find that sellers' outside options, dynamic incentives, and risk preferences affect mechanism choice. Using the estimation results from my model I analyze the welfare effects of a hybrid mechanism (buy-it-now auctions) eBay offers. I find that the existence of buy-it-now auctions increases the consumer surplus and reduces the producer surplus. The reason for this is that buy-it-now auctions diminish sellers' potential for diversification via mechanism choice and thus strengthen competition.

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1 Introduction

Online sales platforms have grown to be a major part of the US and world economy. Goods worth close to 60 billion dollars were sold on the websites of market leader eBay alone in 2009.[1] The rise of these platforms has brought us an abundance of new sale mechanisms. Particularly popular are mechanisms which incorporate features of both auctions and posted prices, like eBay's buy-it-now (BIN) auction.

In a buy-it-now auction, the seller sets two prices: A reserve price and a posted so-called "buy-it-now" price. The first arriving bidder has the option to either purchase the good at the buy-it-now price or to submit an auction bid greater than or equal to the reserve price. In the former case, the listing disappears as the item is sold. In the latter case, the listing turns into a standard eBay auction in which anyone can participate. The buy-it-now auction was introduced by eBay in 2000. Many of eBay's competitors now offer similar mechanisms; examples include eBid's "Buy Now" facility and uBid's "u Buy It" feature. Despite their success, little is known so far about revenue and efficiency implications of these mechanisms.

Besides these questions of mechanism design, online sale platforms also highlight a puzzle of mechanism choice: Why is it that similar or identical goods are sold in so many different ways? This is particularly surprising since one might think that an auction with reserve price r creates weakly more revenue than a posted price sale with price r. While numerous authors have shown that this naive intuition fails in many settings and showed that simple auctions are not always optimal[2] the question remains why multiple mechanism can coexist in one market.

In this paper, I use sales data from eBay to examine both of these questions. I develop and estimate a model of supply and demand in online markets and investigate the factors that drive mechanism choice. Based on my estimation results I then simulate a counterfactual market in which only auctions and fixed price (FP) listings are available, but no hybrid form of the two. This allows me to gain insight into the effects BIN auctions have on consumer and producer surplus.

My main result sheds light on the welfare effects of BIN auctions. One might think that sellers necessarily benefit from the BIN option. After all, both FP listings and auctions are incorporated

[1] eBay Annual Report. San Jose: eBay Inc., 2009.

[2] Standard auctions have been shown not to be optimal when bidders are asymmetric (Myerson 1981); when bidders have information about other bidders' valuations (Crémer and McLean 1985 and 1988); when auctions are costly (Wang 1993); or when buyers have interdependent valuations (Campbell and Levin 2006).

into BIN auctions by setting appropriate BIN prices equal to the reserve or to infinity, respectively. That is to say that BIN auctions weakly dominate both other mechanisms in my study. Contrary to this intuition, I find that sellers achieve lower revenues when BIN auctions are available, compared to a situation in which they can choose only between auctions and FP listings. That is, while it is individually optimal to choose a BIN auction these devices strengthen competition so that the new equilibrium is less attractive to sellers. Instead, buyers benefit from the additional mechanism.

Intuitively, the availability of a hybrid mechanism makes competition between sellers fiercer. Assume there are two sellers, who simultaneously offer their items. Further assume, that some buyers ("FP lovers") prefer to buy at posted prices[3], while others ("neutrals") only care about the price and the quality of the good. Then one seller can list his item at a fixed price, while the other one can target neutrals by offering an auction. In this case, demand should not be very elastic. FP lovers are unlikely to enter the auction, since they prefer posted prices. Neutrals are not prone to enter the FP listings as auctions yield a more efficient outcome: A high value bidder might not receive the item at a posted price because someone else might beat him to it. In the auction however, he has a much higher chance of winning and obtaining the product.

Now compare this to a setting where BIN auctions do exist. We can think of the separation strategy as one seller setting the BIN price equal to the reserve price while the other sets the BIN price equal to infinity. However, now the sellers have incentives to deviate. For instance, the seller with BIN price of infinity (previously the auction seller) will now prefer to reduce the BIN price to a high but finite level. This gives him a chance to sell at a very high price, benefiting from buyers preference for FP purchases. That is, now both sellers will compete for both types of entrants and thus they'll drive each other's prices down much more than before.

This result is reminiscent of two papers from the marketing literature: Lal and Matutes (1989) consider a setting in which two stores each offer two goods. Buyers of two types (rich and poor) want to purchase one unit of each good, where rich buyers have higher transportation costs than their poor counterparts. When the sellers split the market, so that each store charges a high price

[3]There are several reasons why buyers might prefer posted prices over auctions. For instance, risk averse buyers might choose to buy at fixed prices because this allows them to secure a surplus at a certain level, while in auctions they face the risk of competing with a high-value bidder and thus not winning the auction or paying a very high price. Another factor in favor of fixed prices is impatience. Auctions on eBay run for a pre-specified time, while fixed price listings end as soon as a buyer purchases the item. Thus, fixed price listings often allow buyers to receive the item several days earlier than auctions listings.

for one and a low price for the other good, they are better off than in an alternative equilibrium where they compete in both goods. This is because in the former case the stores are able to extract the total rent from rich buyers, who are unwilling to drive from one store to the other in order to get the low prices on both goods. Contrary to that, in the latter equilibrium rich buyers benefit from the stores' competition over poor customers and pay lower aggregate prices. Similarly, Bakos and Brynjolfsson (2000) find that the possibility to bundle goods hurts sellers in a competitive market place. This seems to be the case because by bundling the sellers make their goods more similar to each other and thus increase the substitutability between the two.

To study these effects, I develop a structural model of supply and demand. On both sides of the market, agents make equilibrium decisions. Buyers make purchases based on item and mechanism characteristics. When evaluating the listings offered, they take other buyers' expected decisions into account; thus, a buyer might be hesitant to enter a listing which he deems particularly popular. So far, this equilibrium approach has to my knowledge not been used; instead, previous authors postulated random arrival or reduced the listing choice on the demand side to a single agent problem by ignoring the interdependence with other agents. The advantage of my approach is that it allows us to gain a deeper insight into competition among sellers.

Sellers, on the other hand, set mechanisms and (reserve) prices based on their revenue expectations, their outside options for the tickets, and their listing costs associated with the mechanisms. They also have expectations over buyers' and other sellers' behavior and adjust their decisions accordingly. I contribute to the growing literature of mechanism choice by incorporating BIN auctions into sellers' mechanism options. BIN auctions account for a large share of eBay sales; ignoring them therefore leads to a misspecified model and thus misestimated welfare implications, as demonstrated by my counterfactual result.

I estimate this model using sales data on Major League Baseball Tickets on eBay. On the demand side, I specify an equilibrium entry model with random coefficients. This allows me to uncover the distribution of valuations as a function of item characteristics. On the supply side, I back the outside options out of the first-order condition from the sellers' price-setting problem. My model allows sellers to be heterogeneous with respect to mechanism costs as well as their risk preferences. I assume that sellers' preferences display either risk-neutrality or constant absolute risk aversion. These two parameters together with revenue expectations explain sellers' mechanism choices. I estimate the respective distributions of mechanism costs and risk attitudes by a probit approach.

Event tickets are a particularly interesting target of attention because of the dynamics involved. Intuitively, as the game day draws near, the seller's opportunity costs of sale should fall, since there are fewer possibilities of relisting unsold items. Indeed, I find that the mean outside option decreases over time. This development is reflected in sellers' mechanism choices, as sellers with more valuable outside options are more likely to sell their items in FP listings, while those with relatively poor outside options prefer auctions. This is because in my data auction listings sell with a higher probability, while FP listings achieve a greater revenue if a sale does occur. I also find evidence for significant levels of risk aversion among sellers and show that this, too, is reflected in their mechanism choice.

The estimation of the structural model allows me to understand how sellers' make their listing decisions and how buyers' make entry and purchase decisions. Armed with this information I can uncover the welfare effects of BIN auctions by comparing actual outcomes with those from a simulated marketplace in which only FP listings and auctions exist. I find that buyers benefit from the existence of hybrid mechanisms. The introduction of BIN auctions increases their consumer rents between 0.55% and 5.78%. Sellers, on the other hand, would prefer a situation without BIN auctions. Their utilities would be between 11.91% and 15.84% higher if only posted prices and auctions would exist. eBay itself also would be better off without BIN auctions, earning almost 11% higher revenues from fees.[4]

This paper proceeds as follows. Section 2 places this work into the context of the literature. In section 3, I discuss the institutional background and introduce the data. Section 4 presents the structural model. In section 5, I discuss the modeling assumptions in detail. Section 6 explains the estimation strategy. Section 7 discusses the estimation results. In section 8, I study the welfare effects of BIN auctions. Section 9 concludes.

[4]It is worth noting, however, that this analysis does not take competition effects between different online sales platforms into account. It is possible that buyers, realizing their benefit, are keen to have the BIN option; thus, abandoning the BIN auctions might reduce eBay's buyer base. If this effect is strong enough, it might offset the calculated revenue loss and make offering BIN auctions an optimal strategy for eBay.

2 Literature Review

Ever since its introduction by eBay in 2000, the buy-it-now auction and similar mechanisms have captured the attention of researchers. At first many economists focused on the question of why a finite buy-it-now price might be beneficial to sellers compared to standard auctions. Several reasons have been proposed for why sellers might achieve a higher revenue or higher utility when using hybrid mechanisms:

- risk aversion by buyers or sellers (Reynolds and Wooders (2009), Zhang (2009), Budish and Takeyama (2001), Hidvégi, Wang and Whinston (2006), Ackerberg, Hirano and Shariar (2006, henceforth AHS))
- impatience by buyers or sellers (Matthews (2003), Gallien and Gupta (2007), AHS)
- attracting buyers in a model with endogenous entry (Wang, Montgomery and Srinivasan (2004))
- BIN prices can serve as focal points for buyers' bidding strategies and thus lead to more aggressive bidding (Yoo, Ho, Tam (2006)).
- In common value settings, buyers tend to put too much weight on their private information which might cause them to buy at inflated BIN prices (Shahriar and Wooders (2007)).

These papers generally treat auctioneers as monopolists. To my knowledge the only work that considers the effects of buy prices in a setting of competing auctions is Kirkegaard and Overgaard (2008). In a theoretical model, Kirkegaard and Overgaard investigate BIN auctions in a setting in which two auctioneers compete for buyers in a sequential game. They show that allowing the first auctioneer to set a BIN price increases this seller's revenue. However, total revenue is reduced because of the inefficiency introduced by the BIN auction: since a buyer with a low valuation might arrive first it is not clear anymore that the two bidders with the highest valuations are served. In contrast, I consider a much richer setting: in my model, sellers start simultaneous listings and compete with each other for the available demand at any given time. Also, I give sellers the choice between auctions, FP listings and BIN auctions, whereas all papers mentioned above ignore the existence of FP listings.

In my model, buyers actively decide which listing to enter. This is in contrast to the large array of empirical papers which assume random arrival. Several authors before me have dealt with entry problems in similar contexts. Athey, Levin and Seira (2011), Li and Zheng (2009), and Roberts and Sweeting (2010) present models of entry in auctions. In their models auctions are taken individually and the motivation not to participate comes from a monetary cost associated with entry. In contrast, I allow buyer to choose which listing to enter; that is, there is an opportunity cost of entry since entry in one listing prevents the buyer from entering other concurrent listings. Seim (2006) investigates how firms, upon entering a market, endogenously make a location choice. Similarly, I let buyers choose endogenously among listings; sellers set mechanisms and prices. Agents in both papers face incomplete information when making the entry decision. One important difference between my model and Seim's is that in her model the expected profits of firms come out of a reduced form assumption, while in mine I calculate buyers' expected profits according to the actual bidding process they go through. The advantage of the latter approach is that it allows me to more accurately capture the effect of competition.

Finally, and most closely, my work is related to the literature on mechanism choice. On the theoretical side, a number of authors have studied which mechanisms might arise from competition between sellers. Various settings have been studied. Some authors find a multiplicity of equilibria (Coles and Eeckhout (2003), Kultti (1997)). Others argue that auctions might arise naturally from competition between sellers. They show that auctions form the only symmetric (Virag (2007) and Peters (2001)) or stable equilibrium (Lu and McAfee (1996)) in the respective mechanism choice games studied. Similarly, Julien, Kennes and King (2002) find that when sellers play a sequential game in which they first commit to mechanisms and then set prices, auction arise as the only equilibrium strategy.

In terms of empirics, Zeithammer and Liu (2006) consider several explanations for mechanism multiplicity on eBay. They argue that seller heterogeneity, for instance with respect to inventories, at least partially account for the use of different mechanisms. Similarly, Hammond (2010b) presents evidence that seller's mechanism choices in online markets for compact discs depend on their inventory. Sellers with larger inventory tend to prefer FP sales.

AHS concentrate on the BIN option in eBay auctions. Their agents might choose to purchase at the BIN price rather than bidding in an auction because it allows them to receive the item earlier and with certainty while otherwise they have to go through the auction process. Using data from auctions of different length, AHS are able to separately identify the CARA risk parameter and a discount factor. There are two major differences between their paper and this one: First, in AHS buyers arrive randomly in given auctions while in my model entry in listings is an equilibrium outcome. Second, AHS concentrate on buyers' behavior while I am mainly interested in sellers' mechanism choices. The two groups have very different problems to solve. Buyers choose between two pre-determined alternatives, while sellers face a jointly discrete and continuous problem: They simultaneously choose among three mechanisms and set the optimal price. In addition, sellers have to take buyers' reactions into account, while buyers can maximize as single agents.

Probably most closely related to my work is Hammond (2010a). Hammond uses a data set of compact disc sales on eBay; the mechanisms in the data set include auction and FP listing. Hammond builds a structural model of mechanism choice by buyers and sellers and shows that sellers with better outside options prefer fixed prices while those with low value outside options prefer auctions. Both Hammond and I develop models which allow buyers to choose among listings and sellers among mechanisms. However, my work differs from his in several ways: First, Hammond models buyers' entry decisions as a single agent problem. In contrast, in my model buyers find an entry equilibrium, taking other buyers' expected choices into account. This adds insight to the effect of competition among sellers. Second, Hammond ignores BIN auctions; by explicitly modeling them I'm able to study the welfare effects of the introduction of BIN auction.

3 Data

In this section, I first give a brief description of the institutional details of the market. I then describe my primary data. Afterwards I introduce two supplementary datasets I use.

3.1 Market Description

eBay is a major online sales platform, allowing private users and small businesses to sell items to each other. Several sales mechanisms are offered; the three most common ones are FP sales, standard auctions and BIN auctions. All three are used for single unit sales. In FP listings, items are available at posted prices. The first buyer who presses the buy button receives the item and has to pay the seller's price.[5] Auction participants can bid either like in English auctions or like in second-price sealed bid auctions (SPA). The similarity to English auctions comes from the fact that bidders successively raise their bids. The connection to SPAs is two-fold: First, eBay features an automatic bidding system ("proxy bidding") which allows bidders to enter the maximum amount they are willing to bid and then automatically raises the bid whenever necessary to remain the high bidder. This is continued until the maximum amount indicated is reached. Second, eBay auctions have a pre-specified end time ("hard close") and most bids tend to be submitted close to that time ("sniping").[6] The aim of sniping is to bid so late that no other bidder has a chance to react by submitting a new, higher bid. As long as other bidders do not bid their valuations, a successful sniper can therefore receive the item at a price significantly below the outcome of a standard English auction. BIN auctions are a hybrid between auction and FP sale. The first bidder is given the choice between buying for a posted "buy-it-now" price and submitting a bid in the auction setting. In the former case, the buyer receives the item exactly as he would in FP listings. In the latter case, the BIN option disappears and the listing turns into a standard eBay auction.

Since buyers and sellers in online market places do not usually interact repeatedly, fraud is a major concern on the websites of eBay and its competitors. To address this issue, eBay uses a reputation system. After each transaction, both the buyer and the seller have the opportunity to indicate their satisfaction with their counterparty's conduct. Feedback consists of a positive, neutral, or negative rating and a short comment. Buyers' comments often include remarks about the seller's communication style, shipping speed, and accuracy of description. Buyers observe a feedback score and all feedbacks from the last twelve months before they submit a bid. As previous researchers have shown, sellers' feedback scores are an important determinant of the sale price achieved and thus provide an incentive against fraudulent behavior.[7]

For the estimation I use sales data for Major League Baseball Tickets for home games of the Cincinnati Reds on eBay. The Cincinnati Reds do not themselves sell tickets on eBay. Instead, they offer tickets for instance through their own website (http://cincinnati.reds.mlb.com) or at ticket kiosks. These tickets are purchased by fans as well as ticket brokers and scalpers. Offers on eBay

[5] eBay does not speak of fixed price listings on their website. Instead, these listings are called"Buy-It-Now", but no auction option is offered. In contrast, BIN auctions feature both the Buy-It-Now option and the auction alternative.

[6] Roth and Ockenfels (2002) and Ockenfels and Roth (2006) among others provide evidence for the existence of sniping.

[7] See for instance Lucking-Reiley et. al. (2007).

come from fans who no longer wish to use previously purchased tickets and from professional resellers. This market is particularly thick for MLB tickets since few holders of season tickets are able to attend all 81 home games.

3.2 Primary Data

My primary dataset contains sales of Major League Baseball tickets on eBay. Particularly, I use sales of tickets for home game of the Cincinnati Reds in the 2007 regular season. The data was provided to me by Andrew Sweeting who originally acquired it from Advanced E-Commerce Research Systems, eBay's official data reseller.[8] For each listing I see the mechanism chosen, the seller's identification number, the auction start and end time, the start price (auction start price or fixed price) and the BIN price if applicable. I further observe the number of seats available, the row and section of the seats and the game (home team, away team and game date). Additionally, my data has flags that indicate whether a secret reserve price was set[9] as well as whether the seller used certain options that are meant to advertise listings to buyers like using bold text, including photographs and so on. For each bid[10] I observe the listing it pertains to, the time and date of submission, a bidder identification number, the bid type[11], the bid amount, an indicator for whether the bid was successful, the final price extended to this bidder (0 if the bid was not successful), the bidder feedback score and the seller feedback score.

After some cleaning, which is described in detail in appendix B, my data holds 7,430 bids and 7,382 listings for pairs of tickets for 78 games. In subsection 3.4 I will further discuss this data and provide some summary statistics.

3.3 Secondary Data

A problem with any estimation of demand for baseball tickets is that these tickets are highly differentiated. Buyers' willingness to pay depends on the specific seat location in the stadium as well as the day and opponent of the associated game. In order to address this problem I generate quality

[8] See Sweeting (2010) for an excellent description of his data from which mine is derived.

[9] In eBay auctions, sellers can set up to two different reserve prices. The first one is public and is called the "start price". The second one is secret. Bids below the start price are not accepted. Bids above the start price but below the secret reserve price are accepted, but the item will not be sold unless at least one bid exceeds the secret reserve price.

[10] In this context I use the word "bid" rather loosely both for auction bids and for FP purchases.

[11] This shows categories like "Valid Bid", "Fixed Priced Item Purchase", and "Auto Retracted Bid".

indices for games, rows, and sections using two sets of secondary data.

First, I have listing data from StubHub.com, an online sales platform specialized on event tickets. Contrary to eBay, on StubHub buyers do not see who they buy from. However, StubHub guarantees that the buyer receives tickets no worse than the ones purchased. For 680,495 listings on StubHub I observe home team, away team and game date, number, row and section of tickets and sale price.

Secondly, I have attendance data for all 81 Cincinnati Reds home games of the 2007 regular season. I collected these from www.baseball-reference.com, a website that provides a variety of baseball statistics for past seasons as well as the current one.

I use these data to generate quality indices for games, rows, and sections. This is based on the idea that StubHub users are representative of the total baseball fan population, so that tickets listed for high prices on StubHub are generally more desirable. For the game quality index I also use attendance data, which should give a good indication of how popular certain games are.

For the generation of the game quality index I proceed as follows: For each game I calculate attendance as a percentage of average attendance. Further, I calculate the mean sale price of tickets for this game and divide by the average mean sale price across all games. Both of these numbers should be a fair measure for the relative desirability of games. I then define the game quality index to be the average of the two measures and normalize it to take values between zero and one only.

For row and section quality I first group rows and sections into clusters of rows and sections, respectively[12]. I do this because for some rows or sections I only have few observations in the StubHub data, so that I would not have accurate information for them otherwise. Then I regress prices paid on a constant, the newly created game quality index and dummies for each row and section cluster. I take the coefficients on the dummies as measures of seat quality. As last step I normalize the coefficients to be between zero and one.

My indices pass a few sanity checks: In all cases rows have (weakly) higher index values if they are closer to the field. Sections closer to the infield tend to have higher index values than those at the outfield and those on lower ranks have higher values than the "nose-bleed seats" far from the field. Finally, my two measures of game quality are highly correlated, suggesting that they are both decent predictors for ticket prices.

[12] In Appendix C I give a detailed description of how I group rows and sections.

3.4 Summary Statistics

Table 1 provides some basic summary statistics for the remaining data. The first four rows show different measures of ticket desirability. Tickets sold in the three different formats are relatively similar in terms of quality; however, the items in BIN auctions tend to be slightly more attractive while those in standard auction are slightly less attractive than average.

The following four rows show additional measures which can influence a listing's success. The line "low seller score" refers to a dummy which takes the value one if the seller feedback score is below 10, and zero otherwise. As can be seen, sellers with a low feedback score are more prone to using auction mechanisms than FP listings. One explanation for this might be that inexperienced sellers find auctions a better option, since they do not have the expertise to correctly calculate the optimal posted price. At the same time, being new to selling they have not yet had the time to develop a favorable reputation, so that their feedback scores are lower on average. "Advertising" measures each sellers' use of measures to increase the visibility or attractiveness of his listing. Among these are bold font, the inclusion of pictures, and others. I report total number of advertising features used per sellers.

The following lines show measures of listing success. Particularly interesting is the difference between auction and FP listings. Auctions sell with higher probability; this holds even accounting for listing length. In fact, the average FP listing in my sample is online for a slightly longer time than the average auction. However, if a sale does occur the generated revenue is greater in FP listings. In this sense, FP listings are riskier mechanisms than auctions.

Figure 2 shows how the number of listings available on eBay develops over time. Not surprisingly, there is a steep upwards trend; the number of listings available at the peak, around one week before the game, is almost ten times as high as five weeks earlier. Trading picks up as eBay users get more information about their valuation for the game. In the last few days before the game, the number of listings decreases significantly. Presumably, the reason for this phenomenon is that it often takes some time to finalize plans: unless seller and buyer live in the same town tickets have to be mailed; also, some buyers need to make travel arrangements; and finally they might already have alternative plans.

In the introduction I hinted at how mechanism choice evolves over time. Figure 3 shows this in more detail. The share of auctions is relatively constant, while the share of BIN auctions increases and the share of FP listings decreases. Remember from above that FP listings are riskier than auctions; they sell with lower probability but achieve a higher price if a sale occurs. Intuitively then, early on sellers are more inclined to choose FP listings; if no sale occurs they can just relist. However, in later periods the sale probability becomes more important. When there is no time to list a ticket again, auctions and BIN auctions become more attractive since they provide at least some revenue with high probability; obviously this can be achieved in FP listings, too, by setting the price sufficiently low. However, this also limits the maximum revenue the seller can earn, while auctions leave open the possibility of sales for high prices. Of course other factors influence mechanism choice; I will examine some of these when I discuss the estimation results.

4 Model

I model trade in a discrete time setting. In each period $t = 1, ..., T$ and for each market $g = 1, ..., G$, there is a set $\aleph$ of N risk-neutral, short-lived buyers with unit demand. Buyers arrive randomly in the marketplace with probability α^g. The arriving buyers observe listings $l = (l_1^{gt}, ..., L^{gt})$ which from their perspective are exogenous. Each buyer i enters exactly one listing in which he will bid. Before he makes his entry decision he observes listing shocks ε_{il} and calculates expected profits u_{il} for each available listing. After the entry decisions are made buyers observe their own valuations. That is, their entry decisions are based on expected valuations, while their bids reflect the actual valuations. This assumption is necessary to ensure tractability of the model; in the next section I discuss its justification in detail. Once buyers have learned their valuations, they submit bids in their chosen listings. After that, winners and prices are determined according to rules which depend on the exact mechanism chosen, and trades are finalized. All buyers leave the market permanently, independent of whether or not they received an item, and new buyers join the pool, thus keeping its size N constant.

There is also a set of sellers, each of whom has exactly one item for sale. Each seller l arrives in the marketplace with probability 1; that is, I do not model sellers' arrival but instead take sellers' presence as exogenous.[13] Each seller observes expected demand and supply; to be more precise,

[13] Note that I use the same subscript to denote both sellers and listings. I do so in an effort to simplify notation. This approach is valid because of the assumption that each seller offers exactly one item.

sellers know the distribution of valuations as a function of item characteristics; they also correctly predict prices, mechanisms, and item characteristics of competing listings; and finally they know the number of potential buyers. From these pieces of information sellers can determine the probability distribution over revenues for their items.

Having calculated this, each seller observes two more pieces of information: her opportunity costs of sale v_l^0 and her costs associated with each mechanism m, ω_{lm}. The opportunity costs depend on the seller's outside option. They capture the value the seller associates with retaining her tickets. The mechanism costs, on the other hand, have the function of a random shock in sellers' mechanism choice. They represent disutilty a seller gets from offering a certain mechanism. After the seller observes both types of costs, v_l^0 and ω_{lm}, she can find the optimal mechanism and price to sell her item.

The table below summarizes the timing of the model. I discuss the demand side and supply side, respectively, of the model in more detail in the following two subsections.

Stage 1	Sellers observe
	· expected demand and supply
	· their outside options v_l^0
	· their mechanism costs ω_{lm}
Stage 2	Sellers simultaneously list their items choosing
	· mechanisms m_l
	· prices p_l and/or reserve prices r_l
Stage 3	Buyers arrive in the market and observe
	· item characteristics X_l
	· mechanisms m_l
	· prices p_l and/or reserve prices r_l
Stage 4	Buyers enter exactly one listing irreversibly.
Stage 5	Buyers observe valuations v_{il} and submit bids b_{il}.
Stage 6	Winners are determined, payments made and utilities realized.
Stage 7	All agents leave the market.

4.1 Demand Side

After buyers arrive in the market place they decide to enter exactly one listing. To do so, each buyer i calculates his expected utility from entering listing l, U_{il}. U_{il} consists of two parts: the expected utility from the possibility of buying item l (u_{il}) and a shock associated with the listing (ε_{il}). I will discuss below how the u_{il} are calculated. For now, all we need to know is that u_{il} depends on item characteristics (X_l), the mechanism (m_l) and the posted price and/or reserve price (p_l and r_l respectively). To simplify notation I define:

$$\theta_l = (X_l, m_l, p_l, r_l)$$

Thus, the listing utility is given by

$$U_{il} = E(u_{il}|\theta_l) + \varepsilon_{il} \tag{1}$$

where the expectation is taken with respect to the number of entrants as well as the buyer's own valuation. The listing shocks ε_{il} capture buyer's idiosyncratic preferences over listings. They are i.i.d. draws according to a type I extreme value distribution.

All buyers simultaneously make their entry decisions based on these expected utilities. From buyer i's perspective this is a standard multinomial choice problem so that his probability of entry in listing i, q_{il}, can be written as follows:

$$q_{il} = \frac{\exp(E(u_{il}|\theta_l))}{\sum\limits_{j=l_1^{gt}}^{L^{gt}} \exp(E(u_{ij}|\theta_j))} \tag{2}$$

It is important to note that q_{il} depends on the entry probabilities of other buyers. This is because more bidders in one listing make it less likely to receive the item and might also increase the expected payment. For this reason buyers do not act as single agents but instead follow equilibrium strategies.

Once the entry decisions have been made buyer i perfectly observes his valuation for item l purchased through mechanism m, v_{ilm}. Buyers have independent private valuations distributed according to the cdf $F_{ilm}(v)$ and its associated pdf $f_{ilm}(v)$. This formulation is very flexible. It allows buyers valuations to depend on item characteristics as well as the relevant sale mechanism. In addition, two buyers can react in different ways to specific listing features. However, this leads to extremely complicated expressions. In order to simplify I assume that the distributions of valuations are normal: $F_{ilm}(v) = N(\mu_{ilm}, \sigma)$. I also put more structure on buyer heterogeneity by considering two types of buyers: Some buyers ("neutrals") are indifferent between mechanisms; the others ("FP lovers") prefer fixed price purchases over auctions. The distribution of valuation then depends on a seller's type as well as the method of purchase.[14] I denote neutrals by a subscript N and FP lovers by FP, posted price purchases by a subscript P and auction purchases by A. I assume that for neutrals $f_{NlA}(v) = f_{NlP}(v)$ holds; this allows me to simplify notation by dropping the mechanism subscript, writing $f_{Nl}(v)$. FP lovers receive a constant utility c from buying at posted prices, thus $f_{FPlA}(v) = f_{FPlP}(v + c)$. Whenever possible without creating confusion I will drop the mechanism subscript and use $f_{FPl}(v)$ in order to avoid unnecessarily cluttered notation. I denote the number of FP lovers by N_{FP}, the number of neutrals by $N_N = N - N_{FP}$ and the share of FP lovers in the whole population of buyers by $\lambda = \frac{N_{FP}}{N}$.

After all buyers learn their valuations, bidding starts. The details of the bidding process depend on the specific mechanism m_l. In FP listings, the seller sets a price p_l for the item. Each buyer can submit a bid b_{il} and indicate his willingness to pay the asking price by bidding $b_{il} \geq p_l$. If multiple bidders want to purchase the item, they all obtain the product with equal probability. The randomization is necessary due to the discrete time feature of the model, which establishes a positive probability that multiple buyers try to buy an item simultaneously. Hence, buyer i's expected utility from entering listing l is

$$E(U_{il}|\theta_l, m_l = FP) = \int_{p_l}^{\infty} \sum_{\kappa_l=0}^{N} \frac{v - p_l}{\kappa_l + 1} \rho_l(\kappa_l) f_{ilP}(v) dv + \varepsilon_{il} \tag{3}$$

where κ_l is the number of opponents in listing l who submit a bid and

[14]Recall that there are several reasons why buyers might prefer posted prices over auctions. For instance, risk averse buyers might choose to buy at fixed prices because this allows to secure a surplus at a certain level, while in auctions they face the risk of competing with a high-value bidder and thus not winning the auction or paying a very high price. Another factor in favor of fixed prices is impatience. Auctions on eBay run for a pre-specified time, while fixed price listings end as soon as a buyer purchases the item. Thus, fixed price listings often allow buyers to receive the item several days earlier than auctions listings.

$$\rho_l(\kappa_l) = \sum_{j_1\in\aleph}\sum_{j_2\in\aleph\setminus\{j_1\}}\cdots\sum_{j_{\kappa_l}\in\aleph\setminus\{j_1,\dots,j_{\kappa_l-1}\}}(\alpha^g)^{\kappa_l}\left(q_{j_1l}q_{j_2l}\dots q_{j_{\kappa_l}l}\right) \quad (4)$$
$$\left((1-F_{j_1lP}(p))(1-F_{j_2lP}(p))\dots(1-F_{j_{\kappa_l}lP}(p))\right)\left(\prod_{k\neq j_1,\dots,j_{\kappa_l}}^{N}(1-\alpha^g q_{kl}(1-F_{klP}(p)))\right)$$

is the probability that exactly κ_l want to buy the item.

In auction listings items are sold in a procedure similar to a standard second price sealed-bid auction (SPA). I assume that buyers sequentially have the opportunity to submit bids, but can only do so once. Whoever submits the highest bid wins the item and pays an amount equal to the second highest bid. This structure ensures that, like in SPAs, truthful bidding is a weakly dominant strategy. It also allows me to form expectations over the number of bidders I observe in auctions, a fact that I will use in the estimation.[15] Buyer i's expected profit from auction listing l is

$$E(U_{il}|\theta_l, m_l = A) = \int_{r_l}^{\infty}\sum_{\kappa_l=0}^{N}\int_{-\infty}^{v}(v-\max(r_l,b))g^l_{\kappa_l}(b)db\;\rho_l(\kappa_l)\;f_{ilA}(v)dv + \varepsilon_{il}. \quad (5)$$

$g^l_{\kappa_l}(b)$ denotes the probability density function of the highest opposing bid given κ_l opposing bidders. Buyer i always receives utility at least as big as his listing shock ε_{il}. In addition, if $v_{il} \geq r_l$ he wins the item as long as no other bidder has a higher valuation and pays the maximum of reserve price and second highest bid. The sum over the number of opponents is necessary since buyer i does not know the number of opposing bidders when he makes his entry decision.

BIN auctions are more complicated. After observing his valuation, each buyer decides whether he wants to buy the item or not. There are two conditions under which buyers might want to buy: If the value from buying in an auction is above the reserve price ($v_{ilA} \geq r_l$) or if the value from purchasing at a posted price is above the BIN price ($v_{ilP} \geq p_l$). As above in the FP listing, if multiple buyers want to purchase the item one of them is randomly selected ("bidder 1"). This buyer is now given a choice between buying at the BIN price or bidding in the auction. In the former case, the buyer receives the item and the listing closes. In the latter case, the listing turns

[15] Canals-Cerdá and Pearcy (2008) and following literature put less structure on bidding in a fashion that is similar to Haile and Tamer (2003). Their assumptions are strong enough to ensure truthful bidding at least for the bidder with the second-highest valuation. I choose not to follow their approach since it does not give me information on the expected number of bidders observed in the auction.

into a standard eBay auction and every buyer who entered can submit a bid. Proposition 1 shows that bidders' make this BIN choices depending on their valuation: bidders with high valuations choose to buy at the BIN price while bidders with low valuations start the auction.

Proposition 1. *Assume that the distribution of the highest opposing bid from bidder 1's perspective is continuous and that $p_l > v_l$. Then for neutrals there exists a cutoff valuation $\tilde{v}$ such that bidder 1 chooses the auction for all $v_{1l} < \tilde{v}$ and the BIN purchase for all $v_{1l} \geq \tilde{v}$. For FP lovers there exists a cutoff valuation $\tilde{v}_{FP}$ such that bidder 1 chooses the auction for all $v_{1lA} < \tilde{v}_{FP}$ and the BIN purchase for all $v_{1lA} \geq \tilde{v}_{FP}$. If instead $p_l = v_l$ then bidder 1 always chooses the BIN purchase.*

Proof. See Appendix A. □

To get some intuition assume $p_l > r_l$. Then any neutral's expected profit from the auction is clearly greater than the one from buying now as long as $v_{Nl} \leq p_l$. Now note that the buy-it-now profit follows a 45°-line since the buy-it-now price is constant. Contrary to that, the expected profit from the auction increases more slowly in v_{Nl} because a win occurs with a probability strictly less than one. That is, in the buy-it-now situation a valuation increase by one unit leads to exactly one unit in higher profits (assuming the original valuation was at least as great as the BIN price). In the auction setting the higher valuation leads to a higher profit of approximately one times the probability of winning.

The expected profit in a buy-it-now auction is given by the following expression:

$$
\begin{aligned}
E(U_{il}|\theta_l, m_l = BIN) \quad = \quad & \sum_{\kappa_{FPl}} \sum_{\kappa_{Nl}} \rho_{FPl}(\kappa_{FPl}) \rho_{Nl}(\kappa_{Nl}) \Bigg[\frac{1}{\kappa_{FPl} + \kappa_{Nl} + 1} \\
& \left(\int_{r_l}^{\tilde{v}_{il}} \int_{-\infty}^{v} (v - \max(r_l, b)) g^l(b|\kappa_{FPl}, \kappa_{Nl}) db f_{ilA} dv + \int_{\tilde{v}_{il}}^{\infty} (v - p_l)\, f_{ilP} dv \right) \\
& + \left(1 - \frac{1}{\kappa_{FPl} + \kappa_{Nl} + 1} \right) \qquad (6) \\
& \left(\frac{\kappa_{FPl}}{\kappa_{FPl} + \kappa_{Nl}} \frac{F_{FPl}(\tilde{v}_{FP})}{1 - F_{FPl}(\min(r_l, p_l - c))} + \left(1 - \frac{\kappa_{FPl}}{\kappa_{FPl} + \kappa_{Nl}} \right) \frac{F_{Nl}(\tilde{v})}{1 - F_{Nl}(r_l)} \right) \\
& \int_{r_l}^{\infty} \int_{-\infty}^{v} (v - \max(r_l, b)) g^l(b|\kappa_{FPl}, \kappa_{Nl}) db f_{ilA} dv \Bigg] + \varepsilon_{il}
\end{aligned}
$$

The first part of equation (6) is reminiscent of the related expression for FP listings and gives the probability that buyer i has the opportunity to make a BIN purchase. In this case, he receives the expected surplus from the auction if his valuation is below the cutoff or the payoff from the BIN purchase if the opposite is true. If another buyer is drawn as bidder 1, then i's utility is zero unless an auction is chosen. This happens with probability $\left(\frac{\kappa_{FPl}}{\kappa_{FPl}+\kappa_{Nl}} \frac{F_{FPl}(\tilde{v}_{FP})}{1-F_{FPl}(\min(r_l,p_l-c))} + \left(1-\frac{\kappa_{FPl}}{\kappa_{FPl}+\kappa_{Nl}}\right)\frac{F_{lN}(\tilde{v})}{1-F_{lN}(r_l)}\right)$, where $\frac{\kappa_{FPl}}{\kappa_{FPl}+\kappa_{Nl}}$ is the probability that bidder 1 is an FP lover. The final term is again familiar: Independent of whether and how he buys the item, bidder i always receives at least a listing shock equal to ε_{il}.

I am now in a position to define an equilibrium in this model:

Definition 1

A symmetric Perfect Bayesian Equilibrium on the demand side in period t is for each buyer i entry decisions ξ_i, bidding strategies b_{il} and beliefs over the number of market participants $\phi_i(k)$ and beliefs over other buyer's strategies $\tilde{q}_{jli}$ and $\tilde{b}_{jli}$ such that:

- Bidding behavior is optimal given beliefs: $u_{il}(b_{il}) \geq u_{il}(b') \; \forall l, i, b'$.
- Entry decisions are optimal: For each buyer i, $U_{i\xi_i} \geq U_{il} \; \forall l$ given equations (3), (5),(6) and i's beliefs.
- Beliefs are consistent with the arrival probability, i.e. $\phi_i(k) = \binom{N}{k}(\alpha^g)^k(1-\alpha^g)^{N-k}$ for all buyers i.
- Beliefs are consistent with entry decisions: For all buyers i, j and listing l, $\tilde{q}_{jli} = q_{jl}$.
- Beliefs are consistent with bidding behavior: For all buyers i, j and listing l, $\tilde{b}_{jli} = b_{jl}$.
- Buyers of the same type make identical entry decisions: $q_{il} = q_{FPl}$ if i is an FP lover and $q_{il} = q_{Nl}$ if i is a neutral.

The key issue in the equilibrium is to find entry probabilities which are consistent with other buyers' entry choices. This will be done numerically in the estimation procedure.

4.2 Supply Side

Sellers choose mechanisms and set prices for their listings. They need to form expectations over supply and demand before they can make meaningful decisions. While they do not observe the number of buyers present in the market, the total number of potential buyers N as well as their arrival probability α^g are common knowledge. The lack of knowledge about competing listings is more problematic since this information directly influences entry probabilities. It does seem reasonable that sellers would have a sound understanding of their competition; therefore I follow Hammond (2010a) in assuming that sellers correctly predict buyers' entry probabilities, without explicitly modeling how they arrive at these beliefs.

This allows me to specify sellers l's expected utility for each of the three mechanisms. I use the expected utility instead of expected revenue as this is a more flexible formulation allowing for sellers with different risk attitudes. In particular, I consider risk-neutral sellers and those with CARA utility, but could easily accomodate additional specifications. I denote seller l's utility function by $w_l(x)$ and her expected utility from choosing mechanism m by EW_{lm}. If a sale occurs the seller receives an expected payment; otherwise she keeps the item and gets utility out of her outside option. For FP listings the expected utility is:

$$
\begin{aligned}
EW_{lFP}(p_l) &= P_{lFP}(p_l)w_l(p_l) + (1 - P_{lFP}(p_l))\, w_l(v_l^0) \qquad (7)\\
&\quad \text{where}\\
&\quad P_{lFP}(p_l) = \sum_{\kappa_{Nl}} \sum_{\kappa_{FPl}} \eta_{Nl}(\kappa_{Nl})\eta_{FPl}(\kappa_{FPl}) \left[1 - F_{FPl}(p_l)^{\kappa_{FPl}} - F_{Nl}(p_l)^{\kappa_{Nl}}\right]\\
&\quad \eta_{\tau l}(\kappa_{\tau l}) = \binom{N_\tau}{\kappa_\tau} \left(\alpha^g q_{\tau l}\right)^{\kappa_{\tau l}} \left(1 - \alpha q_{\tau l}\right)^{N_\tau - \kappa_{\tau l}}
\end{aligned}
$$

$P_{lFP}(p_l)$ is the probability that the item is sold. This happens when at least one buyer enters the listing whose valuation is greater or equal to the posted price p_l. $\eta_{\tau l}(\kappa_{\tau l})$ is the probability that exactly $\kappa_{\tau l}$ buyers of type τ enter listing l.

The expected utility in auctions is slightly more complicated as now the payment in the case of a sale is a random variable itself. Particularly, the expected utility depends on the probability distribution of the second highest bid, $H_l(x)$ and its derivative $h_l(x)$:

$$
\begin{aligned}
EW_{lA}(r_l) \;=\; & \sum_{\kappa_{Nl}} \sum_{\kappa_{FPl}} \eta_{Nl}(\kappa_{Nl}) \eta_{FPl}(\kappa_{FPl}) \left\{ \int_{r_l}^{\infty} w_l(x) h_l(x|\kappa_{Nl}, \kappa_{FPl}) dx \right. \\
& + \left[(1 - F_{FPl}(r_l))\, \kappa_{FPl} F_{FPl}(r_l)^{\kappa_{FPl}-1} F_{Nl}(r_l)^{\kappa_{Nl}} \right. \\
& \left. + (1 - F_{Nl}(r_l))\, \kappa_{Nl} F_{Nl}(r_l)^{\kappa_{Nl}-1} F_{FPl}(r_l)^{\kappa_{FPl}} \right] w_l(r_l) \\
& \left. + F_{Nl}(r_l)^{\kappa_{Nl}} F_{FPl}(r_l)^{\kappa_{FPl}} w_l(v_l^0) \right\}
\end{aligned} \tag{8}
$$

The integral on the first line of equation (8) captures the possibility that at least two bidders have valuations above the reserve price. In this case the expected utility can be found by integrating over the distribution of the second highest valuation. The next two lines specify the possibility of selling for the reserve price. This happens when exactly one entrant has a valuation above the reserve price. The final line states that the seller receives the utility from her outside option if no buyer is willing to pay the reserve price for her item. To calculate the expected utility I still need to find the probability distribution of the second highest valuation. This is given by:

$$
\begin{aligned}
H_l(x|\kappa_{Nl}, \kappa_{FPl}) \;=\; & F_{FPl}(x)^{\kappa_{FPl}} F_{Nl}(x)^{\kappa_{Nl}-1} (1 - F_{Nl}(x))\, \kappa_{Nl} \\
& + F_{FPl}(x)^{\kappa_{FPl}-1} (1 - F_{FPl}(x))\, F_{Nl}(x)^{\kappa_{Nl}} \kappa_{FPl} + F_{FPl}(x)^{\kappa_{FPl}} F_{Nl}(x)^{\kappa_{Nl}}
\end{aligned}
$$

That is, the probability that the second highest bid is below some value x consists of three parts: the probability that exactly one FP lover but no neutral has a value above x, the probability that exactly one neutral but no FP lover has a value above x, and the probability that all valuations are below x.

In BIN auctions I encounter another complication as there are now two ways of selling the item. Let, with a slight abuse of notation, $\rho_{\tau l}(\kappa_{\tau l})$ be the probability that there are exactly $\kappa_{\tau l}$ entrants of type τ who want to purchase item l.[16] That is, $\rho_{\tau l}(\kappa_{\tau l})$ is given by the following two expressions:

[16]Recall that in Section 4.1 $\rho_{\tau l}$ stould for the probability distribution over the number of opposing bidders (from buyer i's perspective) who want to buy item l.

$$
\begin{aligned}
\rho_{Nl}(\kappa_{Nl}) &= \binom{N_N}{\kappa_{Nl}} \left(\alpha^g q_{Nl}(1-F_{Nl}(r_l))\right)^{\kappa_{Nl}} \left(1-\alpha^g q_{Nl}(1-F_{Nl}(r_l))\right)^{N_N-\kappa_{Nl}} \\
\rho_{FPl}(\kappa_{FPl}) &= \binom{N_{FP}}{\kappa_{FPl}} \left(\alpha^g q_{FPl}(1-F_{FPl}(\min(r_l,p_l-c)))\right)^{\kappa_{FPl}} \\
&\quad \left(1-\alpha^g q_{FPl}(1-F_{FPl}(\min(r_l,p_l-c)))\right)^{N_{FP}-\kappa_{FPl}}
\end{aligned} \tag{9}
$$

Using this I can write the seller's expected utility as follows:

$$
\begin{aligned}
EW_{lBIN}(p_l,r_l) &= \sum_{\kappa_{Nl}=0}^{N_N} \sum_{\kappa_{FPl}=1-\mathbb{1}(\kappa_{Nl}>0)}^{N_{FP}} \rho_{Nl}(\kappa_{Nl})\rho_{FPl}(\kappa_{FPl}) \left\{ \frac{\kappa_{Nl}}{\kappa_{Nl}+\kappa_{FPl}} \frac{F_{Nl}(\tilde{v}_{Nl})-F_{Nl}(r_l)}{1-F_{Nl}(r_l)} \right. \\
&\left[\int_{r_l}^{\infty} w_l(x) h_l(x|\kappa_{Nl},\kappa_{FPl},A_N)dx + \mathbb{1}(\kappa_{Nl}=1) F_{FPl}(r_l|v_{FPl} \geq \min(r_l,p_l-c))^{\kappa_{FPl}} w_l(r_l) \right] \\
&+ \frac{\kappa_{Nl}}{\kappa_{Nl}+\kappa_{FPl}} \frac{1-F_{Nl}(\tilde{v}_{Nl})}{1-F_{Nl}(r_l)} w_l(p_l) + \frac{\kappa_{FPl}}{\kappa_{Nl}+\kappa_{FPl}} \frac{1-F_{FPl}(\tilde{v}_{FPl})}{1-F_{Nl}(\min(r_l,p_l-c))} w_l(p_l) \\
&+ \frac{\kappa_{FPl}}{\kappa_{Nl}+\kappa_{FPl}} \frac{F_{FPl}(\tilde{v}_{FPl})-F_{Nl}(\min(r_l,p_l-c))}{1-F_{Nl}(\min(r_l,p_l-c))} \\
&\left[\int_{r_l}^{\infty} w_l(x) h_l(x|\kappa_{Nl},\kappa_{FPl},A_{FP})dx + \mathbb{1}(\kappa_{Nl}=0) \right. \\
&\left. \left. F_{FPl}(r_l|v_{FPl} \geq \min(r_l,p_l-c))^{\kappa_{FPl}-1} w_l(r_l) \right] \right\} \\
&+ \rho_{Nl}(\kappa_{Nl}=0)\rho_{FPl}(\kappa_{FPl}=0) w_l(v_l^0)
\end{aligned} \tag{10}
$$

If at least one entrant wants to buy the item after learning his valuation the following happens: With probability $\frac{\kappa_{Nl}}{\kappa_{Nl}+\kappa_{FPl}}$ bidder 1 is neutral. He starts the auction if his valuation is below the relevant cutoff; the probability for this is $\frac{F_{Nl}(\tilde{v}_{Nl})-F_{Nl}(r_l)}{1-F_{Nl}(r_l)}$ since he would not have wanted to buy if his value was below r_l. The seller's expected utility from the auction in this case is given in the second line of the equation. I already know at this point that at least one bidder (bidder 1) has a valuation above the reserve price. If there is no other such bidder then the item is sold for r_l. This happens only if $\kappa_{Nl} = 1$ since neutral entrants are only willing to buy the item if their value is at least as great as the reserve price. FP lovers, on the other hand, might be willing to buy the item even though their valuation is below r_l. This can happen if their utility from a purchase at a posted price is greater than the difference between BIN price and reserve. The expression $F_{FPl}(r_l|v_{FPl} \geq \min(r_l, p_l - c))^{\kappa_{FPl}}$ denotes the probability that no FP lover's valuation for auction purchases is above r_l conditional on him being willing to purchase the item. With the opposite probability there are at least two buyers who are willing to bid more than r_l in the auction. In this case I find the expected revenue by integrating over the pdf of the second highest bid conditioned on κ_{Nl}, κ_{FPl} and on the fact that a neutral bidder chose to start the auction.

The expressions in the case that bidder 1 is an FP lover are very similar to the ones described so that a detailed discussion is not necessary. Therefore I come to the last line of the equation. It indicates that if no entrant is willing to buy the item at either BIN price or reserve price ($\kappa_{Nl} = \kappa_{FPl} = 0$) the seller retains the goods and receives the utility from her outside option.

Since seller l knows all the parameters in (7)-(10) she can maximize these expressions with respect to the price p_l and/or the reserve price r_l in order to work out her optimal pricing strategy. This information is also crucial for the choice of the sales mechanism because of course a mechanism is more attractive the more revenue a seller can expect to earn. However, remember that sellers also incur costs when setting up a listing. I denote seller l's cost associated with mechanism m by ω_{lm}. Thus, the seller chooses the mechanism which gives her the highest net utility:

$$\pi_{lm} = \max_{(p_l, r_l)} EW_{lm}(p_l, r_l) - \omega_{lm}$$

5 Discussion of Assumptions

Having introduced the setup I will now devote a few paragraphs to discussing the major assumptions of the model.

IPV with unit demand I use data from a secondary market for baseball tickets. These items are bought for private use rather than investment purposes.[17] It does not seem likely that one's utility from visiting a game depends on other buyer's willingness to pay. Therefore the IPV assumption seems reasonable. Unit demand might look strange at first given that most people visit events in groups. However, many listings in my dataset are for multiple tickets -

[17] Some re-sellers are active in this market. As explained in the previous section I try to eliminate them from my data.

in fact, I only use data for pairs of tickets. If instead of buying a pair of tickets one bought two single tickets then seats would potentially be far apart which would defy the purpose of going in groups. Therefore the unit demand assumption also is not restrictive.

Short-lived buyers In my model buyers leave the market after one period, whether they successfully purchased an item or not. This is clearly a simplification since in reality buyers who don't buy today have the possibility of buying tomorrow. However, based on my data this does not seem to create a large problem. In my final dataset 85.13% of buyers submit bids only in a single period, 95.66% in no more than two periods. Even among losing bidders less than 25% return for a second period, and less than 8% return for two periods or more. Of course a bidder might participate in the market without submitting bids; still I think that these numbers sufficiently justify this assumption. At the same time this limited deviation from reality greatly simplifies my problem since I do not have to consider forward-looking behavior. That is, since buyers don't care about future periods there is no bid-shading and no updating of expectations I need to keep track of.

Entry in a single listing I do not allow buyers to enter several listings in a period. Probably a more appropriate way of modeling within-period behavior would be to set up a search model in which buyers consider the benefits of several listings before they finally bid on their most preferred alternative. However, 83.34% of observed bidders bid only in a single listing in the respective period, 92.77% in no more than two listings. This makes me believe that buyers do not tend to shop around very much. Note that my modeling choice does not mean buyers do not consider multiple listings. In fact, listing choice is an important part of my model. Recall that buyers' make equilibrium entry decisions based on the characteristics of each listing. I merely do not allow buyers to repeatedly enter and leave listings.

Simulatenous entry In reality, buyers arrive in the market and bid at different times. This might influence their behavior because their options will change over time. For instance, two buyers (A and B) arriving at the same time might choose to enter the same listing. If, however, buyer B arrives just slightly after A his listing choice might be altered if A already submitted a high bid for B's previously preferred listing. In my model I do not consider the sequential nature of the entry game. This again is a simplification of the problem. Otherwise I would have to keep track of a much larger state space and expectations over it. In the above example, A's behavior will depend on his expectation of B's behavior, the possibility of deterring B's entry by submitting a high bid or a bid in a less attractive listing, as well as the possibility that another buyer arrives after A but before B, possibly submitting a bid that makes A's listing of choice more desirable to B by raising the price of another item. The data provides some defense for the assumption of simultaneous entry as more than 25% of bids are submitted within the last six minutes before listings close. Figure 4 shows the timing of auction bids in my dataset during the last five days of auctions. It illustrates how the frequency of bids shoots up as the auction end comes near. Although bidding sometimes happens early on as well, there is a large concentration of bids during the last hour of auctions.

Unknown valuation In my models buyers know the distribution of valuations but not the realization of their own valuation before they enter a listing. To some degree this seems defensible since only after making the listing choice they see the seller's exact description - before, they only see a headline. More realistic would be, however, that buyers have an imperfect signal of their valuation before entry. The problem with modeling this is that it leads to extremely complicated decision making. Each buyer would have a threshold signal for entering a certain listing, but each threshold depends on other listings and on expectations over other buyer's thresholds. Solving this kind of game would be computationally infeasible. At the same time the gain would be very limited. In reality buyers are more likely to enter listings for which they have high valuations; in my model, on the other hand, buyers with different valuations have the same probability of entering a listing. This might lead to an overestimation of valuations. However, when calculating expected revenues the same simplification has the contrary effect on results: For a given distribution of valuations, my method leads to a revenue which is below the true one if in reality high-value types are more likely to enter. Intuitively, the two effects cancel out, so that the calculated revenues are accurate.

Existence of FP lovers I allow for the existence of two different types of buyers: neutrals whose utility does not depend on the mode of purchase and FP lovers who prefer buying at posted prices. As mentioned in the introduction, there are several reasons why rational buyers might prefer FP listings. For instance, impatient buyers might hesitate to bid in auctions since eBay auctions usually run for several days so that the buyer has to wait longer for the item. Also, risk aversion might be a reason for preferring FP listings: In FP listings a buyer can secure himself a certain surplus. In auctions the bidding success depends on other bidders' behavior which makes it less predictable. In any case it should be noted that I do not assume the existence of FP lovers. Instead I allow for it and estimate the share of FP lovers.

Nonexistence of auction lovers It might seem strange that I consider the existence of FP lovers but do not allow for a matching type "Auction lover". As mentioned above there are several arguments why buyers might prefer posted prices. However, in an IPV framework it is hard to find reasons for favoring auctions. Some buyers might just enjoy the competition aspect and see auctions as a pastime. Such behavior would seem more likely in markets without time restrictions, which makes it much easier to bid repeatedly. Trying to implement auction lovers into the game would also require the econometrician to overcome high hurdles. First, it is not clear whether preferences for auction purchases are identified from the data. In the current model the FP preferences are identified from the difference in auction and FP revenues. But there is no additional variation that helps to uncover auction preferences. Second, even if one can devise an ingenious method to overcome this issue, doing so might be computationally too costly. As I don't observe buyers' types I have to integrate them out; thus, each added type increases the computation time significantly.

Distribution of valuations In my model the valuations in listing l are distributed according to $N(\mu_{ilm}, \sigma)$. While any functional form is somewhat arbitrary I think that the normal distribution is not a particularly offensive assumption. It is known that many stochastic processes follow a normal distribution at least approximately. Furthermore, the assumption of normality is common in the literature, for instance for error terms. Another assumption I make about the distribution of valuations is that the expected valuation μ_{ilm} changes across listings but the standard deviation σ does not. I do this in order to simplify the estimation. In principle the model can easily be generalized to allow for the standard deviation to vary across listings. Merely inserting the new probability distribution into the expressions of the model is all that is necessary when adjusting the model. The reason why I use a constant standard deviation is that I believe that its movement is a secondary effect compared to the change of the expected valuation. Since I already estimate a relatively large number of parameters I sacrifice some flexibility of the model for a reduced computational burden. Another concern might be that this formulation allows for negative valuations. For baseball tickets certainly free disposal is a good description of reality, so taken literally this implication of my distributional assumption seems problematic. However, the distribution left of the reserve price does not matter as of course negative payments are excluded. Thus, the normal distribution gives me the same result as if it was truncated at zero. Having said all this, it is worth noting that my model and estimation technique can easily accomodate other distributions.

6 Estimation

6.1 Demand Side

On the demand side I take listing mechanisms and prices as given, so that there are the following variables to estimate: the number of potential entrants (N), the arrival probability (α^g), the distribution of valuations as a function of covariates (β and σ) and the share of FP lovers (λ) as well as the intensity of their preferences (c). I employ a maximum likelihood approach to estimate most of these. However, I devise a different strategy to uncover N, in an attempt to keep both data requirements and computational burden manageable.

First, I divide my data into periods of one day length[18] and find the number of bids submitted in each period[19]. Since according to my model each market participant submits at most one bid, the maximum number of bids submitted in one period is a lower bound for N. In my data this lower bound turns out to be 108. While there is no way of deriving an upper bound I note that in almost 93% of periods no more than 10 bids each are submitted. This suggests that N is not too far above the lower bound specified before. To find a more precise value I estimate my model

[18] I assume that auctions are available only on the last listing day. This is consistent with the observation from the previous section that by far the most bids are submitted in the last minutes before the auction closes. In contrast, FP listings are available on every day from listing start to listing end. BIN auctions are available from the listing start to the day of a BIN sale; or, if the auction option is used, from the start day to the submission of the first bid and again on the last day of the listing.

[19] While any choice of period length is somewhat arbitrary, there are two reasons why I believe that my choice of very short (day-long) periods is acceptable: First, given the abundance of outside options like online ticket brokers or scalpers it seems unlikely that a prolonged search through eBay offers is an efficient use of potential buyer's time. Second, as discussed in section 3, I observe very few bidders who submit bids on different days, suggesting that most users stay in the eBay market only briefly.

assuming different values of N between 100 and 400 and use the estimates which provide the best fit. This happens be provided by the model with $N = 200$.

However, it turns out that the exact value of N is almost irrelevant. The purpose of the demand side estimation is to gain information about expected revenues and sale probabilities which are necessary for the supply side estimation. As table 5 shows these values are virtually independent from the choice of N. The reason for this is that an increase of N is almost perfectly offset by a lower estimate of the arrival probability α^g, thus leaving the expected number of arriving buyers nearly unchanged.[20]

Having established the number of potential entrants I can now turn to the other parameters. Recall from the previous section that the distribution of valuations is normal with mean μ_{ilm} and variance σ^2. I allow the mean to depend on observable ticket characteristics, the buyer's type τ_i and the purchase method which with some abuse of notation I denote m_{il}. I assume an additive separable form for μ_{ilm}:

$$\mu_{ilm} = X_l\beta + \mathbb{1}(\tau_i = FP)\mathbb{1}(m_{il} = P)c$$

X_l is a row vector of a constant and listing characteristics: game quality, row quality, section quality, a dummy for low seller feedback score, and advertising activities by the seller; β is a column vector of coefficients which are to be estimated. The first indicator is one if the seller is an FP lover and zero otherwise; the second one is one if a posted price purchase is made and zero otherwise.

It seems likely that more bidders arrive for more popular games. In order to account for this I allow α^g to depend on game quality. More specifically, I estimate two parameters, α_0 and α_1, and assume that α^g follows the functional form below:

$$\alpha^g = \frac{\exp(\alpha_0 + gamequality_g\ \alpha_1)}{1 + \exp(\alpha_0 + gamequality_g\ \alpha_1)}$$

This specific function has the advantage of restricting the resulting arrival probability to be between zero and one while requiring the estimation of only two parameters.

I use a maximum likelihood approach to uncover the parameters β, λ, c, α_0 and α_1. Given N

[20] This is similar to Seim (2006). In her estimation of profits she includes a variable to capture the unobserved heterogeneity among different markets. When she assumes a large set of potential entrants the estimated mean of this market level effect is small and vice versa. Thus, the expected number of entrants remains constant, and other estimates are virtually independent from the assumed set of potential entrants.

the likelihood function depends on information of sale prices, number of bidders, and BIN choices. In FP listings, I only observe whether the item has been sold or not. The probability of the latter is:

$$P_{NS}^{l,FP} = \sum_{\kappa_{Nl}=0}^{N_N} \sum_{\kappa_{FPl}=0}^{N_{FP}} \prod_{\tau \in \{N,FP\}} \eta_{\tau l}(\kappa_{\tau l})[F_{\tau lP}(p_l)]^{\kappa_{\tau l}} \tag{11}$$

As before, $\eta_{\tau l}(\kappa_{\tau l})$ which is defined in equation (7) is the probability to have $\kappa_{\tau l}$ entrants of type τ. $[F_{\tau lP}(p_{\tau l})]^{\kappa_{\tau l}}$ is the probability that all entrants of type τ have a valuation below the price for good l. I multiply over types and sum over the number of potential entrants, so that the right-hand side of (11) gives me the probability that all buyers have a value below the posted price. The probability of a fixed price item being sold is now easy to find:

$$P_S^{l,FP} = 1 - P_{NS}^{l,FP} \tag{12}$$

For auction listings, the probability that the item is not sold looks just like for FP listings, except that the fixed price p_l is replaced with the reserve price r_l:

$$P_{NS}^{l,A} = \sum_{\kappa_{Nl}=0}^{N_N} \sum_{\kappa_{FPl}=0}^{N_{FP}} \prod_{\tau \in \{N,FP\}} \eta_{\tau l}(\kappa_{\tau l})[F_{\tau lP}(r_l)]^{\kappa_{\tau l}} \tag{13}$$

In the case of the item being sold the likelihood looks different, because in this case the revenue of the auction is informative. Note that in auctions both types of bidders have the same distribution of valuations; hence, I drop the type subscript to simplify notation. Analogously to equation (7) I define $\eta_l(\kappa_l)$ as the probability to have exactly κ_l entrants:

$$\eta_l(\kappa_l) = \sum_{\kappa_{FP}=0}^{\kappa_l} \binom{N_{FP}}{\kappa_{FP}} (\alpha^g q_{FPl})^{\kappa_{FP}} (1-\alpha q_{FPl})^{N_{FP}-\kappa_{FP}} \binom{N_N}{\kappa_N} (\alpha^g q_{Nl})^{\kappa_l-\kappa_{FP}} (1-\alpha q_{Nl})^{N_N-(\kappa_l-\kappa_{FP})} \tag{14}$$

This expression uses the fact that the κ_l entrants can consist of different shares of the two bidder types. That is, there can be many FP lovers which then in turn means few neutrals, or vice versa.

The probability of selling at the reserve price can now be written as:

$$P_S^{l,A}(r_l) = \sum_{\kappa_l=1}^{N} \kappa_l \eta_l(\kappa_l)[F_l(r_l)]^{\kappa_l-1}(1-F_l(r_l))$$

As before, $\eta_l(\kappa_l)$ is the probability that exactly κ_l buyers enter listing l. $[F_l(r_l)]^{\kappa_l-1}$ is the probability that $\kappa_l - 1$ entrants have valuations below the reserve price and therefore decide not to bid. $(1 - F_l(r_l))$ is the probability that one entrant has a valuation above the reserve price and submits a bid reflecting this.

If the item was sold for a price above the reserve price we have even more information. I assume that all bidders use proxy bidding. I also ignore the minimum bid increment, which tends to be small for the listings in my dataset. Together, these two assumptions imply that the second highest bid is equal to the second highest valuation, a fact that can be used to uncover the distribution of valuations. In order to be able to identify α^g I also take the number of observed bidders into account. I denote by $W^l_n(\kappa_l)$ the probability of observing n bids given κ_l entrants. $W^l_n(\kappa_l)$ is somewhat tricky to calculate because each entrant's probability of bidding depends on previous bids. Since in this context ordering matters, the number of cases that need to be considered quickly becomes overwhelming. In order to tackle this problem I therefore resort to a simulation method.

Note that the probability distribution over the number of observed bidders depends on several factors: the number of entrants, the distribution of valuations, and the reserve price. I therefore simulate auctions on a grid over those parameters. For every simulated auction I make sure to note the order of arrival of bidders, so that I can count the number of bids submitted. After sufficiently many repetitions I thus create a probability distribution over the number of bidders. I choose to simulate 1,000,000 auctions per grid point; this ensures that I get highly accurate results.

In order to calculate the probability of selling for a price above the reserve, let b_{l2} denote the second highest bid in the auction. Remember that the second highest bid is equal to the second highest valuation in this case. Then the probability for selling at b_{l2} can be written as

$$P^{l,A}_S(b_{l2}) = \sum_{\kappa_l=2}^{N} \eta_l(\kappa_l) \cdot W^l_n(\kappa_l) \cdot n(n-1) \left[\frac{F_l(b_{l2}) - F_l(r_l)}{1 - F_l(r_l)}\right]^{n-2} \frac{1 - F_l(b_{l2})}{1 - F_l(r_l)} \frac{f_l(b_{l,2})}{1 - F_l(r_l)}. \tag{15}$$

As noted above, $\eta_l(\kappa_l)$ is the probability of having κ_l entrants, and $W^l_n(\kappa_l)$ is the probability that exactly n bids are submitted given κ_l. Since I observe the second highest valuation, $b_{l,2}$, I know that exactly one bidder has a valuation weakly above $b_{l,2}$; the probability of this is captured in the term $\frac{1-F_l(b_{l2})}{1-F_l(r_l)}$. Note that I already took into account the fact that this person submitted a bit which implies that his valuation is above the reserve price. I condition on this fact to calculate the necessary probability. I also know that one bidder has a valuation exactly equal to b_{l2}; the probability of this is $\frac{f_l(b_{l,2})}{1-F_l(r_l)}$. And finally, all the other bidders have valuations below b_{l2} but above r_l since otherwise they would not have submitted bids in the first place. The probability for this is $\left[\frac{F_l(b_{l2})-F_l(r_l)}{1-F_l(r_l)}\right]^{n-2}$.

In BIN auctions there are three possibilities how the item can sell. It can be sold for the BIN price, for the reserve price, or for any price above the reserve price in an auction. A BIN sale occurs if the first entrant has a value above the relevant cutoff. The probability of a BIN sale can therefore expressed as follows:

$$\begin{aligned} P_{BIN}^{l,BIN} \quad = \quad & \sum_{\kappa_{Nl}=0}^{N_N} \sum_{\kappa_{FPl}=1-\mathbb{1}(\kappa_{Nl}>0)}^{N_{FP}} \rho_{Nl}(\kappa_{Nl})\rho_{FPl}(\kappa_{FPl}) \left[\frac{\kappa_{Nl}}{\kappa_{Nl}+\kappa_{FPl}} \frac{1-F_{Nl}(\tilde{v}_{Nl})}{1-F_{Nl}(r_l)} \right. \\ & \left. + \frac{\kappa_{FPl}}{\kappa_{Nl}+\kappa_{FPl}} \frac{1-F_{FPl}(\tilde{v}_{FPl})}{1-F_{Nl}(\min(r_l, p_l-c))}\right] \end{aligned} \tag{16}$$

$\rho_{\tau l}(\kappa_{\tau l})$ is the probability of observing exactly $\kappa_{\tau l}$ bidders who are willing to buy the item and is defined in (9). $\frac{\kappa_{Nl}}{\kappa_{Nl}+\kappa_{FPl}}$ is the probability that the first entrant is neutral given the $\kappa_{\tau l}$, and $\frac{1-F_{Nl}(\tilde{v}_{Nl})}{1-F_{Nl}(r_l)}$ the probability that he prefers a BIN purchase to starting the auction. The second line of (16) gives the corresponding expressions for FP lovers.

If instead the auction is started, a reserve price sale occurs only if no bidder besides the first entrant has a value above the reserve price:

$$\begin{aligned} P_{A}^{l,BIN}(r_l) \quad = \quad & \sum_{\kappa_{Nl}=0}^{N_N} \sum_{\kappa_{FPl}=1-\mathbb{1}(\kappa_{Nl}>0)}^{N_{FP}} \rho_{Nl}(\kappa_{Nl})\rho_{FPl}(\kappa_{FPl}) \left[\frac{\kappa_{Nl}}{\kappa_{Nl}+\kappa_{FPl}} \right. \\ & \frac{F_{Nl}(\tilde{v}_{Nl})-F_{Nl}(r_l)}{1-F_{Nl}(r_l)} \mathbb{1}(\kappa_{Nl}=1) F_{FPl}(r_l|v_{FPl} \geq \min(r_l, p_l-c))^{\kappa_{FPl}} \\ & + \frac{\kappa_{FPl}}{\kappa_{Nl}+\kappa_{FPl}} \frac{F_{FPl}(\tilde{v}_{FPl})-F_{Nl}(\min(r_l, p_l-c))}{1-F_{Nl}(\min(r_l, p_l-c))} \\ & \left. \mathbb{1}(\kappa_{Nl}=0) F_{FPl}(r_l|v_{FPl} \geq \min(r_l, p_l-c))^{\kappa_{FPl}-1}\right] \end{aligned} \tag{17}$$

The first bidder starts the auction if his valuation is below the cutoff value for type τ, $\tilde{v}_{\tau l}$. Following my assumption about bidding behavior he submits a proxy bid. Thus, the high bid at this point is equal to the reserve price. If any other bidder has a valuation above the reserve price he submits a bid himself. In this case, the item will necessarily be sold for a price above the reserve. This means that reserve price sales can only occur if only one bidder, the first bidder, has a valuation above r_l.

The probability to achieve a revenue of $b_{l2} > r_l$ can be calculated as follows:

$$
\begin{aligned}
P_A^{l,BIN}(b_{l2}) \quad = \quad & \sum_{\kappa_{Nl}=0}^{N_N} \sum_{\kappa_{FPl}=1-\mathbb{1}(\kappa_{Nl}>0)}^{N_{FP}} \rho_{Nl}(\kappa_{Nl})\rho_{FPl}(\kappa_{FPl}) \left\{ \frac{\kappa_{Nl}}{\kappa_{Nl}+\kappa_{FPl}} \frac{F_{Nl}(\tilde{v}_{Nl}) - F_{Nl}(r_l)}{1 - F_{Nl}(r_l)} \right. \\
& h_l(b_{l2}|\kappa_{Nl}, \kappa_{FPl}, A_N)dx + \frac{\kappa_{FPl}}{\kappa_{Nl}+\kappa_{FPl}} \qquad (18) \\
& \left. \frac{F_{FPl}(\tilde{v}_{FPl}) - F_{Nl}(\min(r_l, p_l - c))}{1 - F_{Nl}(\min(r_l, p_l - c))} h_l(b_{l2}|\kappa_{Nl}, \kappa_{FPl}, A_{FP}) \right\}
\end{aligned}
$$

Recall from above that $h_l(b_{l2}|\kappa_{Nl}, \kappa_{FPl}, A_\tau)$ is the distribution of the second highest valuation given the number of entrants of both types and the fact that a bidder of type τ started the auction.

Finally, the probability that an item in a BIN auction is not sold is equal to the probability that no entrant wants to buy the item for the specified prices:

$$
P_{NS}^{l,BIN} = \rho_{Nl}(0)\rho_{FPl}(0) \qquad (19)
$$

To calculate the likelihood out of (11)- (19) let D_{FP}^l be the indicator function for fixed price listings, D_A^l an indicator for auctions, D_{pS}^l an indicator for a fixed price or BIN sale and D_{aS}^l an indicator for an auction sale. Then the likelihood function is

$$
\begin{aligned}
L \quad = \quad & \prod_{t=1}^{T} \prod_{g=1}^{G} \prod_{l=l_1^{gt}}^{L^{gt}} \left\{ \left[\left(P_S^{l,FP} \right)^{D_{pS}^l} \left(P_{NS}^{l,FP} \right)^{1-D_{pS}^l} \right]^{D_{FP}^l} \left[\left(P_S^{l,A}(\tilde{p}_l) \right)^{D_{aS}^l} \left(P_{NS}^{l,A} \right)^{1-D_{aS}^l} \right]^{D_A^l} \right. \qquad (20) \\
& \left. \left[\left(P_A^{l,BIN}(\tilde{p}_l) \right)^{D_{aS}^l} \left(P_{BIN}^{l,BIN} \right)^{D_{pS}^l} \left(P_{NS}^{l,BIN} \right)^{1-D_{pS}^l-D_{aS}^l} \right]^{1-D_{FP}^l-D_A^l} \right\}
\end{aligned}
$$

where $\tilde{p}_l$ is the revenue of listing l. That is, I calculate the likelihood as follows: For each listings, observe whether and how it was sold. Then apply the appropriate expression from (11)- (19) and multiply across all listings.

Note that this likelihood function is an approximation since it does not take the interdependence of listings into account. In reality the number of entrants into one period's listings follows a multivariate hypergeometric distribution (drawing without replacement); in (11) - (19) I use a binomial distribution (drawing with replacement). In other words, according to my model bidders who enter one listing cannot enter another listing as well. Contrary to that, when calculating the likelihood I pretend that the entry decision into each listing is independent from other entry decisions. I do this because this way of calculating the likelihood is much less computationally intensive than using the exact function with the hypergeometric distribution. While not completely accurate, the binomial distribution is a reasonable approximation for the hypergeometric distribution as long as the arrival probability α is small enough. Given that, as discussed before, I use $N = 200$ and I observe many periods with few bids it seems safe to assume this condition satisfied. Estimation results with different N support this view; if the binomial approximation would pose a major problem then estimations with larger N should provide very different results. However, the parameter estimates barely change when I vary N.

6.1.1 Identification

In this subsection I provide some intuition for identification. While not a formal proof this will show the reasoning behind my estimation technique. First, given α^g the distribution of valuations would be identified by the distribution of bids as shown by Athey and Haile (2002). In order to see whether identification with unknown α^g is possible, consider the following: A large α^g means more entrants on average and therefore higher expected revenue. The contrapositive is also true, i.e. a small value of α^g is associated with lower revenue. I will now argue that large α^g and large β can be distinguished.

It is immediately clear that only the coefficient on the constant could have the same effect as α^g, since the other coefficients never have an impact on all listings while α^g does. However, an increase in α^g always means an increase in the expected number of bids; an increase in β leaves the expected number of bids virtually untouched unless the reserve price is high. This is because once the reserve price has been exceeded the number of bids depends on the timing of bidders' bids and the order of their valuations; these parameters are not affected by a constant shift of valuations. Thus, a change in α^g cannot be mistaken for a change in β.

By a similar argument I will now show that changes in α^g and σ can be clearly distinguished. A larger α^g always means that on average more bids are submitted; thus, the sale probability increases unambiguously. However, intuitively an increase in σ only leads to an increased sale probability if $r_l > \mu_l$ while the sale probability and expected number of bids decreases if $r_l < \mu_l$. This is because in the former case submission of a bid requires the valuation to be (potentially far) above μ_l, while in the latter case a bid is submitted unless the valuation is sufficiently far below μ_l. The larger σ, the greater is the probability of both these cases since on average valuations are going to be further from the mean.

Finally, imagine that σ and the coefficient on the constant in μ_l both increase. This is similar to an increase in α^g in that all sales probabilities increase. However, again the argument from above is valid: The change in α^g affects listings differently depending on their entry probability. The change in μ_l and σ depends on the reserve price; thus the two lead to different bidding behavior in some listings.

6.2 Supply Side

On the supply side I need to uncover the outside options as well as the distribution of mechanisms costs and sellers' risk attitudes. First, I assume there are several types of sellers with respect to their risk attitudes. Particularly, I consider risk-neutrality ($w(x) = x$), and constant absolute risk aversion ($w(x) = 1 - \exp(-\xi x)$) with $\xi = 0.01$ and with $\xi = 0.1$. These parameter choices represent a low and a high degree of risk aversion, respectively.[21] Given the risk attitudes I can now back out the opportunity costs of selling. Recall from the previous section that the seller finds the optimal price from the first-order conditions of the expected revenue maximization (equations (7),(8) and (10)). I invert this process: I observe prices and reserve prices and plug them into the first-order conditions. Now I can solve for the precise values of v_l^0. For FP listings and auctions this is straightforward. For BIN auctions I actually have two first-order conditions which in general give me different v_l^0. I uncover three sets of outside options: one out of each first-order condition and one using both first-order conditions and allowing for an additional variable which captures a seller's preference over selling at a posted price. The values uncovered from the reserve price seem slightly more sensible than the ones from the other two methods. Therefore I decide to use opportunity costs of sale backed out of the first-order condition with respect to r_l.

Having pinned down v_l^0 I can calculate the expected revenue for each item, mechanism and

[21]For instance, for a lottery that awards \$10 and \$50 with probability of 0.5 each, the certainty equivalent is 28.01 if $\xi = 0.01$ and 16.75 if $\xi = 0.1$.

risk attitude. This puts me in a position to turn my attention to mechanism costs ω_{lm} and types of risk attitudes. These are in general estimable from the observed mechanism choice. However, the magnitude of ω_{lm} is not identified. This is because I do not observe sellers' decision whether or not to list on eBay. Instead, I do observe the choice of mechanisms for those sellers who do list on eBay. This identifies the difference in costs between mechanisms. Therefore I define $\gamma_{lA} = \omega_{lA} - \omega_{lFP}$, $\gamma_{lBIN} = \omega_{lBIN} - \omega_{lFP}$ and $\gamma_{lFP} = 0$ and estimate the distribution of the difference of mechanism costs. I assume that γ_{lm} ($m = A, BIN$) is distributed normally with mean μ_m^γ and standard deviation σ_m^γ. This allows me to estimate the distribution of mechanism costs in a multivariate probit estimation. In the same process I also estimate the distribution of risk attitude types. Since I can calculate expected revenues for each utility function I can find which parameterization best explains the observed mechanism choice. When sellers choose mechanisms they of course know their own utility function and can therefore pick the correct expected utility. As the econometrician, on the other hand, I do not have this luxury. Instead, I estimate the shares of sellers of each risk type. Then I weight the three different expected utilities by the probability that a seller is of the respective type. That is, I integrate out sellers' unobserved risk preferences and determine the choice probabilities based on this weighted utility.

Seller l chooses mechanism m_l if it gives her a higher utility than selling at either of the other two mechanisms, m' and m''. The probability of this is:

$$\begin{aligned} P_l(m_l) &= P\left[\left(EW_{lm}(p_l, r_l) - w_l(\gamma_{lm}) > EW_{lm'}(p_l', r_l') - w_l(\gamma_{lm'})\right)\right. \\ &\quad \left.\wedge \left(EW_{lm}(p_l, r_l) - w_l(\gamma_{lm}) > EW_{lm''}(p_l'', r_l'') - w_l(\gamma_{lm''})\right)\right] \end{aligned}$$

The two probabilities, $P\left(EW_{lm}(p_l, r_l) - w_l(\gamma_{lm}) > EW_{lm'}(p_l', r_l') - w_l(\gamma_{lm'}\right)$ and $P\left(EW_{lm}(p_l, r_l) - w_l(\gamma_{lm}) > EW_{lm'}(p_l', r_l') - w_l(\gamma_{lm'}\right)$, are clearly not independent since γ_{lm} influences both events. Thus, the estimation does not follow a standard probit procedure; instead I use the multivariate probit.

7 Results

7.1 Demand Side

It is likely that the conditions on both the demand side and the supply side change over time. Therefore, I perform the demand side estimation on three different time intervals: less than 10 days before the game, 11-20 days before the game and 21-40 days before the game. I provide the parameter estimates for each interval in table 4. All parameters have the expected sign. Valuations increase in the quality indices and advertising. The willingness to pay is lower when the seller has a low reputation score. The expected valuation for an average pair of tickets is 71.16 dollars less than 10 days before the game, 58.29 dollars 11-20 days before the game, and 55.97 dollars 21-40 days before the game.[22]

A fair number of buyers has a significant preference for buying at posted prices. The share of FP lovers, λ, ranges from 0.26 to more than 0.32. The intensity of the FP preference, c, comes out at values above 20 dollars.

The arrival probability increases drastically over time. In early listings the arrival probability for a game of average interest is estimated to be 0.0178, while close to the game it is 0.0732. This means that the expected number of bidders in the market place increases from 3.6 to 14.6.

In order to test the accuracy of my model I calculate expected revenues and sale probabilities based on the estimates from the demand section. Table 6 reports these values and compares with their actual counterparts. Overall I get a good fit. Recall that I estimate the model by maximum likelihood, not by a method of moments; thus, the moments do not necessarily have to match.

7.2 Supply Side

I divide sellers into two types, small and large; large sellers are sellers who list more than 200 pairs of baseball tickets during the year. Note that this includes listings for other teams' home games. My rationale is that large sellers might be more experienced in price setting and therefore have different mechanism costs and risk preferences. In fact it seems likely that these large sellers are professionals and small firms who specialize on eBay sales. About 7.5% of sellers are classified as

[22] To obtain these numbers I calculate the expected valuation of a ticket assuming game quality = row quality = section quality = 0.5, and further assuming that no advertising was chosen and that the dummy for low seller score was 0. That is, I calculate $\beta_1 + \frac{1}{2}(\beta_2 + \beta_3 + \beta_4)$.

large. These sellers account for more than 40% of listings. In table 7 I report the mechanism choice by seller type. Large sellers are much more likely to choose FP listings or BIN auctions, while almost two thirds of listings by small sellers are auctions. This is consistent with the aforementioned thoughts about experience, since it might be easier to set reserve prices, which do not completely determine revenue, than fixed prices.

I estimate the supply side separately for each type. Figure 5 shows the estimated opportunity costs of selling for both types of sellers. Two phenomena are immediately obvious: First, large sellers have slightly higher opportunity costs on average. Second, there is a relatively large number of negative values. Two arguments can explain why I find more valuable outside options for large sellers. Small sellers are less experienced and therefore might underprice; and large sellers might face smaller costs of relisting as they often sell tickets semi-professionally or professionally. Small sellers on the other hand might be tempted to avoid the hustle of having to list the tickets again.

For baseball tickets, free disposal is certainly a good description of reality. Therefore it seems odd to find a large number of sellers with negative opportunity costs. There are several reasons why a seller's outside option might come out negative. First, the face value might serve as a focal point. Some states have laws against the sale of tickets for more than the face value. While this is not the case in Ohio, such a law does exist in neighboring Kentucky. Even if no law exists, some sellers might have moral qualms against selling the ticket for a profit. Indeed, I find that start prices have a mass point at the level of the respective face value. Second, tickets are generally checked at the stadium and possibly section entrance but not at the individual seat. Thus, as long as the stadium is not sold out ticket holders can move to better places. Realizing this sellers might charge a low price even for good seats; otherwise buyers can simply buy a cheap ticket and move to a better place. My model does not control for this, so that it would overestimate buyers' willingness to pay. Finally, sellers make mistakes. The fact that negative v^0 are more prevalent with small sellers might indicate that this can at least partially explain the results.

Figures 6 and 7 help with further analysis of the outside options. For large sellers there is a clear distinction: They select FP listings or BIN auctions if they have a valuable outside option and an auction if they have a poor one. As mentioned above this is reasonable. Sellers with less valuable outside options will feel a higher urgency of selling their tickets. Therefore they tend to choose auctions, which provide the highest sale probability among the available mechanisms. For small sellers, on the other hand, the three distributions of opportunity costs look almost perfectly alike. Again I attribute this difference to small sellers' lack of experience.

Finally, table 9 shows how the mean outside options decrease as the game approaches. This effect is not strong; however, it fits the idea that fewer possibilities for relisting lead to lower opportunity costs of sale. Recall from above that large sellers tend to choose auctions if the value of their outside option is low and FP listings or BIN auctions otherwise. Thus, the decreasing opportunity costs are one explanation why FP listings are less favored close to the game. An alternative explanation for decreasing opportunity costs is that particularly valuable tickets are offered early. However, my data does not support this argument. In fact, table 10 shows that the mean quality of tickets stays almost perfectly constant over time.

The results from the probit estimation are provided in tables 8 and 11. Large sellers are virtually indifferent between mechanisms; they choose almost exclusively based on their revenue expectations and risk preferences. Small sellers also don't show significant preferences over mechanisms. However, they do seem to somewhat prefer auctions over FP listings and FP listings over BIN auctions. I also note that the variance of sellers' mechanism costs is very small. This is comforting as it implies that sellers' utility can explain most mechanism choices. Thus I conclude that sellers' risk attitudes as well as their outside options are important determinants of mechanism choice.

Large sellers on average are also less risk averse than their smaller counterparts. Almost two thirds of large sellers are risk neutral; for small sellers this share is close to one third and the largest group is that of strongly risk averse agents which comprises of almost 40% of small sellers. It is intuitive that large sellers show less signs of risk aversion. They list on average more than 1200 sets of tickets over the course of the baseball season. Thus, the risk associated with an individual listing almost completely cancels out.

8 Counterfactual: Welfare Effect of BIN Auctions

In this section I discuss how the existence of BIN auctions affects consumer and producer surplus. I use the estimates describing buyer and seller behavior from the previous section and calculate the expected utility for buyers, the utility from net revenue for sellers, and the revenue from fees for eBay.

Then I consider the market without BIN auctions. I can calculate the expected seller utility for each mechanism and alter mechanism choice of sellers who originally chose BIN auctions. I simulate sellers' new mechanism choice; that is, given their expected utilities from each mechanism and the distribution of mechanism costs I determine the probability that a given seller chooses mechanism m. Then I simulate the new mechanism 500 times. In each simulation of the altered market, I again calculate the expected utility for buyers and sellers as well as eBay's expected fee income.

Recall from table 1 that in the actual market about 50% of listings are auctions, about 12% are FP listings, and close to 38% are BIN auctions. Under the counterfactual market structure obviously the share of BIN auctions goes to zero. These listings are split among auction and FP listings roughly in a ratio of 1:2. This results in new mechanism shares of approximately 61.3% for auctions and 38.7% for FP listings. Thus, the new market makes it easy for FP lovers to find their desired sale method while providing the efficiency of auctions in most listings.

I find that buyers benefit from BIN auctions: Their surplus goes up by 0.55% for FP lovers and by 5.78% for neutrals. Sellers on the other hand are better off in a market which offers only FP listings and auctions. The BIN auction reduces their utilities by 11.91% for small sellers and 15.84% for large sellers. eBay's fees largely depend on sellers' revenues. Therefore it is not surprising that eBay also would benefit from abandoning the BIN auction. Its fee revenue would go up by 10.63%. Note however that this analysis does not consider the effect of competition with other sales platforms. It is possible that buyers, understanding how BIN auctions increase their welfare, would switch to other sales platforms if eBay did abandon BIN auctions. Thus, the competitive pressure might force eBay to allow for BIN auctions.

In the counterfactual market structure, sellers can split the market. Some sellers offer FP listings, catering to buyers who prefer posted prices. Others offer auctions; auctions are attractive for selling to neutral buyers because they are more efficient than FP listings. In equilibrium, sellers in both mechanisms earn the same amount. Thus, neither type of seller has an incentive to deviate; instead both can use features of their mechanism to earn a relatively high revenue: Sellers offering FP listings benefit from FP lovers' higher willingness to pay. Sellers offering auctions have the chance of selling for a high price if multiple high-value bidders enter.

In contrast, in the original market structure with BIN auctions, this market splitting does not constitute equilibrium behavior. Auction sellers now have an incentive to deviate. They can use the BIN price to attract FP lovers in addition to neutral bidders. Similarly, FP sellers might wish to offer an auction option; again, this makes it more likely that buyers of both types enter and therefore increases revenue expectations. That is, the existence of BIN auctions increases competition between sellers as BIN auctions attract both types of buyers. Thus, sellers find themselves in a Prisoner's Dilemma situation. Offering BIN auctions is individually rational. However, in equilibrium it hurts sellers since it takes away the possibility of differentiation by mechanism choice.

This result is consistent with several papers in the marketing literature. They show that bundling, which is revenue maximizing at an individual level, reduces revenues in competitive markets. The underlying reason for this is that bundling makes the items offered by different sellers more similar by averaging out inherent product specific differences.

9 Conclusion

I examine competition in markets which feature multiple sales mechanisms. On the demand side I model buyers' listing choice as equilibrium decisions. That is, each buyer takes expected entry decisions of other buyers into account. On the supply side I analyze sellers' mechanism choice. I find that sellers with valuable outside options are more likely to choose FP listings and BIN auctions; those with poor outside options prefer auctions. I also estimate risk attitudes of sellers and find that small sellers show significant levels of risk aversion while most large sellers are risk neutral. Taken together risk preferences and outside options explain sellers' mechanism choice well.

Based on my results I examine the welfare effects of BIN auction. I find that buyers benefit from the existence of BIN auctions while sellers and eBay itself would prefer a world without the hybrid mechanism. This conforms to the intuition discussed in detail in the previous section. Sellers can use mechanism choice as a means of product differentiation. This breaks down when BIN auctions are available, because as a hybrid mechanism BIN auctions attract buyers of both types. Thus, their existence strengthens competition.

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Appendix A: Proof of Proposition 1

Proof. The second part of the proposition is trivially true since in the case of $p_l = r_l$ the BIN purchase is a weakly dominant strategy. Hence, I can now concentrate on the first part of the proposition and the more interesting case $p_l > r_l$. I show the proof for the case of a neutral bidder 1. If bidder 1 is an FP lover, the same steps are sufficient to complete the proof. However, the notation is slightly more tedious since in this case a distinction has to be made between the valuation for buying in the auction and buying at the BIN price.

The proof proceeds in the following steps. First, I derive expressions for bidder 1's profit from a BIN purchase ($\pi_{BIN}(v)$) and his expected profit from starting the auction ($\pi_a(v)$). Then I will note that both of these expressions are continuous in v. After that I will show that there always exists a v for which the auction is preferable. Finally, I'll show that if the BIN purchase is chosen for one v it is also chosen for all $v' > v$ in the support.

Step 1:

Let $G(x)$ be the probability distribution over the highest competing bid from bidder 1's perspective, let $g(x)$ be its derivative, and let χ be its support. Then $\pi_{BIN}(v)$ and $\pi_a(v)$ can be written as:

$$\begin{aligned}
\pi_{BIN}(v) &= v - p_{BIN} \\
\pi_a(v) &= \int_r^v (v-x)g(x)dx \\
&= \int_r^v vg(x)dx - \int_r^v xg(x)dx \\
&= v(G(v) - G(r)) - \int_r^v xg(x)dx
\end{aligned}$$

Step 2:

Clearly, $\pi_{BIN}(v)$ and $\pi_a(v)$ are continuous because they are sums of continuous functions.

Step 3:

Clearly, $\pi_a(v) > \pi_{BIN}(v)\ \forall r \leq v < p_{BIN}$ since the profit from BIN purchase is negative for these valuations.

Step 4:

I will now show that if $\pi_{BIN}(v) \geq \pi_a(v)$ then $\nexists\, v' > v$ in χ such that $\pi_{BIN}(v') \leq \pi_a(v')$. Assume $\pi_{BIN}(v) \geq \pi_a(v)$ for some v with $G(v) < 1$ (with $G(v) = 1$ there is no greater v in the support, so the claim is immediately true). I will show that $\pi_{BIN}(v') > \pi_a(v')$ for all $v' > v$. Let $\delta \equiv v' - v > 0$. I can then write:

$$
\begin{aligned}
\pi_{BIN}(v') = v + \delta - p_{BIN} &\geq \delta + [G(v) - G(r)]v - \int_r^v xg(x)dx \\
&= [1 - (G(v) - G(r))]\delta + [G(v) - G(r)]v' - \int_r^v xg(x)dx \\
&= [1 - (G(v) - G(r))]\delta + [G(v) - G(v')]v' + [G(v') - G(r)]v' - \int_r^v xg(x)dx \\
&= [1 - (G(v) - G(r))]\delta + [G(v) - G(v')]v' + \int_v^{v'} xg(x)dx \\
&\quad + [G(v') - G(r)]v' - \int_r^{v'} xg(x)dx \\
&= [1 - (G(v) - G(r))]\delta + [G(v) - G(v')]v' + \int_v^{v'} xg(x)dx + \pi_a(v')
\end{aligned}
$$

Now I only have to show that $A \equiv [1 - (G(v) - G(r))]\delta + [G(v) - G(v')]v' + \int_v^{v'} xg(x)dx > 0$. For this, note that $\int_v^{v'} xg(x)dx \geq v \int_v^{v'} g(x)dx = v[G(v') - G(v)]$. The inequality holds because on the left-hand side $g(x)$ is multiplied by values ever increasing from their start point v while on the right-hand side each $g(x)$ is just multiplied by v. This allows me to write:

$$
\begin{aligned}
A &\geq [1 - (G(v) - G(r))]\delta + [G(v) - G(v')]v' + v[G(v') - G(v)] \\
&= [1 - (G(v) - G(r))]\delta + (v' - v)[G(v) - G(v')] \\
&= [1 - G(v) + G(r)]\delta + \delta[G(v) - G(v')] \\
&= \delta[1 + G(r) - G(v')] \\
&\geq 0
\end{aligned}
$$

The last inequality holds because $\delta > 0$ and because $G(x)$ is a cdf, implying $G(v') - G(r) \leq 1$. Note that the equality can only be reached if $G(v') = 1$; so if $G(v') < 1$ we know that $A > 0$ and we are done. If $G(v') = 1$ then we only know $\pi_{BIN}(v') \geq \pi_a(v')$, so the choice of bidder 1 could change if he is indifferent for both v and v'. However, by continuity of G there is a v'' between v and v' such that $G(v'') < 1$. Since $G(v'') < 1$, the inequalities hold strictly for comparing choices at

v and v'' (i.e. $A > 0$), thus proving that $\pi_{BIN}(v'') > \pi_a(v'')$. Now compare choices at v'' and v'. In this case A might be equal to zero. However, the first inequality in step 4 is strict because we know that $\pi_{BIN}(v'') > \pi_a(v'')$; thus, $\pi_{BIN}(v') > \pi_a(v')$. $\square$

Appendix B: Data Cleaning

Originally I have data for all 81 home games of the Cincinnati Reds in the 2007 regular season. There are 16,812 listings with a total of 18,875 bids and the number of tickets per listing range from one to six. In order to get a more uniform dataset and because I do not believe that there is much competition between listings with different ticket numbers I keep only listings offering exactly two tickets. The market for pairs of tickets is the thickest, leaving me with 14,309 listings and 15,919 bids.

I drop all listings for the first three games of the season. The beginning of a new season seems to have spurred excitement among baseball fans; thus, these games drew much more interest than others in my sample. In fact, they account for 29.6% of listings and 46.0% of bids in the data, leaving me to believe that the market for these tickets was significantly different from the one for later games. For a similar reason I drop listings for tickets in the "Diamond Seats" section immediately behind the home plate (these are sections 1-6 in figure 1). These tickets are significantly superior to others, but account for only a small number of sales (less than 0.6% of listings and less than 1.0% of bids). Thus, dropping these listings allows me to concentrate on the effects that drive competition between more common listings without creating a major misrepresentation of the market.

I now drop all listings that end more than 40 days before the game (17.3% of listings). The early markets are relatively thin compared to those closer to the event; thus I am concerned that the competitive situation is significantly different in this period. Next I drop a few bids (2.8%) for which the bid type in the data signal problems. These are bids that are listed as "Auto Retracted" (47 bids), "Auto Cancelled" (136 bids) or "Motors" (1 bid). I also drop listings that I consider problematic. First, there are 149 listings which sell for less than the listed price. Secondly, I drop 138 listings for which the seat row is missing. This information is essential since in the estimation I use it as one of my covariates. At this point my data still contains rare listing types, namely 27 cases of multi-unit auctions and 74 personal offers, which I also drop in order to focus on the three major mechanisms auction, FP listings and BIN. Now I remove likely resellers of tickets. I do this because resellers face a very different problem from buyers who purchase for personal use. First, in my model I assume that buyers have independent private values; for resellers this assumption is questionable since holding the ticket has no value per se. Second, resellers are likely to be in the market for extended periods of time, while I assume that my buyers are short-lived and only active for one period. In order to eliminate resellers, I drop all bids by buyers who buy more than four pairs of tickets for a single game (0.9% of bids). Furthermore, I do not observe secret reserve prices. Since these might influence bidding and certainly have an impact on sellers' revenue expectations I drop all listings with secret reserve prices (1.2% of listings).

Most listings in the data are available for no more than one week. However, there are some cases of extremely long listings, in very few cases reaching more than 200 days. In order to remove this kind of variation I drop listings lasting more than 10 days (4.2%). After this I finally end up with 7,430 bids and 7,382 listings left.

Appendix C: Tables and Figures

	Auctions		FP listings		BIN auctions	
	mean	std. dev.	mean	std. dev.	mean	std. dev.
face value	25.87	12.86	27.72	9.63	31.07	13.70
game quality	0.410	0.245	0.434	0.248	0.447	0.248
section quality	0.251	0.177	0.288	0.163	0.319	0.193
row quality	0.646	0.295	0.675	0.289	0.568	0.315
start price	22.68	30.11	73.12	57.05	68.74	66.95
BIN price	N/A		N/A		96.33	73.36
low seller score	0.060	0.237	0.017	0.129	0.046	0.210
"advertising"	0.534	0.772	0.239	0.497	0.526	0.899
length in days	4.581	2.475	4.717	2.424	3.541	2.529
number of bids	1.554	1.849	N/A		0.540	0.937
sale probability	0.589		0.215		0.361	
revenue in case of sale	40.27	39.98	68.92	39.67	69.24	57.00
number of listings	3,698		890		2,794	

Table 1: Summary Statistics for listings by mechanism type.

Group	Rows	Row Quality
1	1	1
2	2-3	0.870
3	4-10	0.655
4	11-19	0.463
5	20-26	0.238
6	27+	0

Table 2: Grouping of rows and row quality index. The rows are counted from the field, so that in each section the row closest to the field is assigned number 1.

Figure 1: Section plan of the Great American Ballpark. Source: http://www.ticketsolutions.com/

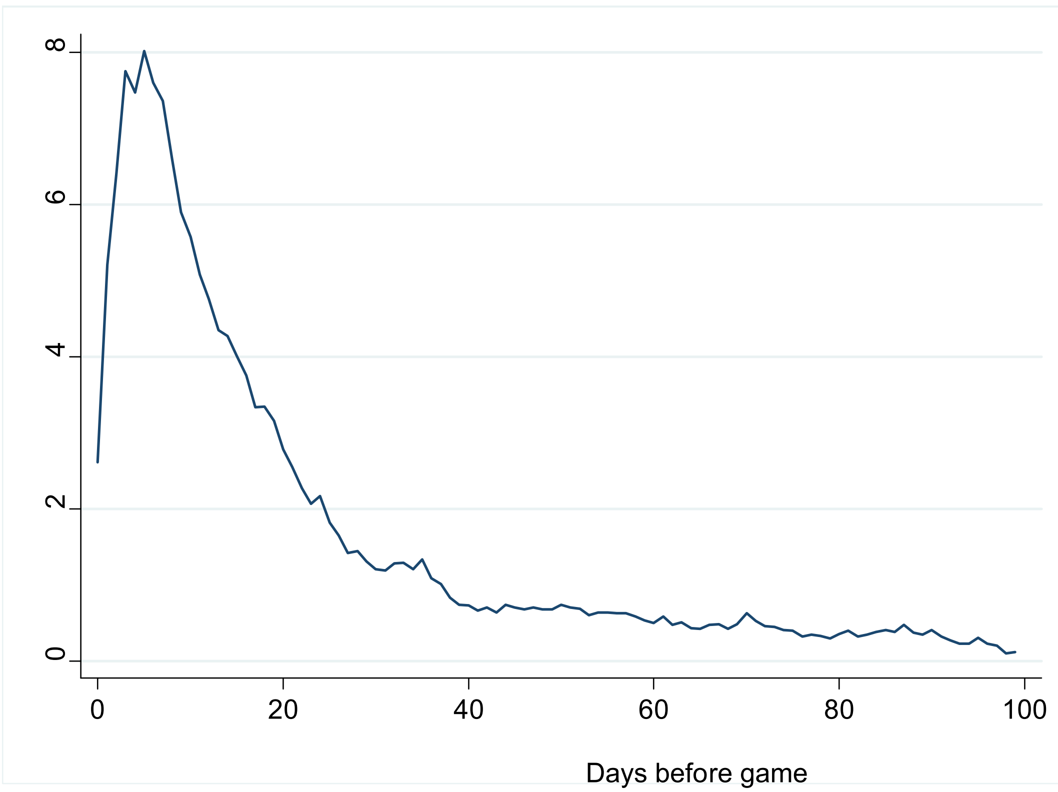

Figure 2: Average number of available listings over time

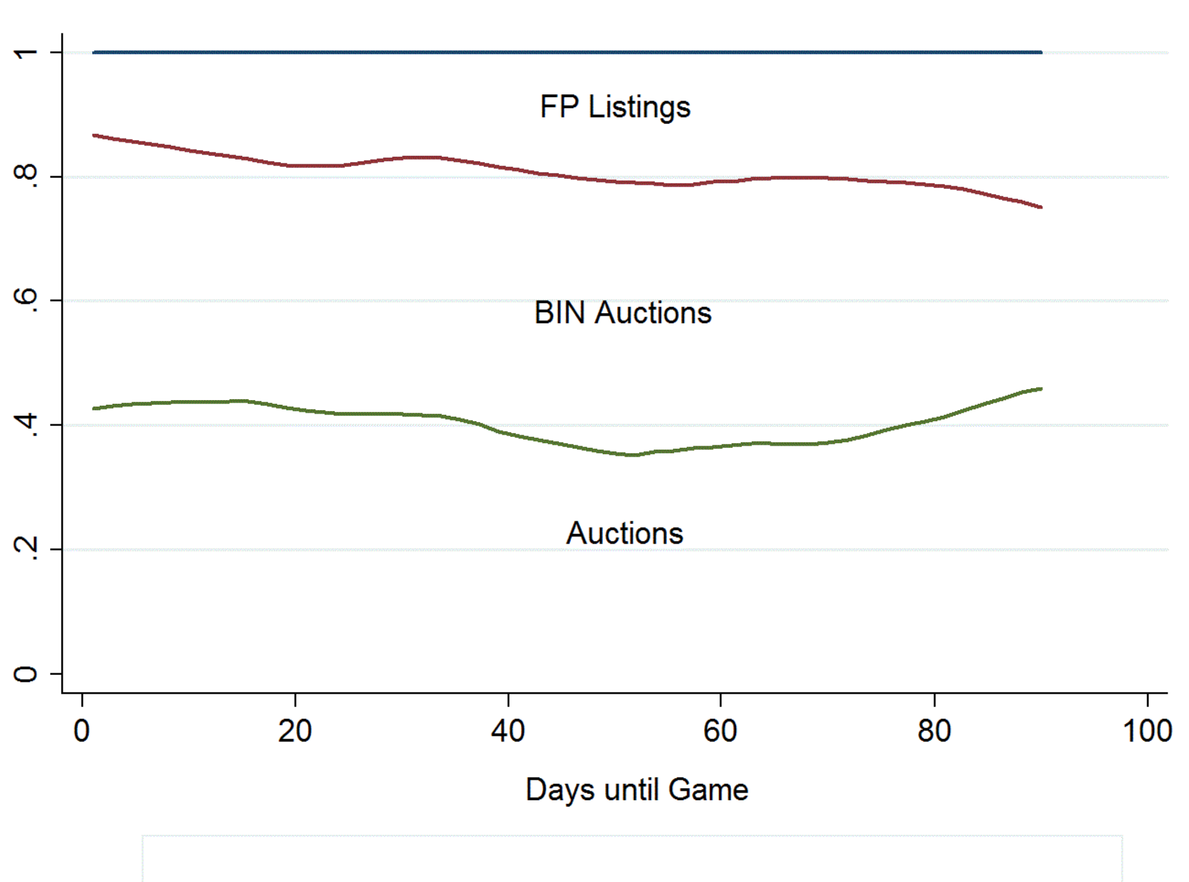

Figure 3: Development of mechanism choice over time

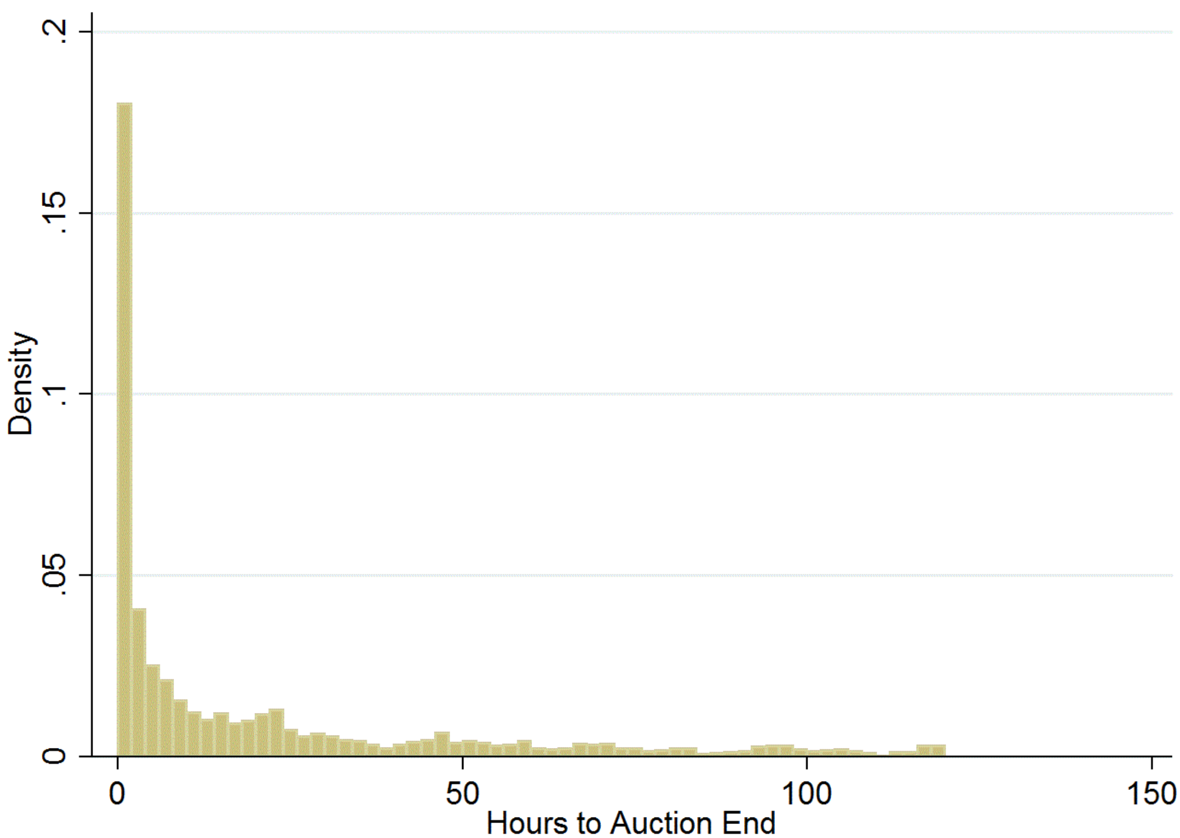

Figure 4: Timing of bids during the last five days of the auction.

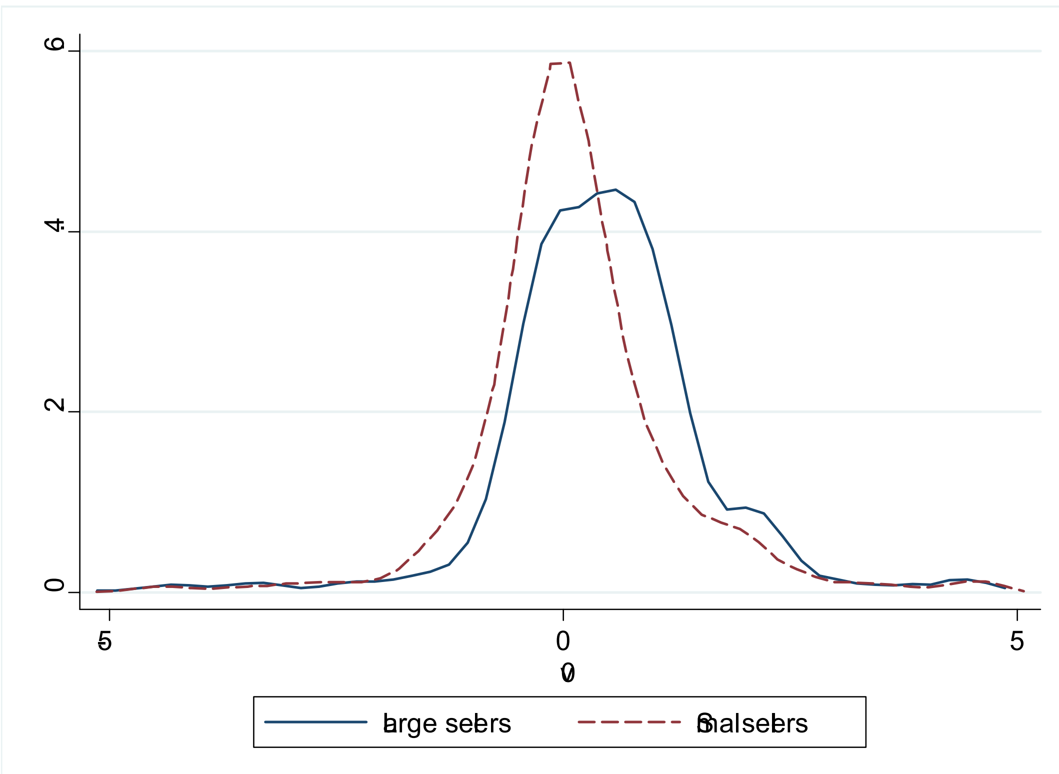

Figure 5: Distribution of outside option values relative to face value by seller size

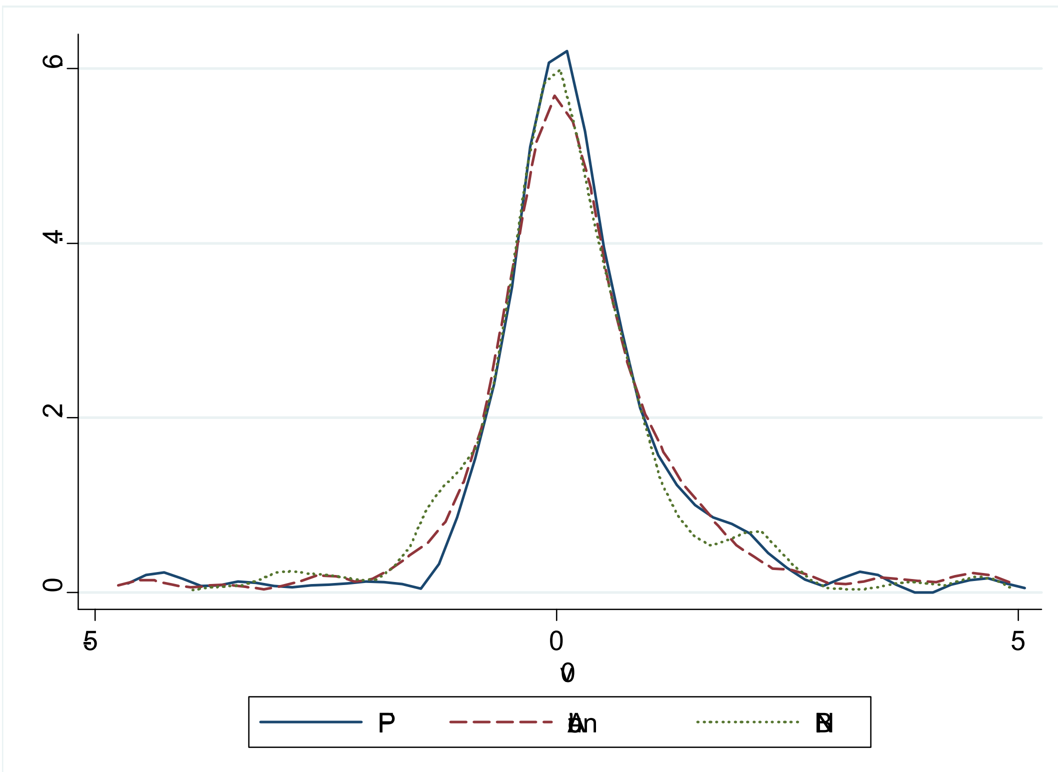

Figure 6: Distribution of small sellers' outside option values relative to face value by mechanism.

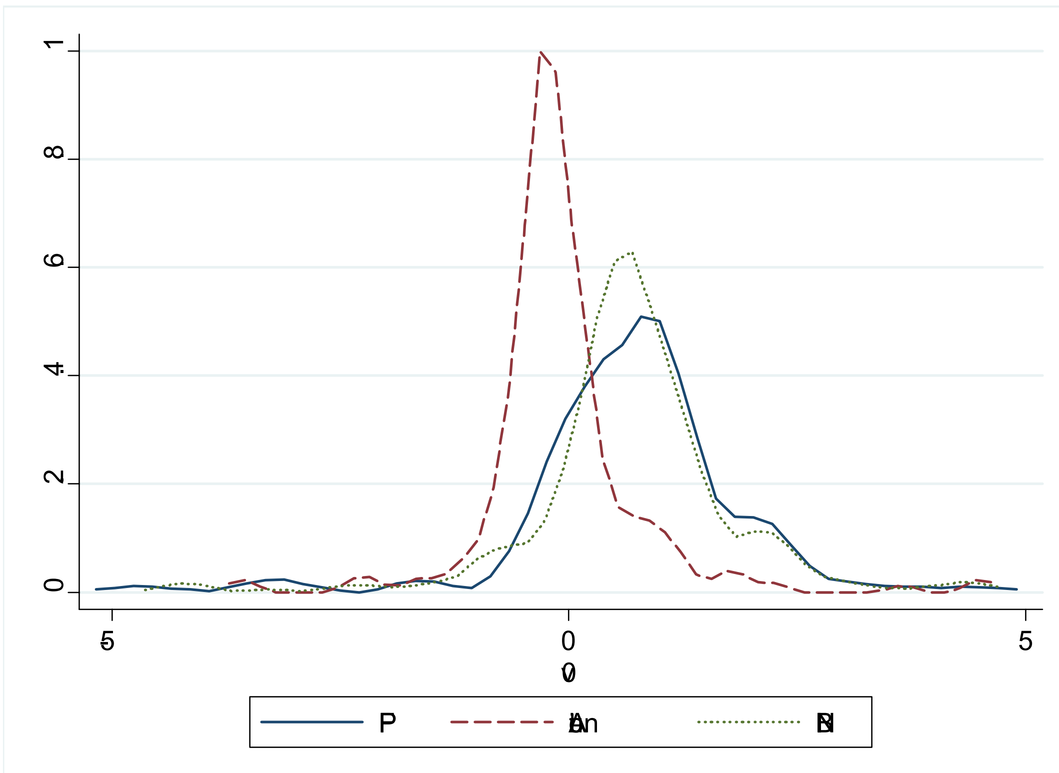

Figure 7: Distribution of large sellers' outside option values relative to face value by mechanism.

Group	Section	Section Quality
1	22-25	1
2	122-126	0.585
3	110-113, 133-136	0.420
4	114, 115, 131, 132	0.471
5	116-118, 129-130	0.485
6	119-121, 127-128	0.517
7	108-109, 137-139	0.303
8	140-146	0.192
9	101-107	0.146
10	401-406	0.019
11	408-410	0
12	411-414	0.121
13	415-419	0.175
14	220-228,301-307	0.257
15	420-431	0.231
16	432-437	0.104
17	509+	0.022

Table 3: Grouping of sections and section quality index.

		Days before game		
		1-10	11-20	21-40
constant	β_1	-22.4589	-27.0525	-22.4055
		(0.0005)	(0.0028)	(0.0021)
game quality	β_2	58.2609	49.5130	43.4314
		(0.0006)	(0.0034)	(0.0021)
row quality	β_3	9.7331	10.4477	8.2725
		(0.0007)	(0.0048)	(0.0024)
section quality	β_4	119.2380	112.7180	105.0501
		(0.0006)	(0.0114)	(0.0019)
low seller score	β_5	-6.0248	-5.5073	-5.3684
		(0.0059)	(0.3230)	(0.2735)
"advertising "	β_6	2.6001	3.1460	2.8735
		(0.0034)	(0.0175)	(0.0185)
FP preference	c	23.8230	24.1303	21.7427
		(0.0126)	(0.0486)	(0.0680)
share of FP lovers	λ	0.3229	0.2604	0.2908
		(0.0029)	(0.0136)	(0.0254)
arrival prob. (const.)	α_0	-2.6806	-3.4493	-4.1185
		(0.0016)	(0.0208)	(0.0227)
arrival prob. (game qual).	α_1	0.2837	0.2486	0.2176
		(0.0089)	(0.0324)	(0.0356)
std. dev. of valuations	σ	15.4842	19.2504	23.8347
		(0.0005)	(0.0066)	(0.0022)
Observations		4,584	1,606	1,192

Table 4: Estimates of demand side parameters. Standard deviations in parentheses. All estimates are significant at the 99% level.

		N = 100	N = 200	N = 300	N = 400
Auctions	Exp. Revenue	12.79	12.62	12.69	12.64
	Sale Probability	0.4755	0.4732	0.4740	0.4728
FP listings	Exp. Revenue	6.17	6.03	6.16	6.06
	Sale Probability	0.2144	0.2119	0.2139	0.2116
BIN Auctions	Exp. Revenue	8.47	8.31	8.37	8.38
	Sale Probability	0.2018	0.1994	0.2000	0.1999

Table 5: Predicted moments for several values of N. Reported are the average predicted moments for 100 game/day combinations between 21 and 40 days before the game. Predictions based on 100,000 simulations for each listing.

		true	predicted
FP listings	sale prob.	0.215	0.176
	exp. rev.	13.75	12.06
Auctions	sale prob.	0.589	0.602
	exp. rev.	23.99	24.47
BIN auctions	sale prob.	0.361	.348
	exp. rev.	23.25	22.19

Table 6: Predicted and true values for the share of sold items and expected revenue by mechanism.

	FP listings	Auctions	BIN Auctions
Small Sellers	6.63%	65.89%	27.48%
Large Sellers	21.69%	24.12%	54.20%

Table 7: Mechanism choice by seller size

	risk neutral	$\xi = .01$	$\xi = .1$
small sellers	34.14%	26.36%	39.51%
large sellers	63.66%	11.41%	24.93%

Table 8: Risk attitudes by seller size

	Small Sellers		Large Sellers	
Days to game	mean	std. dev.	mean	std. dev.
21-40	0.2248	1.0769	0.5043	1.1432
11-20	0.2066	0.9982	0.4534	0.9746
1-10	0.0851	1.0961	0.4050	1.1692

Table 9: Development of outside options over time

	Days before Game					
	1-10		11-20		21-40	
	mean	std. dev.	mean	std. dev.	mean	std. dev.
face value	27.8654	13.3834	27.9572	12.8288	27.4209	12.1163
game quality	0.4327	0.2485	0.4202	0.2465	0.4284	0.2415
row quality	0.6233	0.2951	0.6221	0.3080	0.6295	0.3223
section quality	0.2800	0.1906	0.2833	0.1827	0.2692	0.1683

Table 10: Development of several measures of ticket quality over time

	small sellers	large sellers
μ^{γ}_{BIN}	0.3485	0.0056
σ^{γ}_{BIN}	0.3853	0.2263
$\mu^{\gamma}_{Auction}$	-0.3223	-0.0020
$\sigma^{\gamma}_{Auction}$	0.2190	0.2863

Table 11: Estimated distributions for sellers' mechanism costs