Analysis of Dynamic Selling Mechanism Choice: An application to an online ticket resale market

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March 29, 2018

Draft

Abstract

Perishable goods, such as tickets, are often resold on different platforms by various dynamic selling mechanisms. These platforms are different from each other in many other dimensions, such as search algorithms, market thickness and commission fees. This paper analyzes participants' behavior on eBay's baseball ticket resale market and focus on the question that how characteristics of a platform would affect sellers' dynamic mechanism choices. By modeling and structurally estimating buyers' two-stage decision process, I find that buyers are sensitive to price but the sensitivity has moderate magnitude. Given the demand estimation, the dynamics of a seller's mechanism choice and pricing strategy can be captured by a dynamic model with an outside option in the end. Counterfactual analysis suggests that when sellers are more patient about future sales, they have less incentive to use auctions. When a platform's search algorithm is more related to prices, or when there are more competitive listings available in the market, average auction share and average market price would decrease. The average expected profits of sellers are also reduced. Besides, the average auction share would not change significantly when increasing the commission fees from sellers. Finally, if sellers are only allowed to use posted prices, both average market prices and sellers' average profits will decrease if buyers' arrival process is the same.

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1 Introduction

The lower cost of changing prices on internet allows platforms to set more flexible and various selling mechanisms to facilitate trading. Perishable goods, such as sports tickets, are often resold online by various dynamic selling mechanisms. Different platforms prefer offering different menus of selling mechanisms. For example, eBay allows sellers to sell their goods by sequential auctions or dynamic posted prices.

While a batch of literature (Hammond (2013)[19], Hummel (2015)[23] and Waisman (2017)[31]) using eBay's data shows that the multiple mechanisms will benefit sellers, buyers or the platform, in real life, some big ticket resale platforms, such as Stubhub, work well with only dynamic posted prices. These platforms are different from each other in many dimensions other than selling mechanisms. Some important questions to ask are how sellers decide their pricing strategies and selling mechanism choices in the dynamic setting and whether they will be affected by other characteristics of a platform. This paper tries to disentangle these questions by assessing participants' behavior on eBay's ticket resale market.

According to the existing literature and empirical applications, the reasons why participants choose auctions usually follow three arguments. 1) Competitive price discovery: sellers are uncertain about buyers' valuation. 2) Buyers' or sellers' heterogeneity: for example, buyers who have low valuation and high patience level or risk tolerance are more likely to choose auctions. 3) Easy to sell: auctions always have higher sales rates than posted prices. In a dynamic market, some of these advantages can be achieved to some extent by dynamic posted prices only. For example, even sellers cannot sell their goods in the current period, they are able to sell them later. This continuation value lowers the sellers' incentive to sell their goods in the current period. On the other hand, it is not always costless to use auctions along with dynamic posted prices. Even homogeneous goods can be differentiated by different selling mechanisms, which will decrease the price competition among sellers. If the reduction of competition is big, it may result in higher market prices even though auctions always have lower transaction prices than posted prices. This may make the platform less attractive to buyers in long run.

Participants' selling mechanism choices may be affected by other characteristics of a platform. Consider eBay for example, as an online platform with various goods to sell, the amount of tickets available to resale on eBay is not large. On eBay, sellers have more freedom regarding the ways to list their goods, such as using different forms of their titles and different shipment fees. Since there is no strict policy could guarantee buyers the tickets they want, the reputation (to be specific, the feedback score) will affect sales. Also, the default search algorithm on eBay is Best Match (Dinerstein(2014))[14] which is less related to prices. All of these will make buyers' choices among listings less sensitive to price, leading to less price competition among sellers. Further, this will affect sellers' mechanism choices. To be specific, let's consider one example. Since sellers with higher quality goods usually set higher prices, they can attract more buyers when buyers pay less attention to prices. Because the profit of an auction increases significantly with one additional bidder as long as the total number of bidders in the auction is moderate, the relative profits from auctions to posted prices is higher for these sellers when buyers are less price sensitive. In the model part, I will use some specific simulations to show how the relative profits from posted prices to auctions varies when some interesting parameters of the model change.

In this paper, I give a comprehensive empirical model to describe buyers' and sellers' behavior. On the demand side, I divide a buyer's problem into two stages. In the first stage, a buyer chooses a listing to enter within her consideration set according to her knowledge of prices, non-ticket information and noisy information about the tickets. In the second stage, based on more specific information about the tickets, she decides whether to buy the ticket and how much to bid if it is an auction. To simplify the problem, I assume that buyers are myopic and their arrival rate to a specific game's listings in one period of one selling mechanism is determined by the game's characteristics and the time left to the game. On the supply side, sellers are forward-looking. In each period, a seller makes decisions about which selling mechanism to use and how much price to set based upon a dynamic model and his knowledge of demand. Combining these two sides, I am able to figure out the conditions for equilibrium prices and the probability of choosing each selling mechanism.

To get some evidence from real markets, I use Chicago Cubs 2015 MLB season single home game tickets data from eBay. After doing some simple reduced form analysis, I structurally estimate the parameters in my model. To be specific, on the demand side, I use two-step method—uncover the distribution of willingness-to-pay first using observed two highest bids and then solve for the arrival process/entry problem using sales data. To overcome the sample selection bias caused by the incomplete data and the endogeneous price resulting from unobservables, I use a two-step method and instruments respectively in the estimation part. Given the estimated parameters on the demand side, I estimate outside options on the supply side by solving a dynamic game for the inner loop and using GMM estimation for the outer loop. Considering the difficulty to solve a dynamic competition game with selling mechanism choice, in the empirical part, I assume sellers are perfect foresight and the observed market strategies are the results of the dynamic model. Therefore, instead of solving the dynamic game for all the sellers simultaneously by backward induction, I plug the observed market information about a seller's opponents into his best response function directly. Therefore, the problem is like a partial single-agent problem which can capture the price competition to some extent

The estimation results show that both ticket and non-ticket characteristics will affect buyers' arrival rates to listings. The coefficient of price is significantly negative but with small magnitude. The parameters in the entry model for auctions and posted prices have different estimated values. The arrival rates to posted prices are always higher than the arrival rates to auctions given the assumption that value distribution is the same across different mechanisms. On the supply side, the results indicate that when sellers make decisions, they also consider outside options in the end besides continuation value from the dynamic model. The estimation results can predict well the market aggregate observables, such as dynamics of auction share, equilibrium start price level and its dynamics across time.

In light of the counterfactual analysis of this paper, I first consider how the participants' preferences, such as their patience about future, will affect their selling mechanism choice. The results show that when sellers are more patient, they have less incentive to use auctions. Then I focus on how the changes of market characteristics, like the search algorithm, availability of listings and commission fees, will affect the seller's mechanism choice and the equilibrium prices. By transforming the changes of market characteristics to the changes of price sensitivity and constant in the arrival process, I show that when the search algorithm is more related to prices or when there are more listings available in the market, average auction share and price will decrease. What's more, the equilibrium prices will be less dispersed. Finally, by eliminating auctions from the mechanism menu, I quantify how the market prices would change when sellers are only allowed to use posted prices. The decrease of prices in this scenario can be explained by the lower continuation values of sellers who prefer using auctions. Besides, sellers' expected profits will decrease if we keep other things the same. However, this result may be reversed if the lower market prices can attract more buyers from other platforms in long run.

Although the literature about selling mechanism choice, dynamic pricing or sequential auctions is not rare, only Waisman (2017) structurally models and estimates the dynamic pricing and selling mechanism choice problem for perishable goods as far as I know. That paper, however, doesn't explicitly model buyers' entry problem to listings, especially, it doesn't consider how buyers are sensitive to price when they make their entry decisions. Besides, that paper treats each seller's decision as a single-agent problem and doesn't take the price competition into account, which is different from my paper. In the empirical part, to capture more market information, I also try to rationalize both observed market prices and mechanism choices rather than mechanism choices only. Finally, this paper also more focuses on how characteristics of a platform will change the mechanism choices and market prices. These new things mentioned in the paper will not only contribute to the existing literature but also give some implication for better platform design in practice.

Road Map

The rest of the paper is organized as follows. Section 2 briefly reviews the literature related to this paper. In section 3, I introduce the online tickets resale market and specifically describe how the search pages look like on different platforms. Also, I give a summary statistics of the data I use in the empirical part. Section 4 is the model part for both buyers and sellers. I give some simple simulations after constructing the general model. Section 5 describes the identification strategy and estimation procedure of the paper. In section 6, after some reduced form analysis, I show the structural estimation results of the paper. Given the estimation results, section 7 lists some counterfactual scenarios for analysis. Section 8 concludes. Finally, in Appendix C, I depict another model which has different assumptions about the sellers' arrival process. I do one-step estimation and counterfactual analysis using a subsample of the data.

2 Literature Review

Literature related to this paper mainly includes three branches: mechanism choice, dynamic pricing and sequential auctions, search and online platform. I briefly summarize the related literature in each area here.

2.1 Mechanism Choice

The trade-off between auctions and posted prices has been studied in some theoretical models. Wang (1993)[32] presents a model to analyze the choice between auctions and fixed posted-price selling. He proves that a uniformly steeper marginal-revenue curve favors auctions. The global steepness of the marginal-revenue curve is the same to the dispersion around mean for a number of standard distributions. Caldentey and Vulcanowe (2007)[9] analyze a single-period model in which a seller operates a multi-unit, uniform price, online auction, offering multiple units of a homogeneous good. Consumers can get the product from an alternative list price channel. They consider two variants of this problem: In the first variant, the list price is an external channel run by another firm. In the second one, the seller manages both the auction and the list price channels. Ziegler and Lazear (2003)[35] model the auction cost as impatience and found that posted prices will be chosen if the seller is sufficiently impatient because they yield immediate transactions, while auctions have to last for a amount of time regardless of whether a willing buyer arrives.

Recently, the arise of online markets provides more opportunities for sellers to use various selling mechanisms with low transaction costs and for researchers to get more available data. Waisman (2017)[31] analyzes the choices of sellers between auctions and posted prices using NFL tickets. He finds that sellers benefit from the availability of different mechanisms. Einav et al.(2016)[15] models the choice between auctions and posted price as a trade-off between competitive price discovery and convenience. Hammond (2013)[19] shows that differences across sellers' outside options are important: the value of the outside option segments the market with high outside-option sellers choosing to post a fixed price. Hummel (2015)[23] constructs a model that several identical goods are sold simultaneously via an auction and posted price mechanism. He shows that bidders incline to bid more frequently near the end of the auction and sellers prefer to simultaneously using auctions and posted prices. Zeithammer and Liu (2006)[34] empirically test several possible explanations of the coexistence of various selling mechanisms for selling the same good. Their empirical test shows that both observed and unobserved seller heterogeneity are important for seller's mechanism-choice. Chen et al.(2017)[10] investigate sellers' choices among fixed-price posting, buy-it-now auction and regular auction. Coey et al.(2016)[12] model buyers in the markets as having a deadline by which the good have to be purchased and model sellers' choice between auctions and posted price mechanisms in continuous time. They find that as the deadline approaches, buyers tend to bid higher and are more likely to buy through posted-price listings. Their empirical work uses listings of new-in-box items on eBay to support their model.

Some papers focus the introduction of Buy-it-now option to auctions. Budish and Takeyama (2001)[8] show that introduce an English auction with a buy-it-now option can improve the seller's profits by attracting some risk-averse bidders. Bauner (2011)[3] studies the effect of BIN option in auctions for eBay sales of Major League Baseball tickets. He models the choices on both sides. On the demand side, buyers' choice among available listings; on the supply side, sellers make equilibrium decisions when choosing sales mechanisms and prices. Anwar and Zheng (2015)[1] show that with the buy-it-now option, some high valuation buyers buy the item before the auction starts. When there is a single seller with many items for sale, this will increase allocative efficiency and increases the seller's expected revenue. When there are many competing sellers, if sellers choose between the strategies of auction and buy-it-now auctions, the buy-it-now auctions will be adopted with positive probability in all equilibria.

2.2 Dynamic Pricing and Sequential Auctions

Sweeting (2012)[30] models and estimates sellers' dynamic pricing strategies for perishable goods using eBay sales of baseball tickets. The analysis focus on the posted price mechanism. It shows that some of the simplest dynamic pricing model can describe seller behavior very accurately. Dynamic posted prices Deneckere and Peck (2012)[13] studies a dynamic model of perfectly competitive price posting under uncertain demand. After produce in advance, firms set prices for their rest output. In each period, on the demand side, a batch of consumers is randomly activated. Existing customers decide to purchase at the lowest available price or delay their purchase after observing the posted prices. They describe a sequential equilibrium where the output is produced and its allocation is efficient. Their model can depict the price pattern for airline tickets.

Jofre-Bonet and Pesendorfer (2003)[24] firstly attack estimation in a dynamic auction game. Subsequent to this, a number of papers have looked at this dynamics. Zeithammer and Adams (2010)[33] develop a model with forward-looking bidders, and showed both theoretically and empirically that bidders shade down current bids in response to the presence of upcoming auctions of similar objects. Budish (2008)[7] examines the optimality of eBay's market design with respect to the sequencing of sales and information revelation. Backus and Lewis (2012)[2] provide a framework for estimating demand in a large auction market with a dynamic population of buyers with unit demand and heterogeneous preferences over a unite set of differentiated products. Hendricks and Sorensen (2014) offer a model, similar to Backus and Lewis (2012)[2] but in continuous time and with a single product type, and analyze the efficiency of the eBay trading mechanism.These two papers focus on the buyer's decision and don't consider the seller's pricing decision. Bodoh-Creed et.al (2016)[6] provides a model of decentralized auction platform like eBay and accounts for the endogenous entry of agents and the impact of intertemporal optimization on bids. They estimate the structural primitives of their model using Kindle sales on eBay. They find that over one third of Kindle auctions on eBay result in an inefficient allocation and partial centralization would eliminate a large fraction of the inefficiency, but yield lower seller revenues.

2.3 Search and Online Platform

Goldfarb and Tucker (2017)[18] summarize the five distinct economic costs associate with the digital economy: search cost, reputation costs, transportation costs, tracking costs and verification costs. Dinerstein et al.(2014) [14] studies a key trade-off associated with two important roles of efficient platform search algorithm design in guiding consumers to their most desired product while also strengthening seller incentives to provide low prices. They combine detailed browsing data from eBay and an equilibrium model of consumer search and price competition to quantitatively assess the trade-off related to a change in eBay's search algorithm design. Ellison and Ellison (2009) [16] show that retailers may engage in obfuscation—practices that frustrate consumer search or make it less damaging to firms which results in much less price sensitivity on some other products. Blake et al.(2016) [5] collect a dataset of search and purchase behavior from eBay to quantify the implied costs of consumer search on the internet. Hortaçsu and Syverson (2004)[22] investigate the role that nonportfolio fund differentiation and information search frictions play in explaining the large number of funds and the sizable dispersion in fund fees.

Several papers combine the tickets primary market with the secondary market. Leslie and Sorensen (2013)[25] estimate an equilibrium model of ticket resale in which consumers and brokers make decisions in the the primary market based on rational expectations about the resale market. They show which the presence of a resale market permits tickets to be traded from low-value to high-value consumers, it also encourages costly efforts by consumers and brokers to obtain underpriced tickets in the primary market. Bhave and Budish (2014) [4] studies the introduction of a novel variant of position auctions into this market by Ticketmaster. Combining with secondary-market resale data on eBay, they show that the auctions on average eliminated the arbitrage profits associated with underpriced tickets.

3 Data and Market

3.1 Tickets resale market

The data used in this paper is Chicago Cubs 2015 MLB regular season single home game tickets from eBay. After the teams sell their tickets in the primary market (e.g. via Ticketmaster in 2015), some of these tickets are resold on in the secondary market. Sellers in the secondary market include brokers and fans who cannot attend the games.

Tickets can be resold in secondary market via different sources. Most of them are sold on some platforms which are specialized in selling tickets, such as Stubhub. Relative small amount of tickets are resold on ebay which sells a wide variety of goods. There are many differences between these two types of platforms. On Stubhub, sellers are only allowed to list their tickets by posted prices. When buyers search Chicago cubs's tickets on Stubhub, they will see all available games in this season are listed according to the event time. Some preliminary information is given on the first page, such as the lowest price of the tickets for each game. When they enter the second page after clicking one game, buyers can observe the section, row and price information for each listing. The default ranking algorithm is from lowest price to highest price. Buyers cannot observe any information about the sellers. Stubhub offer a guarantee that buyers can receive the tickets they want, so the reputation of sellers is not important here. Also, since most of the tickets are electronic tickets, no shipping fee is needed. Stubhub charges average commission fees of 25% over transaction prices (15% from sellers and 10% from buyers). See Figure A4 and A5.

Unlike Stubhub, on eBay, sellers can sell their tickets via different selling mechanisms: auctions, hybrid auctions with a buy-it-now option, posted prices and posted prices with an option for bargaining. The available amount of tickets sold on eBay is relative small. When buyers search Chicago Cub's tickets on eBay, they will find different games' tickets are listed according to the best match algorithm by default. Buyers can choose to buy from auctions or posted prices using the options on the page. Further, buyers can search tickets for a specific game (see Figure A1 and A2). Still, the default ranking is not from lowest price to highest price. Except the row, section and prices information about tickets, different listings also differentiated by their shipping fees, sellers' feedback score, listing titles and even images. Some listings don't list all the information such as row and section on the first page, buyers have to enter the second page to get more information (see Figure A3). Although sellers will be punished, for instance, getting lower feedback score, if they cannot offer the tickets they list to the buyers, no strict policy guarantee buyers the they want in the end. Partially because of this, eBay only collects 10% commission fee from sellers.

These differences between two platforms mentioned above give us some ideas about how to construct the counterfactual scenarios later.

3.2 Summary Statistics

The data sample I use includes listings of 2015 Chicago cubs 102 home games listed 15 days before the event time. For each listing, I can observe the title of the listing, row and section numbers of the tickets, event time, listing time, selling mechanism, start prices, transaction prices, reserve prices, two highest bids for auctions, duration of auctions, sellers' id and first three zipcode, buyers' id and first three zipcode, stadium zipcode, the number of tickets listed in each listing and the number of items sold. According to the event time, I can identify different games and opponent teams in the games. Further, I can find the opponent teams' performance rankings in that season. Since it is hard to find the face value for each single game with specific seats number, here I use the season ticket information (see Figure A6 and A7) to collect the face value information of each ticket.

Table A1-Table A9 report the summary statistics of the characteristics. Here weekdays is 1 if the game is on Friday and Saturday, 2 if the game is on Sunday and 3 otherwise. The smaller the number of opponent means the higher ranking the opponent has in 2015 season. To simplify the problem, I treat a buy-it-now auction as an auction unless its buy-it-now option is executed. To simplify the problem, if a listing sells multiple tickets, I repeat the listing by the number of its tickets. By doing this, I can ensure each listing only sell unit ticket. In other words, I will not consider the complementarity of a ticket package. From Table A8. we see about 2/3 of the tickets listed in posted prices and 1/3 of them are listed in auction format. Auctions have relative higher sales rate than posted prices. Table A9 summarizes the relative prices (start price/face value and transaction price/face value) for each mechanism. The average relative transaction price is higher than relative start price. The relative prices for auctions are lower than those for posted prices.

Figure 1 and 2 show how the relative start prices and transaction prices vary across time. When it is close to the game, the relative prices decrease. Along with the decreasing prices, the transaction rate increases dramatically along with the time except the last two days for auctions.

Finally, Figure 3 and 4 depict how the auction share of all the listings and of transaction listings across time. We see, overall, the auction share decreases dramatically when there is less than 5 days left to the event time.

According to the figures and data, I find there is only two listings of auctions being sold in the last period. The start prices of auctions in the last period are high and the same as ending prices except one auction listing. In the last period, since games will begin soon, auctions are similar to posted prices. Also, in the estimation part, I find if I include auction listings in the last period, it is hard to estimate the arrival process of auctions given the value distribution estimated from observed bids. Therefore, I treat the auction listings in the last period as posted price listings.

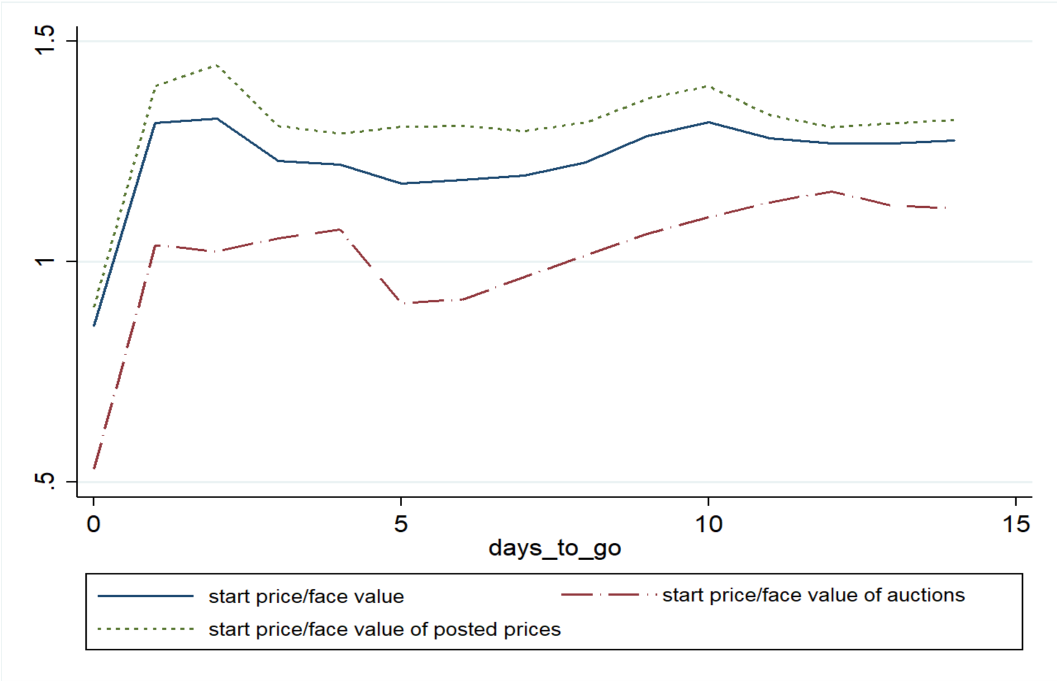

Figure 1: Start Price/Face Value over Time

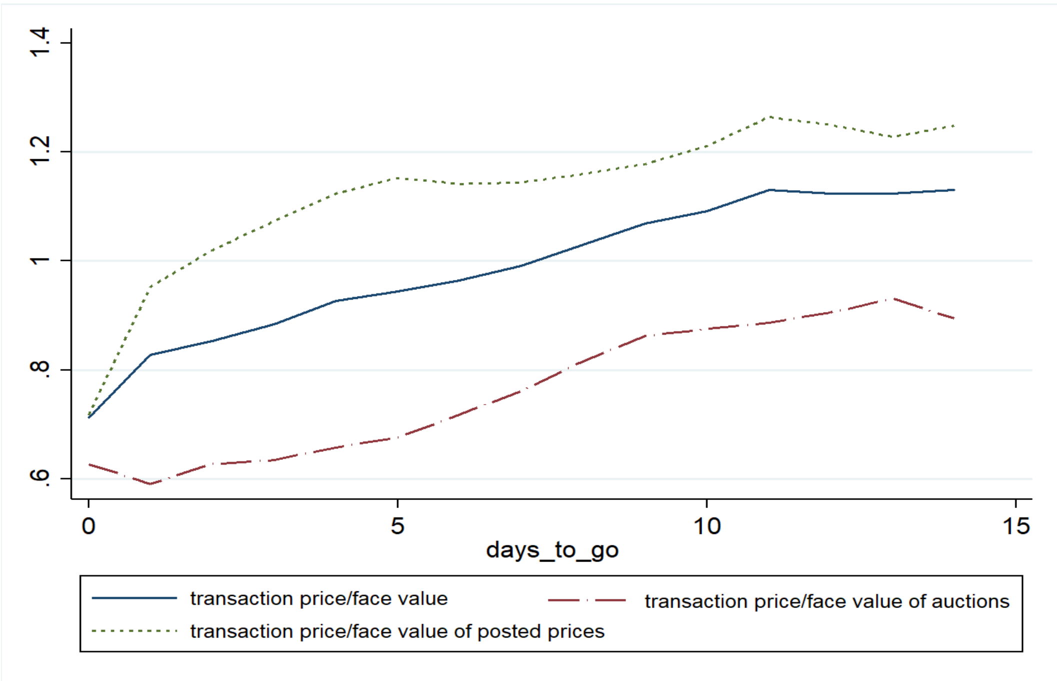

Figure 2: Transaction Price/Face Value over Time

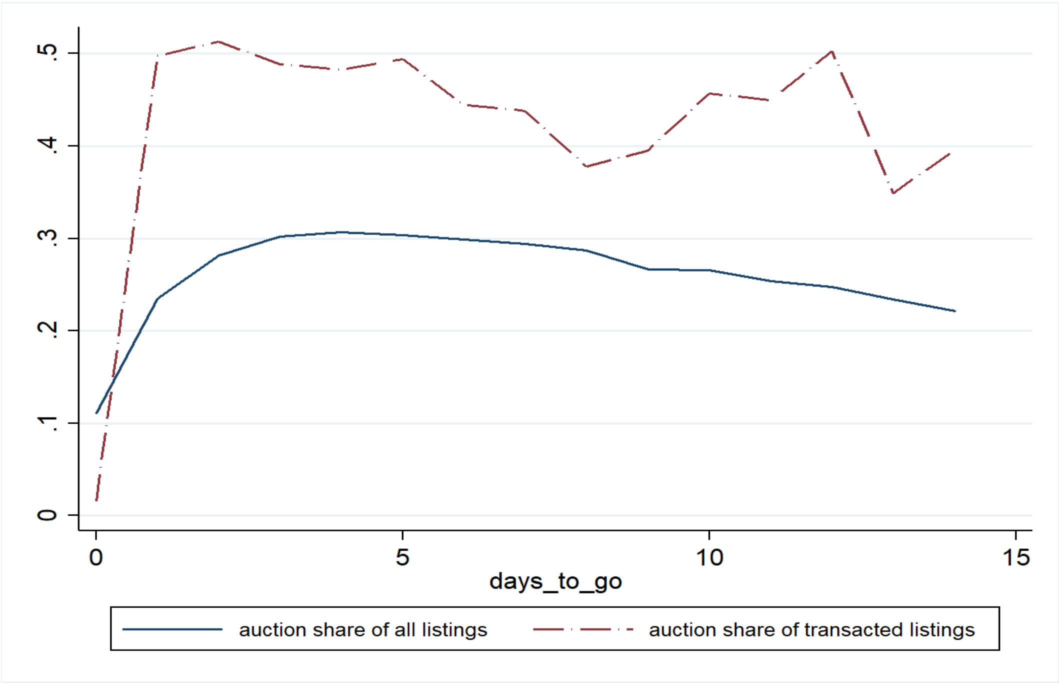

Figure 3: Auction Share over Time

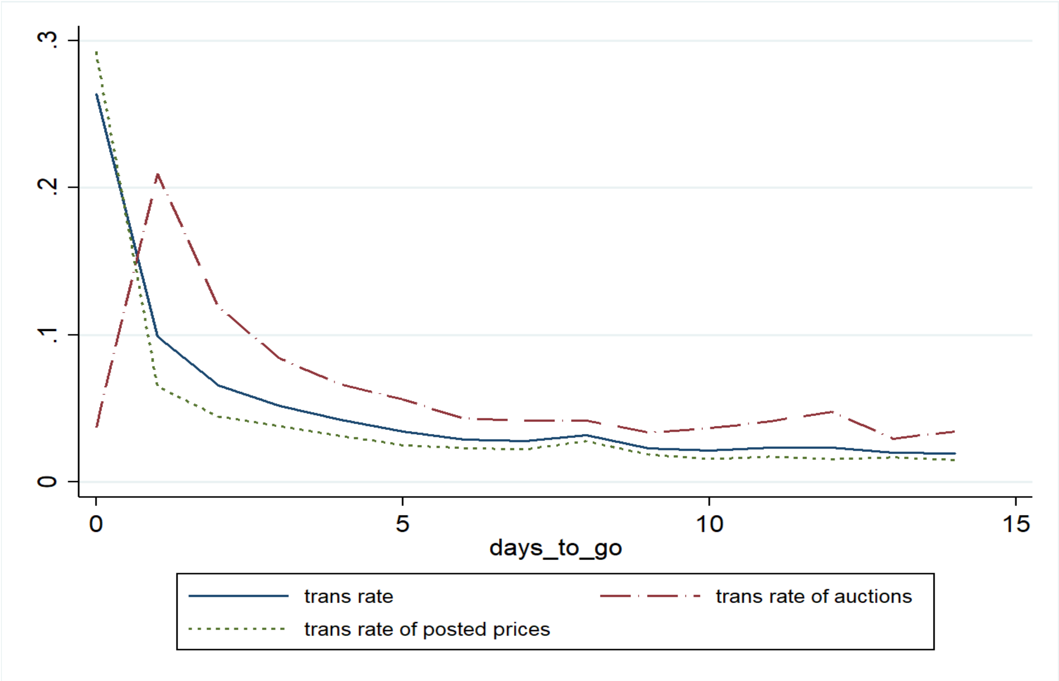

Figure 4: Transaction Rate over Time

4 Model

4.1 Setting

There are T periods before the game. Each seller and buyer have unit supply and demand. In period t, the number of buyers who arrive game g and mechanism M is N_{gt}^{MB}, which follows a Poisson distribution, namely, $N_{gt}^{MB} \sim Possion(\lambda_{gt}^{MB})$.

Assumption 1 *The arrival rate of buyers λ_{gt}^{MB} follows the exponential model*

$$\lambda_{gt}^{MB} = exp(\rho_0^{MB} + \rho_1^{MB} t + \rho_2^{MB} X_g^1);$$

Here X_g^1 contains the general information of game g, such as the opponent team's ranking in season 2015 and the weekdays of game g. $\rho_0^{MB}, \rho_1^{MB}, \rho_2^{MB}$ are observable to the sellers and buyers but unobservable to researchers.

Sellers randomly arrive each game. Denote the set of listings of game g with mechanism M in period t as G_t^M.

In the Appendix C, I show a model where the arrival rate of sellers also follows a Poisson distribution.

The platform collects commission fees from buyers and seller. The rate of commission fees are τ_1 and τ_2 respectively.

4.2 Demand

Before entering a listing in G_t^M, each buyer only has noisy information X_j^2 related to the payoff from each listing. Except the game information X_g^1, the noisy information may include the section and row numbers, prices and shipping fee listing on the first page. Buyers choose one listing to enter based on this noise information. We express the payoffs of entering listing j$\in G_t^M$ based on the noisy information as

$$V_{ijt}^M = \alpha_1^M p_{jt} + \alpha_2^M X_j^2 + \alpha_3^M X_g^1 + \varepsilon_{ijt}^1, \forall i,$$

where ε_{ijt}^1 follows extreme type one distribution.

According to the property of Poisson-Multinomial distribution(Chen(2017)[11]), the arrival rate for the listing j.

$$\lambda_{jt}^{MB} = \lambda_{gt}^{MB} \frac{exp(\alpha_1^M p_{jt} + \alpha_2^M X_j^2)}{\sum_{j\in G_t^M} exp(\alpha_1^M p_{jt} + \alpha_2^M X_j^2)},$$

$$or$$

$$log(\lambda_{jt}^{MB}) = \rho_0^{MB} + \rho_1^{MB} t + \rho_2^{MB} X_g^1 + \alpha_1^M p_{jt} + \alpha_2^M x_{jt} - log(\sum_{j\in G_t^M} exp(\alpha_1^M p_{jt} + \alpha_2^M x_j)).$$

To simplify the notation below, I denote all the parameters in the arrival process model as Θ^1.

There are some points I need to mention here. First, the model implies buyers exogenously choose among games and then endogenously choose among different listings within same games. Second, in this model, α_1^M capture the price sensitivity in a buyer's entry problem. α_2^M can represent how the entry decision of each buyer is related to the good's characteristics or quality. If information of the good's characteristics is more noisy, the arrival rate may be less related with X_j^2, namely, α_2^M is smaller. According to the Poisson distribution, we have

$$Prob(N_{jt}^{MB} = n) = Prob(\Theta, p_{jt}, X_j^1, X_j^2) = \frac{e^{-\lambda_{jt}^{MB}}(\lambda_{jt}^{MB})^n}{n!}.$$

After entering the listing, each buyer realizes her value from the good. For $\forall$ buyer i, her value for listing j is v_{ij} which is independently drawn from a distribution $F_v(\cdot|X_j^3)$. X_j^3 includes the specific characteristics of the ticket, for example, ticket's face value, row and section numbers on the second page. I can parametrize the distribution, for example, in the empirical part I assume $log(v_{ij}) = \gamma_1 X_j^3 + \zeta_g + \varepsilon_i^2, \varepsilon_i^2$ follows normal distribution with mean μ_v and standard deviation σ_v,ζ_g is the fixed effect of the game. Denote the parameters in the value distribution as Θ^2.

I assume buyers are myopic, which can be extended in the future. If ticket j is sold by posted price, then buyer i's expected payoff is

$$V_{ijt}(X_j, p_t, \Theta)$$
$$= \sum_n [\frac{1}{n}(v_{ij} - (1+\tau_1)p_{jt})] Prob(N_{jt}^{PB} = n | \lambda_{jt}^{PB}, N_{jt}^{PB} \geq 1),$$

where $X_j = \{X_j^1, X_j^2, X_j^3\}$ and $\theta = \{\theta^1, \theta^2\}$.

Buyers will buy the ticket as long as $v_{ij} > (1+\tau_1)p_{jt}$.

If ticket j is sold by auction, then buyer i's expected payoff is

$$V_{ijt}(\beta_1, X_j, p_t, \Theta)$$
$$= \sum_n \max_{b_{ijt}} [\int_{\underline{v}}^{B^{-1}(b_{ijt})} (\beta_1^{D_{jt}} v_{ij} - (1+\tau_1)B(v)) dF_V^2(v|X_j, n-1)$$
$$+(\beta_1^{D_{jt}}(v_{ij}) - (1+\tau_1)r_{jt})F_V^2(\underline{v}|X_j, n-1)] Prob(N_{1jt\sim t+D-1}^{AB} = n | \lambda_{jt}^{AB}, N_{1jt\sim t+D_{jt}-1}^{AB} \geq 1).$$

Here, $F_V^2(v|X_j^3, n)$ is the distribution of the second highest value among n buyers who arrive auction j during the auction duration D_{jt}. $\beta_1^{D_{jt}}$ is buyer's discount rate of an auction if the auction's duration is D_{jt}. If we simplify eBay's auction to second prices auctions[1] , then we can solve for the buyer's optimal bidding strategy:

$$(1+\tau_1)b_{ijt} = \beta_1^{D_{jt}} v_{ij}.$$

[1]Here, I ignore the snipping problem in eBay's auctions. Snipping in eBay's auctions has attract a lot market designer's attention, such as Roth and Ockenfels (2002)[27] and Ely and Hossain (2009)[17]. Also, if we consider the discrete bid increments in eBay's auction, the bidders at electronic auctions tend to engage in shading instead of revealing their valuations as in the second price auctions. See Hickman et al.(2017)[21].

4.3 Supply

Each seller makes his decision in two stages: first, he chooses which selling mechanism to use; secondly, he decides the price and auction duration. Since it is a finite period problem, I use backward induction to solve his optimal decision. Here I assume sellers are risk neutral.

4.3.1 Myopic sellers

If the seller choose a posted price, then his value function is

$$\Pi^P_{jt}(X_j, \Theta)$$
$$= \max_{p^P_{jt}} E[(1-\tau_2)(p^P_{jt} - c_j)Prob(v^{(1)}_n \geq p^P_{jt})|N^{PB}_{jt} = n] \times Prob(N^{PB}_{jt} = n|\lambda^{PB}_{jt}) + \epsilon^P_{jt}$$
$$= \overline{\Pi}^P_{jtD}(X_j, \Theta) + \epsilon^P_{jt}.$$

If the seller choose an auction, then his value function is

$$\Pi^A_{jtD}(X_j, \Theta, \beta_1)$$

$$= \max_{r_{jt}} \sum_{n_t}, ... \sum_{n_{t+D_{jt}-1}} E[Prob(\beta_1^{D_{jt}} v^{(1)}_{n_t+...+n_{t+D_{jt}-1}} \geq r_{jt} \geq \beta_1^{D_{jt}} v^{(2)}_{n_t+...+n_{t+D_{jt}-1}})(1-\tau_2)(r_{jt}-c_j)$$
$$+Prob(\beta_1^{D_{jt}} v^{(2)}_{n_t+...+n_{t+D_{jt}-1}} \geq r_{jt})$$
$$E[(1-\tau_2)(v^{(2)}_{n_t+...+n_{t+D_{jt}-1}} - c_j)|\beta_1^{D_{jt}} v^{(2)}_{n_t+...+n_{t+D_{jt}-1}} \geq r_{jt}]|N^{AB}_{jt} = n_t, ..., N^{AB}_{jt+D_{jt}-1} = n_{t+D_{jt}-1}]\times$$
$$Prob(N^{AB}_{jt} = n_t, ..., N^{AB}_{jt+D_{jt}-1} = n_{t+D_{jt}-1}|\lambda^{AB}_{jt}, ..., \lambda^{AB}_{jt+D_{jt}-1}) + \epsilon^A_{jt}$$
$$= \max_{r_{jt}} \overline{\pi}^A_{jtD}(X_j, \Theta) + \epsilon^A_{jt}$$
$$= \overline{\Pi}^A_{jtD}(X_j, \Theta) + \epsilon^A_{jt}.$$

Here ϵ^A_{jt} is a seller-mechanism-platform-specific idiosyncratic shock which is independent of price and c_j is the cost.

Assumption 2 *Sellers have perfect foresight of the market evolution process and list auctions until they end.*

According to the property of Poisson distribution, if buyers' arrival rates to listing j are $\{\lambda_{jt}, \lambda_{jt-1}, ..., \lambda_{jt+D_{jt}-1}\}$, the number of buyers arrive auction j with duration D in period t, namely $N^{AB}_{jt...jt-D}$, follows Poisson distribution with $\lambda_{jt...D_{jt}-1} = \sum_{\tau=t}^{\tau=t+D_{jt}-1} \lambda_{j\tau}$.

Given Assumption 2, we have

$$\Pi^A_{jtD}(X_j,\Theta,\beta_1) = \max_{r_{jt}} \sum_n E[Prob(\beta_1^{D_{jt}} v_n^{(1)} \geq r_{jt} \geq \beta_1^{D_{jt}} v_n^{(2)})(1-\tau_2)(r_{jt}-c_j)$$

$$+Prob(\beta_1^{D_{jt}} v_n^{(2)} \geq r_{jt}) E((1-\tau_2) v_n^{(2)} | \beta_1^{D_{jt}} v_n^{(2)} \geq r_{jt})] | N^{AB}_{jt..jt-D_{jt}-1} = n]$$

$$\times Prob(N^{AB}_{jt..jt-D_{jt}-1} = n | \lambda_{jt...D_{jt}-1}) + \epsilon^A_{jt}$$

$$= \max_{r_{jt}} \overline{\pi}^A_{jtD}(X_j,\Theta,\beta_1) + \epsilon^A_{jt}$$

$$= \overline{\Pi}^A_{jtD}(X_j,\Theta,\beta_1) + \epsilon^A_{jt}.$$

$$D^*_{jt} = argmax_{D_{jt}} \Pi^A_{jtD}(X_j,\Theta,\beta_1) \Rightarrow \Pi^A_{jt}(X_j,\Theta,\beta_1)$$

The choice of D_{jt} is a complicated problem. On the one hand, if the auction has longer duration, it can attract more buyers; on the other hand, buyers will discount their bids duration is longer.

4.3.2 Forward-looking sellers

If the seller choose a posted price, then

$$\Pi^P_{jt}(X_j,\Theta,\beta_2)$$

$$= \max_{p^P_{jt}} E[(1-\tau_2)(p^P_{jt}-c_j) Prob(v_n^{(1)} \geq p^P_{jt})$$

$$+Prob(v_n^{(1)} < p^P_{jt}) \beta_2 \Pi_{jt+1}(X_j,\Theta) | N^{PB}_{jt} = n] \times Prob(N^{PB}_{jt} = n | \lambda^{PB}_{jt}) + \epsilon^P_{jt}$$

$$= \overline{\Pi}^P_{jt}(X_j,\Theta) + \epsilon^P_{jt}.$$

If the seller choose an auction, his value function from the auction given he chooses duration D_{jt} is

$$\Pi^A_{jtD}(X_j,\Theta,\beta_1) = \max_{r_{jt}} \sum_n E[Prob(\beta_1^{D_{jt}} v_n^{(1)} \geq r_{jt} \geq \beta_1^{D_{jt}} v_n^{(2)})(1-\tau_2)(r_{jt}-c_j)$$

$$+Prob(\beta_1^{D_{jt}} v_n^{(2)} \geq r_{jt}) E((1-\tau_2) v_n^{(2)} | \beta_1^{D_{jt}} v_n^{(2)} \geq r_{jt})] | N^{AB}_{jt..jt-D_{jt}-1} = n]$$

$$+Prob(v_n^{(1)} < r_{jt}) \beta_2 \Pi_{jt-D}(X_j,\Theta,\beta_1,\beta_2) | N^{AB}_{jt..jt-D_{jt}-1} = n] \times Prob(N^{AB}_{jt..jt-D_{jt}-1} = n | \lambda_{jt...D_{jt}-1}) + \epsilon^A_{jt}$$

$$= \max_{r_{jt}} \overline{\pi}^A_{jtD}(X_j,\Theta,\beta_1,\beta_2) + \epsilon^A_{jt}$$

$$= \overline{\Pi}^A_{jtD}(X_j,\Theta,\beta_1,\beta_2) + \epsilon^A_{jt}.$$

$$D^*_j = argmax_{D_j} \Pi^A_{jtD}(X_j,\Theta,\beta_1,\beta_2) \Rightarrow \Pi^A_{jt}(X_j,\Theta,\beta_1,\beta_2)$$

Here β_2 is the discount rate of the continuation value.
Outside choice

$$\Pi_{jt}^{O} = \overline{\Pi}_{jt}^{O} + \epsilon_{jt}^{O}.$$

Choose mechanism has highest value.

$$\Pi_{jt}(X_j, \Theta, \beta_1, \beta_2) = \max_{M \in \{A,P,O\}} \{\Pi_{jt}^{A}(X_j, \Theta, \beta_1, \beta_2), \Pi_{jt}^{P}(X_j, \Theta, \beta_2)\}, \Pi_{jt}^{O}\}.$$

Since ϵ_{jt}^{M} follows extreme type one distribution and similar to Rust(1987)[28], I construct $\overline{\Pi}_{jt}^{O}$ in the following way.

$$\overline{\Pi}_{jt}^{O} = \begin{cases} \beta_2 log(exp(\overline{\Pi}_{jt+1}^{A}(X_j, \Theta)) + exp(\overline{\Pi}_{jt+1}^{P}(X_j, \Theta)) + exp(\beta_2 \overline{\Pi}_{jt+1}^{O}(X_j, \Theta))) & t < T; \\ \beta_2 * outside_j & t = T \end{cases}$$

where $outside_j = \gamma_2^0 + \gamma_2^1 \times facevalue_j$. Denote $\gamma_2 = \{\gamma_2^0, \gamma_2^1\}$.

The equilibrium prices for different selling mechanisms can be solved by the first order conditions of expected profits.

$$\frac{\partial \overline{\Pi_{jt}^{P}}(X_j, \Theta, \beta_2)}{\partial p_{jt}^{P}}$$

$$= \sum_n \{E[(1-\tau_2)Prob(v_n^1 \geq p_{jt}^{P}) + p_{jt}^{P}(1-\tau_2)\frac{\partial Prob(v_n^{(1)} \geq p_{jt}^{P})}{\partial p_{jt}^{P}}$$

$$+\beta_2 \Pi_{jt-1}(X_j, \Theta)\frac{\partial Prob(v_n^{(1)} \leq p_{jt}^{P})}{\partial p_{jt}^{P}} | N_{jt} = n]$$

$$\times Prob(N_{1jt} = n | \lambda_{jt}^{PB})$$

$$+E[p_{jt}^{P}(1-\tau_2)Prob(v_n \geq p_{jt}^{P}) | N_{jt} = n]\frac{\partial Prob(N_{jt} = n | p_{jt}, X_j, \Theta)}{\partial p_{jt}^{P}}\} = 0.$$

where

$$Prob(v_n^{(1)} \geq p_{jt}^{P}) = (1 - F(p_{jt}^{P})^n)$$

,

$$\frac{\partial Prob(v_n \geq p_{jt}^{P})}{\partial p_{jt}^{P}} = -nF(p_{jt}^{P})^{n-1} f(p_{jt}^{P}),$$

$$\frac{\partial Prob(v_n \leq p_{jt}^{P})}{\partial p_{jt}^{P}} = nF(p_{jt}^{P})^{n-1} f(p_{jt}^{P}),$$

$$Prob(N_{1jt} = n | p_{jt}^{P}, X_j, \Theta) = \frac{e^{-\lambda_{jt}^{PB}} (\lambda_{jt}^{PB})^n}{n!},$$

$$and$$
$$\frac{\partial Prob(N_{1jt}=n|p_{jt}^{P},X_j,\Theta)}{\partial p_{jt}^{P}}$$
$$=\frac{-e^{-\lambda_{jt}^{PB}}(\lambda_{jt}^{PB})^{n}+ne^{-\lambda_{jt}^{PB}}(\lambda_{jt}^{PB})^{n-1}}{n!}\lambda_{jt}^{PB}\alpha_1^{M}.$$
$$\Rightarrow p_{jt}^{P*}(\Theta)$$

Similarly,

$$\frac{\partial\overline{\Pi_{jtD}^{A}}(X_j,\Theta,\beta_1,\beta_2)}{\partial r_{jt}}$$
$$=\sum_n\{E[Prob(\beta_1^{D_{jt}}v_n^{(1)}\geq r_{jt}^{*}\geq\beta_1^{D_{jt}}v_n^{(2)})(1-\tau_2)r_{jt}^{*}$$
$$+Prob(\beta_1^{D_{jt}}v_n^{(2)}\geq r_{jt}^{*})(1-\tau_2)E[v_n^{(2)}|\beta_1^{D_{jt}}v_n^{(2)}\geq r_{jt}^{*}]$$
$$+Prob(\beta_1^{D_{jt}}v_n^{(1)}<r_{jt})\beta_2\Pi_{jt-D}(X_j,\Theta,\beta_1,\beta_2)|N_{jt}=n]$$
$$\frac{\partial Prob(N_{1jt}=n|\lambda_{jt\ldots D_{jt}-1})}{\partial r_{jt}}$$

$$+\sum_n\{E[(1-\tau_2)nF(\frac{r_{jt}}{\beta_1^{D_{jt}}})^{n-1}(1-F(\frac{r_{jt}}{\beta_1^{D_{jt}}}))-n\frac{r_{jt}}{\beta_1^{D_{jt}}}(1-\tau_2)F(\frac{r_{jt}}{\beta_1^{D_{jt}}})^{n-1}f(\frac{r_{jt}}{\beta_1^{D_{jt}}})$$
$$+nF(\frac{r_{jt}}{\beta_1^{D_{jt}}})^{n-1}f(\frac{r_{jt}}{\beta_1^{D_{jt}}})\frac{\Pi_{jt-D}(X_j,\Theta,\beta_1,\beta_2)}{\beta_1^{D_{jt}}}|N_{jt}=n]$$
$$\times Prob(N_{1jt}=n|r_{jt},X_j,\Theta)\}=0,$$

$$where$$
$$Prob(N_{1jt}=n|r_{jt},X_j,\Theta)=\frac{e^{-\lambda_{jt}^{AB}}(\lambda_{jt}^{AB})^{n}}{n!}$$
$$and$$
$$\frac{\partial Prob(N_{1jt}=n|\lambda_{jt\ldots D_{jt}-1})}{\partial r_{jt}}$$
$$=\frac{-e^{-\lambda_{jt}^{AB}}(\lambda_{jt}^{AB})^{n}+ne^{-\lambda_{jt}^{AB}}(\lambda_{jt}^{AB})^{n-1}}{n!}\lambda_{jt}^{AB}\alpha_1^{M}.$$
$$\Rightarrow r_{jt}^{*}(\Theta)$$

Notice that these FOCs are a seller's best response functions to other sellers' pricing and selling mechanism strategy. Solving this dynamic game simultaneously is very complicated. Also, there is no existing model which solves both dynamic prices and dynamic selling strategies for competing sellers. To make the problem tractable, in this empirical part, I assume the observed market prices and choices of mechanisms are solved by this dynamic model. Combining with Assumption 2, when solving a seller's dynamic optimization problem, I will put the observed other seller's strategy into the seller's best response function. This simplification makes the game like a partial single-agent problem which can be solved and estimated in the empirical part.

4.4 Analysis of two-stage models

Before I empirically solve the dynamic model, here I analyze two-stage games with different specifications to see how the difference of profits between posted prices and auctions will change when some interesting parameters in the model change.

To be specific, I compare $\Pi^P_{jt}(X_j,\Theta)$ and $\Pi^A_{jt}(X_j,\Theta)$ with the change of price sensitivity α^M_1, constant in the arrival process ρ^{MB}_0, β_1 and β_2. The comparison can be divided into comparing $\Pi^P_{jt}(X_j,\overline{\Theta}),\beta_1$ and $\Pi^A_{jt}(X_j,\overline{\Theta},\beta_1,\beta_2)$, $\frac{\partial\Pi^P_{jt}(X_j,\Theta,\beta_1)}{\partial\Theta}$ and $\frac{\partial\Pi^A_{jt}(X_j,\Theta,\beta_1,\beta_2)}{\partial\Theta}$. For example, for α^M_1,

$$\frac{\partial\Pi^P_{jt}(X_j,\Theta,\beta_2)}{\partial\alpha^P_1}$$

$$=\sum_n\{E[p^*_{jt}(1-\tau_2)Prob(v_n\geq p^*_{jt})+Prob(v^{(1)}_n<p^P_{jt})\beta_2\Pi_{jt-1}(X_j,\Theta)|N_{jt}=n]$$

$$\times\frac{-e^{-\lambda^{PB}_{jt}}(\lambda^{PB}_{jt})^n+ne^{-\lambda^{PB}_{jt}}(\lambda^{PB}_{jt})^{n-1}}{n!}\}\lambda^{PB}_{gt}$$

$$\times\frac{p_{jt}exp(\alpha^P_1p^*_{jt}+\alpha^P_2X^2_j)\sum exp(\alpha^P_1p^*_{jt}+\alpha^P_2X^2_j)-exp(\alpha^P_1p^*_{jt}+\alpha^P_2X^2_j)\sum exp(\alpha^P_1p^*_{jt}+\alpha^P_2X^2_j)p_{jt}}{[\sum exp(\alpha^P_1p^*_{jt}+\alpha^P_2X^2_j)]^2}\};$$

$$\frac{\partial\Pi^A_{jt}(X_j,\Theta,\beta_1,\beta_2)}{\partial\alpha^A_1}$$

$$=\sum_n\{E[Prob(\beta_1^{D_{jt}}v^{(1)}_n\geq r^*_{jt}\geq\beta_1^{D_{jt}}v^{(2)}_n)(1-\tau_2)r^*_{jt}+Prob(\beta_1^{D_{jt}}v^{(2)}_n\geq r^*_{jt})(1-\tau_2)E[v^{(2)}_n|\beta^{D_{jt}}v^{(2)}_n\geq r^*_{jt}]$$

$$+Prob(v^{(1)}_n<r_{jt})\beta_2\Pi_{jt-D}(X_j,\Theta,\beta_1,\beta_2)|N_{jt}=n]$$

$$\frac{-e^{-\lambda^{AB}_{jt}}(\lambda^{AB}_{jt})^n+ne^{-\lambda^{AB}_{jt}}(\lambda^{AB}_{jt})^{n-1}}{n!}\}lambda^{PB}_{gt}$$

$$\frac{r_{jt}exp(\alpha^A_1r^*_{jt}+\alpha^A_2X^2_j)\sum exp(\alpha^A_1r^*_{jt}+\alpha^A_2X^2_j)-exp(\alpha^A_1r^*_{jt}+\alpha^A_2X^2_j)\sum exp(\alpha^A_1r^*_{jt}+\alpha^A_2X^2_j)r_{it}}{[\sum exp(\alpha^A_1r^*_{jt}+\alpha^A_2X^2_j)]^2}\};$$

Similar to other parameters. and $\frac{\partial\Pi^A_{jt}(X_j,\Theta,\beta_1,\beta_2)}{\partial\rho^A_0}$.

For $\overline{\Theta}$, I use $\rho^M_0=0$ or $\alpha^M_1=0$ or $\beta_1=1$ or $\beta_2=1$.

The information we can get for the bound is when $\alpha_1^M = 0$, we have $1 - F_v(r_{jt}^*) = r_{jt}^* f_v(r_{jt}^*)$.

$$\Pi_{jt}^A(X_j, 0) =$$

$$\sum_n \{E[(1-\tau_2)(1-F(p_{jt}^*)^n) - np_{jt}(1-\tau_2)F(p_{jt}^*)^{n-1} f(p_{jt}^*)|N_{jt} = n] \times Prob(N_{1jt} = n|\lambda_{jt}^{AB}) = 0.$$

Since the comparison depends on how we set other parameters. Here, I solve the problem in four simple cases. For all of the following cases, I assume there are five listings $j \in 1, ..., 5$ in the market for the same game in each period of each selling mechanism. Sellers make their price strategy simultaneously in each period. $X_j^2 = X_j^3 = j$, $\gamma_1 = 1$, $\sigma_v = 1$ and $v_{ij}\ N(X_j^3, \sigma_v)$. $\rho_1^{MB} = \rho_2^{MB} = 0$,i.e.,$\lambda gt^{MB} = exp(\rho_0^{MB})$ and $\beta_1 \in \{0.9, 1\}$.When $t = 2$,$t = 0$ and $D = 1$.

Case 1. $outside = 0.5 * j$,$\beta_2 = 1$,$\alpha_2^M = 0.5$ and $\rho_0^{MB} = 1$,$\alpha_1^A = \alpha_1^P$ which change from -0.5 to 0

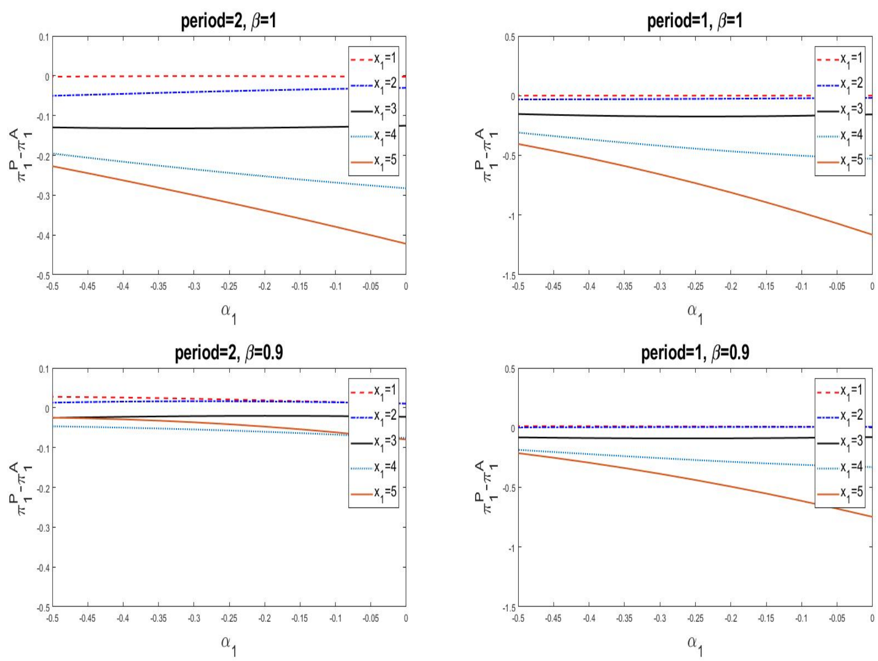

Figure 5: Simulation under Case 1

Case 2. $outside = 1 + 0.5 * j$,$\beta_2 = 1$,$\alpha_1^M = -0.5$ and $\alpha_2^M = 0.25$,$\rho_0^{AB} = \rho_0^{PB}$ which from 0.8 to 1.2.

Case 3. $outside = 0.5 * j$,$\beta_2 = 1$,$\alpha_1^M = -0.5$ and $\alpha_2^M = 0.25$,$\rho_0^{AB} = \rho_0^{PB}$ which from 0.8 to 1.2.

Case 4. $outside = 1 + 0.5 * j$,$\alpha_1^M = -0.5$, $\alpha_2^M = 0.5$,$\rho_0^{AB} = \rho_0^{PB} = 1$ and β_2 change from 0.8 to 1.

Under these settings, we see from Figure 5,6,8,9 overall, the relative profits of posted prices to auctions increase when buyers are more sensitive to price, the average

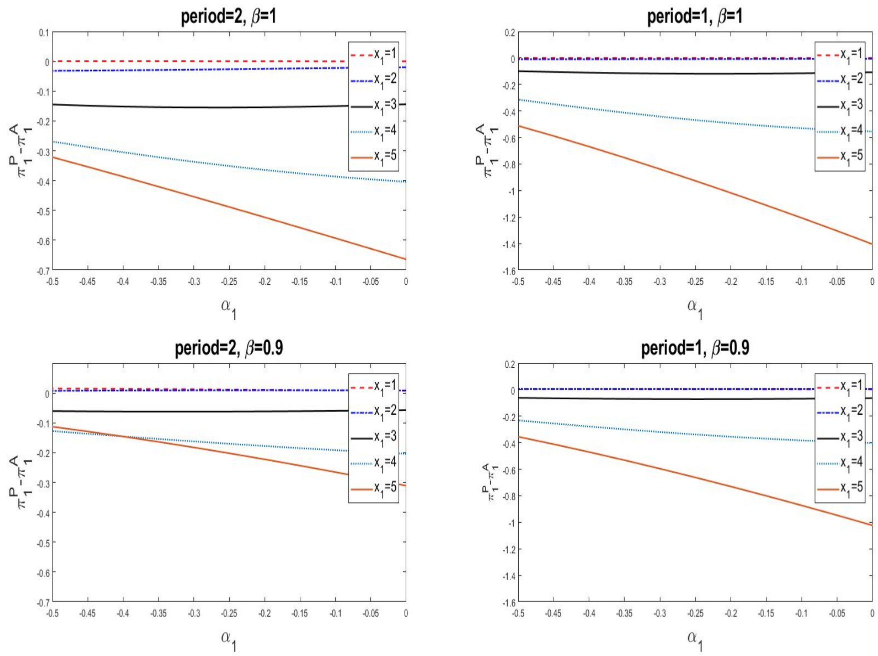

Figure 6: Simulation under Case 2

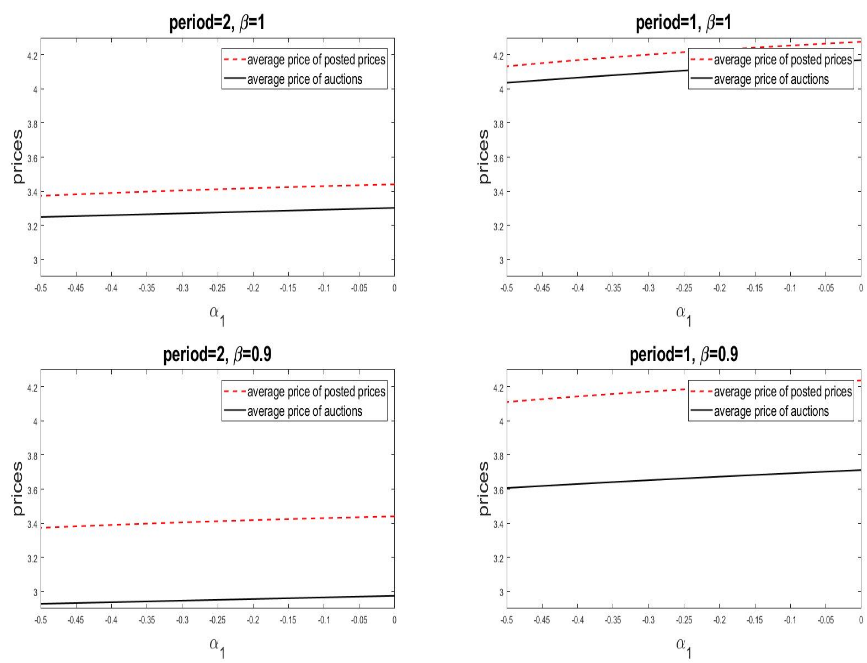

Figure 7: Simulation under Case 2(2)

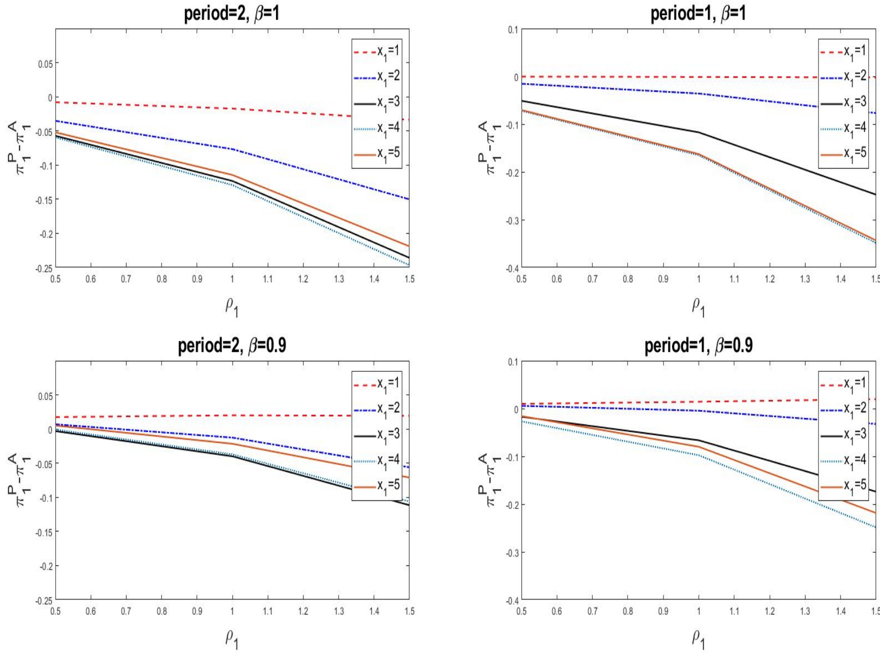

Figure 8: Simulation under case 3

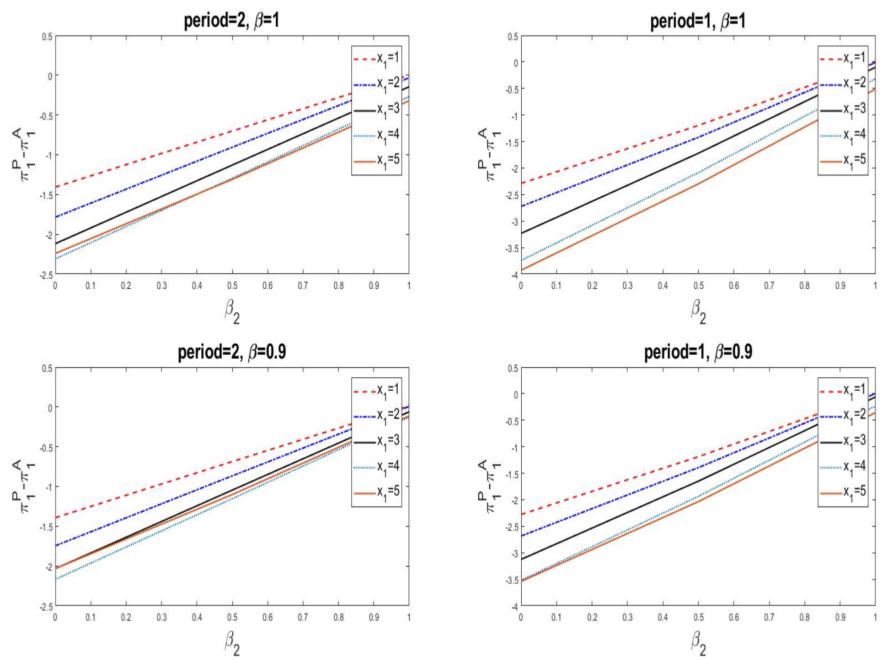

Figure 9: Simulation under Case 4

ratio of buyers to sellers decreases, buyers discount auction more or sellers discount continuous value less. This is especially true for the listings with high values. This is because these listings always set higher price than average market price. When buyers are less sensitive to price in the entry stage, more buyers will enter their auctions which significantly increases the auction profit when the number of bidders is moderate. Also, from Figure 7, we see the average prices of all the listings decrease as buyers are more sensitive to price for both selling mechanisms. This can be explained by the fiercer price competition among sellers.

Since in the empirical part, I assume the observed market prices are the optimal prices from solving the dynamic problem. Here, I check how each seller's price strategy will change when plugging other listings' optimal prices directly into its dynamic model. The differences between prices in the new setting and original setting are all smaller than 10^{-12}.

5 Identification and Estimation

In this section, I discuss the identification strategy of the paper. Then I present estimation procedure which is based on the identification argument.

5.1 Identification

The primitives in the model we wish to identify include θ, β_1 ,β_2 and the γ_2 in the outside option. I will show how θ and γ_2 can be recovered using observed data given β_1 and β_2.

First, using auction bids and the sales data of both posted prices and auctions, I can recover the primitives on demand side. According to the model part, we know a buyer's bid in an auction satisfies the following one-to-one mapping given the buyer is myopic and β_1.

$$(1+\tau_1)b_{ijt} = v_{ij}^{\beta_1^{D_{jt}}}.$$

The distribution of bids and the distribution of values satisfy

$$F^b(b) = Prob(b_{jt} < b) = Prob(\frac{v_{ij}^{\beta_1^{D_{jt}}}}{1+\tau_1} < b) = F^v(((1+\tau_1)b)^{\frac{1}{\beta_1^{D_{jt}}}}).$$

Therefore, given β_1, we can identify the distribution of values based on the distribution of bids. However, usually, we have no information about the potential number of bidders for an auction and can only observe a truncated distribution of the bids. To solve this problem, I use the method given by Song (2004)[29] and make use of the two highest bids to recover the distribution of bids. Denote $b_1$and b_2 as the highest and second highest bids.

$$g^b(b_1|b_2) = \frac{f^b(b_1)}{1-F^b(b_2)}.$$

Evaluating it at $b_2 = b_1 = b$.

$$f^b(b) = F^{b'}(b) = g^b(b|b) - g^b(b|b)F^b(b).$$

Since there is only limited data, considering the high dimensionality problem with nonparametric method, I use parametric estimation. Assume v follows log normal distribution.

$$log(v_{ij}) = \gamma_1 X_j^3 + \zeta_g + \varepsilon_i^2$$

where ε_i^2 follows normal distribution with mean μ_v and standard deviation σ_v. ζ_g is a game specific fixed-effect. I assume μ_v and σ_v are the same across all the listings in the market.

$$\begin{aligned} log(b_{ij}) &= \beta_1 log(v_{ij}) \\ &= \beta_1(\gamma_1 X_j^3 + \zeta_g + \varepsilon_i^2) \\ &= \gamma_1^b X_j^3 + \zeta_g^b + \varepsilon_{ib} \end{aligned}$$

where ε_{ib} follows normal distribution with mean μ_b and standard deviation σ_b. ζ_g^b is a game specific fixed-effect.

Assume the error term is still independent of X_j^3 and ζ_g^b. We can regress the two highest bids on X_j^3 without constant first and get the consistent estimation of γ_1^b and ζ_j^b . Using the consistent error term $log(b_{ij}) - \gamma_1^b X_j^3 + \zeta_g^b$ and $g^b(b_1|b_2) = \frac{f^b(b_1)}{1-F^b(b_2)}$, we can recover μ_b and σ_b by MLE (similar to Waisman(2017)[31]).

Without knowing β_1, it is hard to identify $F^v(\cdot)$ from $F^b(\cdot)$. However, we can utilize the identified information about $F^b(\cdot)$ to uncover the arrival process of buyers to auctions. Based on the model, the probability of making a sale for an auction is

$$\begin{aligned} Prob(sell_{jA}) &= \sum_{n=1}^{\infty} Prob(N_{jt} = n)(1 - Prob(v^{\beta^{D_{jt}}} < (1+\tau_1)r_{jt})^n) \\ &= \sum_{n=1}^{\infty} \frac{e^{-\lambda_{jt}^{AB}} (\lambda_{jt}^{AB})^n}{n!} (1 - F^b(1+\tau_1)r_{jt})^n) \end{aligned}$$

Since

$$\lambda_{jt}^{AB} = \lambda_{gt}^{AB} \frac{exp(\alpha_1^A r_{jt} + \alpha_2^A X_{jt}^2)}{\sum_j exp(\alpha_1^A r_{jt} + \alpha_2^A X_{jt}^2)},$$

.

We can recover $\{\rho^{AB}, \alpha_A\}$ using the observed sales data and identified distribution of bids.

On the other hand, the probability of making a sale for a posted price is

$$Prob(sell_{jp}) = \sum_{n=1}^{\infty} Prob(N_{jt} = n)(1 - Prob(v < (1+\tau_1)p_{jt})^n)$$

$$= \sum_{n=1}^{\infty} Prob(N_{jt} = n)(1 - Prob(v^{\beta_1^{D_{jt}}} < [(1+\tau_1)p_{jt}]^{\beta_1^{D_{jt}}})^n)$$

$$= \sum_{n=1}^{\infty} \frac{e^{-\lambda_{jt}}(\lambda_{jt})^n}{n!}(1 - F^b([(1+\tau_1)p_{jt}]^{\beta_1^{D_{jt}}})^n),$$

The identification among the constant in the arrival process, price coefficient and β_1 heavily depends on the function form given the limited data. To get a better identification of other parameters. In the estimation part, I will make some assumption about the value of β_1.

Note that since prices come from seller's maximization problem with the expected demand in equilibrium, there is an identification problem of the coefficient of p_{jt} if there is some unobservables on demand side. I will use instrument later. One potential instrument is the distance between sellers and stadium[2].

So far, we have identified all primitives on demand side. For seller's part, if we assume sellers are risk neutral, the only thing we need to recover is the parameter γ_2 in outside options. Given the discount rate of future β_2, we can identify γ_2 well using the observed prices and mechanism choices data of sellers.

5.2 Estimation Procedure

5.2.1 Demand Side

According to the data I have, X_j^3 includes face value, row and section numbers of the tickets. Also, I can observe the two highest bids $b_j^{(1)}$ and $b_j^{(2)}$. I use LSDV method to estimate γ^b and ζ_g^b. After getting the residual $\widehat{\varepsilon_b^{(1)}}$ and $\widehat{\varepsilon_b^{(2)}}$,we can recover μ_b and σ_b by MLE according to

$$g(\varepsilon_b^{(1)}|\varepsilon_b^{(2)}) = \frac{\phi(\varepsilon_b^{(1)})}{1 - \Phi(\varepsilon_b^{(2)})},$$

$$LLK_1(\mu_b, \sigma_b) = \sum_i log(\frac{\phi(\varepsilon_{ib}^{(1)})}{1 - \Phi(\varepsilon_{ib}^{(2)})}).$$

Given the bid distribution for the games with auctions transacted, we can use this information to continue the estimation of the arrival process for these games' auction listings by MLE, including the ones haven't transacted. First, for auctions,

$$LLK_2(\rho^{AB}, \alpha^A) = \sum_j log[Prob(sell_{jA}|\rho^{AB}, \alpha^A)].$$

Since when we estimate the distribution of bids, we only use the listings who have two highest bids. There is a potential sample selection bias (Heckman(1979)[20]). To overcome this, I use a two-step method similar to Powell(1994) [26]. I first estimate the probabilities that a listing has two highest bids given the initial estimation

[2]This instrument is also used in Sweeting (2012)[30].

$$Prob(n_b \geq 2) = \sum_{n=2}^{\infty} Prob(N_{jt} = n)(1 - Prob(v^{\beta^{D_{jt}}} < (1+\tau_1)r_{jt})^n$$
$$-nProb(v^{\beta^{D_{jt}}} < (1+\tau_1)r_{jt})^{n-1} \times Prob(v^{\beta^{D_{jt}}} > (1+\tau_1)r_{jt}).$$

Then plug them into parametric part of the bids function and re-estimate all the parameters.

For posted prices, we estimate $\{\rho^{PB}, \alpha_P\}$ using MLE for $\beta_1 = 1$,namely, assume the distribution of value is the same across different selling mechanisms and the distribution of value is the same to the distribution of bids given $\tau_1 = 0$. The log likelihood in this process is

$$LLK_3(\rho^{PB}, \alpha_P) = \sum_j log[Prob(sell_{jP}|\rho^{PB}, \alpha_P)].$$

To overcome the endogenous problem of price in the arrival process, I choose the distance between sellers and the stadium as instruments. These instruments are potentially workable because they are not related to the unobservables on the demand side but related to the prices. Sellers who live near the stadium are more easily to attend the game when their tickets are not sold than sellers who live far away.

5.2.2 Supply Side

I assume all the sellers are forward-looking. They set their prices and mechanism choices based on a dynamic problem given their expectation about demand and other listing's characteristics, including prices. As mentioned above, to simplify the problem, I assume the observed market prices and mechanism choices are solved by this dynamic model. Combining with Assumption 2, the problem is similar to solve a partial single-agent dynamic problem. To be specific, for a listing j in period t for game g, we solve the seller's dynamic problem by backward induction from period T to t for both selling mechanisms. In each period $\tau \in [t, T]$, the opponents of listing j are the listings observed in period with specific selling mechanism M except listing j. The observed market information about opponent listings' characteristics and prices are plugged into seller's best response function from t to τ. Combining with the estimated demand information, we can solve for each seller's optimal prices and corresponding expected profits. Given the expected profits $\{\Pi^A_{jt}, \Pi^p_{jt}\}$, sellers compare them with the outside option Π^O_{jt} and choose which mechanism to use and whether to sell in the current period or not. Given the probability of choosing each mechanism in period t and the pseudo prices from the dynamic problem, we can construct moments using the observed mechanism choices and prices. I use GMM to estimate the parameters γ_2

The objective function of the GMM estimation is

$$obj = [\begin{array}{c} I^A_t - Prob(\widehat{Auction}) \\ p^M_t - \widehat{p^M_t} \end{array}]cov^{-1}[\begin{array}{c} I^A_t - Prob(\widehat{Auction}) \\ p^M_t - \widehat{p^M_t} \end{array}]',$$

$$\text{where}$$
$$Prob_{jt}(\widehat{Auction})$$
$$= \frac{exp(\overline{\Pi}^{A}_{jt+1}(X_{jt+1}, \Theta, \beta_1, \beta_2))}{exp(\overline{\Pi}^{A}_{jt+1}(X_{jt+1}, \Theta, \beta_1, \beta_2)) + exp(\overline{\Pi}^{P}_{jt+1}(X_{jt+1}, \Theta, \beta_1)) + exp(\overline{\Pi}^{O}_{jt})}$$

$$\overline{\Pi}^{O}_{jt} = \begin{cases} \beta_2 log(exp(\overline{\Pi}^{A}_{jt+1}(X_j, \Theta)) + exp(\overline{\Pi}^{P}_{jt+1}(X_j, \Theta)) + exp(\beta_2 \overline{\Pi}^{O}_{jt+1}(X_j, \Theta))) & t < T; \\ \beta_2 * outside_j & t = T \end{cases}$$

where $outside_j = \gamma_2^0 + \gamma_2^1 \times facevalue_j$.

In addition to the simplification above, when doing estimation, I use some other tricks to reduce the computation burden. First, I use grids of the observed linear part $\gamma_1 X_j^3 + \zeta_g$ in the buyer's value distribution part for each period. I assume the optimal prices, selling mechanism decision and the seller's profit in each period are functions of the linear part. This simplification implies that if two listings have same $\gamma_1 X_j^3 + \zeta_g$ in period t, they must have same $\alpha_2^M X_j^2 + \alpha_3^M X_g^1$,$\lambda_{gt}^{MB}$ and opponents in period t. It may be true because the linear part in value distribution includes more specific information about the tickets. There are two violations of this: 1) Two listings sell exactly the same tickets in the same period but with very different non-ticket characteristics; 2) two tickets have the exactly same realization of the linear part but for different games. These cases are not common considering the small volume of tickets sold on eBay. Then after solving for the optimal sellers' strategies for the selected grids, I can use interpolation to get the decisions and profits for other realizations of the linear part. Also, considering I treat the auction listings in the last period as posted price listings, I restrict a seller's selling mechanism to be posted price only for the last period when solving the model.

6 Results

6.1 Reduced Form Analysis

According to the model I construct above, I first do some reduced form analysis. Table B1 shows how the probability of a listing to be chosen is related to the listing's characteristics. Columns 1-3 use simply linear models and column 4 is the result of conditional logit model where a group is defined as the set of listings for the same game in the same period. Overall, we see a listing is more likely to be sold if it is sold by auctions. Face value, sections and other characteristics of the tickets significantly affect the probability of transaction. Similar to Figure 2, transaction probability decreases when the time is close to the event. The coefficients of log(start price) are always negative as expected. Finally, some non-ticket information, such as shipping fee, also affect the probability of transaction. To see how the results change within different selling mechanisms. Table B2 and Table B3 report the results for auctions and posted prices respectively. They show similar results.

Next, I run simple regression to see how the transaction prices and start prices are affected by the listing characteristics. From Table B4, we see auctions always have lower transaction prices. The transaction prices decrease as the time is close to the event and concave overtime. Table B5 shows the start prices also have the same pattern.

Finally, we briefly see how the selling mechanism choice affected. Column 2 in Table B6 shows auction share decreases as the time approaches the event and is concave with time. Also, tickets with higher face value seem more likely to be sold by auctions.

6.2 Structural Estimation

6.2.1 Demand

I first estimate the distribution of bids and arrival process on demand side without considering the endogenous problem of prices. The first two columns in Table 2 give the estimation results for auctions and posted prices respectively. Correction means whether the estimation for the distribution of bids has been corrected for the potential sample selection problem. The estimation results in the arrival part are the ones after the correction. We see the coefficients of prices are positive in both mechanisms, which counters our intuition. Therefore, I use instruments to deal with the potential endogeneity. As mentioned above, I use the distance from sellers to stadium as instruments. I denote the instruments as $\{distance1, distance2anddistance3\}$ meaning the distance is less 25 miles, 25 125 miles and more than 125 miles respectively. Table 1 shows the results for regression of start prices on the instruments and other control variables. The start price is significantly related with the distance variables. The coefficients of distance2 and distance3 are negative because sellers are more difficult to attend the games by themselves when they live far away from the stadium and thus they are more likely to set lower prices than sellers who live near the stadium.

The results with IV are also shown in Table 2. First, from the lower part of the table, we can find the estimation of γ_1 in the bid distribution part, all the sign of the coefficients are consistent with our expectation. When buyer's valuation of a ticket is higher when the face value of the tickets is higher, when the section number is lower or when the row number is lower. Variable Prob represents the probability that we can observe two highest bids in the auction. From Figure 10, we see the correction sightly change the value distribution (red solid line v.s. black solid line). In the arrival process part, we see weekdays, days to go and prices significantly affect the arrival rate for both auctions and posted prices. The weekend game attracts more buyers. When the time is close to the event, overall, the arrival rate of buyers is higher. Also, the start price will affect the arrival rate to each listing significantly although the magnitude is not large. For posted prices, some other characteristics of the listings such as the lower shipping fee will attract more buyers. I also try $\beta_2 = 0.95$. I find the estimation results of arrival process are similar (see last column in Table 2).

Figure 11 shows how the arrival rates of both selling mechanisms change over time. We see both of them are not large and increase over time. Since, as mentioned above, I treat the auction in period T of the data sample as fixed prices, we can see that in period T, the arrival rate of posted prices significantly increases. Figure 12 reports how the estimation results perform for both selling mechanisms, where the red solid lines depict the observed market transaction rates and the black dash lines represent the predicted transaction rates. We see with the given estimation parameters, we can generally predict the dynamic pattern of transaction rates across time well.

Table 1: Test IV

	(2)		(3)	
Variable	Auction	Posted Price	Auction	Posted Price
constant	63.0796***	69.9661***	55.1472***	69.2244***
	(1.5207)	(0.9463)	(1.5955)	(0.9899)
Distance2	-6.0050***	-1.3950***	-5.2058***	-1.4734***
	(0.6967)	(0.4947)	(0.6945)	(0.4956)
Distance3	-5.1008***	-8.9107***	-5.5601***	-8.9921***
	(0.6567)	(0.4188)	(0.6535)	(0.4200)
titlsection	0.1641	-0.0113	0.1177	-0.0159
	(0.0895)	(0.0591)	(0.0890)	(0.0591)
titlrow	-0.0147	0.0173	-0.0363	0.0158
	(0.0859)	(0.0562)	(0.0854)	(0.0562)
shipping	1.6127***	-0.9183***	1.5334***	-0.9202***
	(0.0527)	(0.0393)	(0.0526)	(0.0394)
opponent	-0.1455***	0.4520***	-0.1643***	0.4511***
	(0.0492)	(0.0304)	(0.0489)	(0.0304)
weekdays	-9.5948***	-8.1363***	-9.3046***	-8.1295***
	(0.3254)	(0.2047)	(0.3240)	(0.2047)
daystogo			1.0912***	0.1102
			(0.0700)	(0.0432)

6.2.2 Supply

Using the results from demand part, with the tricks I mentioned above, I solve the inner loop of the dynamic game and use GMM to estimate γ_2^0 and γ_2^1 in sellers' outside options $\gamma_2^0 + \gamma_2^1 \times facevalue$. When $\hat{\gamma_2^0} = 26.5562$ and $\hat{\gamma_2^1} = 0.2064$, the GMM objective function can optimized given $\beta_2 = 0.99$. The value of the objective function is 2.70e-09. To see the performance of the estimated results, I draw Figure 13 and 14. Figure 13 gives the average market price and average predicted price in each period given their observed prices mechanism choice. Figure 14 reports how the observed market auction share and predict auction share change across time. We can see the estimation results can predict the average prices well but give a little higher prediction of auction share than observed one. This is especially true for period T-2. There are two reasons for this dramatic increase. First, in period 3, sellers can set auction duration to be 1 or 3 rather than 1 only and the arrival rates of buyers in period T-1 and T-2 are relative high. The model predicts the relative profits from auctions increase a lot considering much more buyers enter the auctions given $\beta_2 = 0.99$. Second, in period T-2, the continues valuation from the remaining periods is low. Therefore, the profits

Table 2: Estimation Results of Demand Side

		without IV		with IV		
		Auction	Posted Prices	Auction	Posted Prices	Posted Prices
Arrival	constant	8.2413**	8.0130***	13.7287***	11.2348***	11.2514***
		(4.2917)	(2.1550)	(0.9431)	(0.2556)	(0.0839)
	opponent	0.0781	0.0599	0.0029	0.0264***	0.0384***
		(0.0812)	(16.5719)	(0.0057)	(0.0089)	(0.0060)
	weekdays	-0.4384	-0.3716	-2.2075***	-1.3601***	-1.4078***
		(1.0809)	(12.6336)	(0.2059)	(0.0725)	(0.0168)
	daystogo	-0.0020	0.0485	-0.1202***	-0.0857***	-0.0933***
		(0.0148)	(13.5370)	(0.0264)	(0.0067)	(0.0070)
	titlsection	0.0266	-0.0143	-0.0125	-0.0305***	-0.0327***
		(0.1143)	(0.9405)	(0.0117)	(0.0087)	(0.0075)
	titlrow	-0.0143	0.0151	-0.0086	-0.0401***	-0.0426***
		(0.0462)	(10.6222)	(0.0225)	(0.0092)	(0.0083)
	start price	0.0286**	0.0146	-0.1949***	-0.1183***	-0.1279***
		(0.0114)	(10.8730)	(0.0217)	(0.0042)	(0.0033)
	shipping	-0.0354	-0.0477	0.0267	-0.1996***	-0.2015***
		(0.0611)	(4.9830)	(0.0260)	(0.0110)	(0.0115)
	llk				-19777	-17000
	correction	No	Yes	No	Yes	Yes
Distribution of Bids	face value	0.0178	0.0177	0.0178	0.0175	0.0175
	section	-0.0273	-0.0271	-0.0273	-0.0280	-0.0280
	row	-0.0055	-0.0058	-0.0055	-0.0058	-0.0058
	prob		-0.6292		-0.8905	-0.8905
	σ_b	0.3367	0.3297	0.3367	0.3391	0.3391
	μ_b	-1.2156	-1.1246	-1.2156	-1.1047	-1.1047
	β_1	1	1	1	1	0.95

from posted prices are not high. Overall, however, the model can capture the average market information in these two figures well.

However, I should mention here. The model hasn't capture the variation of prices very well. Also the average prices of auctions is relative high compared to the observed ones (see Table 3 and Figure 15). These differences may be explained by several reasons. First, people are not so patient as we model, which means the continuation value should have less influence than the model specification. Second, buyers may discount auctions more. Finally, the format of outside option is more flexible than the model depicts. I will try different discount rates and more flexible outside option in the future. Another thing I can do is changing sellers from risk neutral to risk averse (Similar to Waisman(2017)). Since the profits from auctions are more fluctuated than those from posted prices for same listings, this may lower the relative profits from auctions.

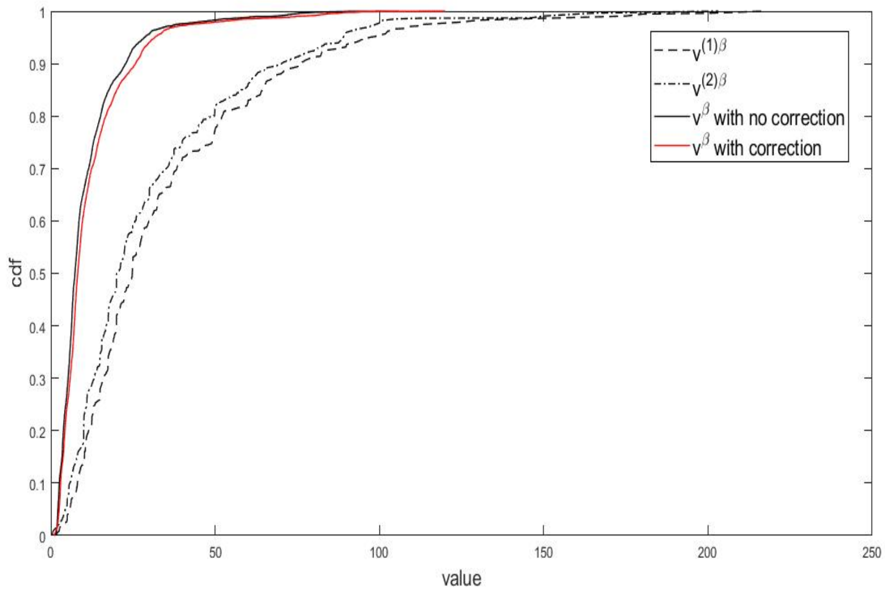

Figure 10: Distribution of Bids

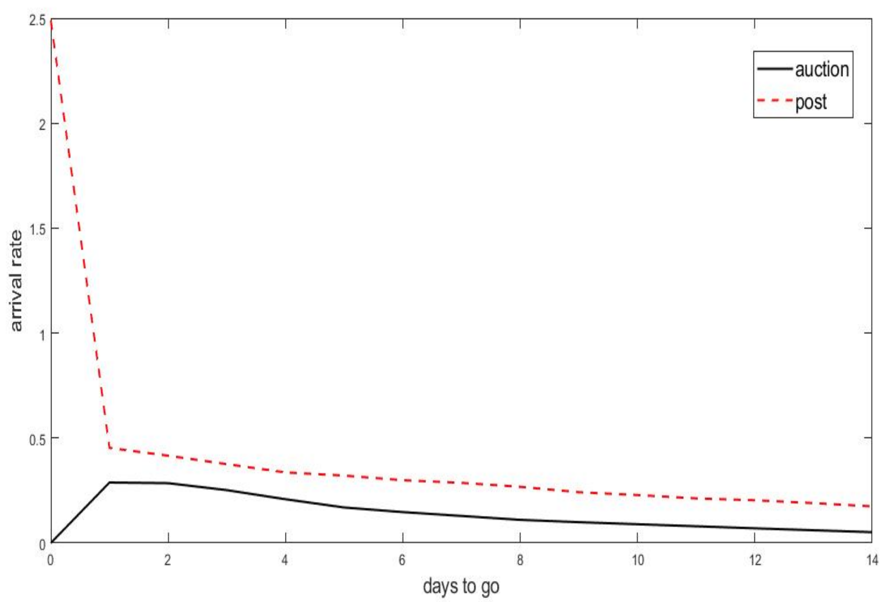

Figure 11: Estimated Arrival Rates

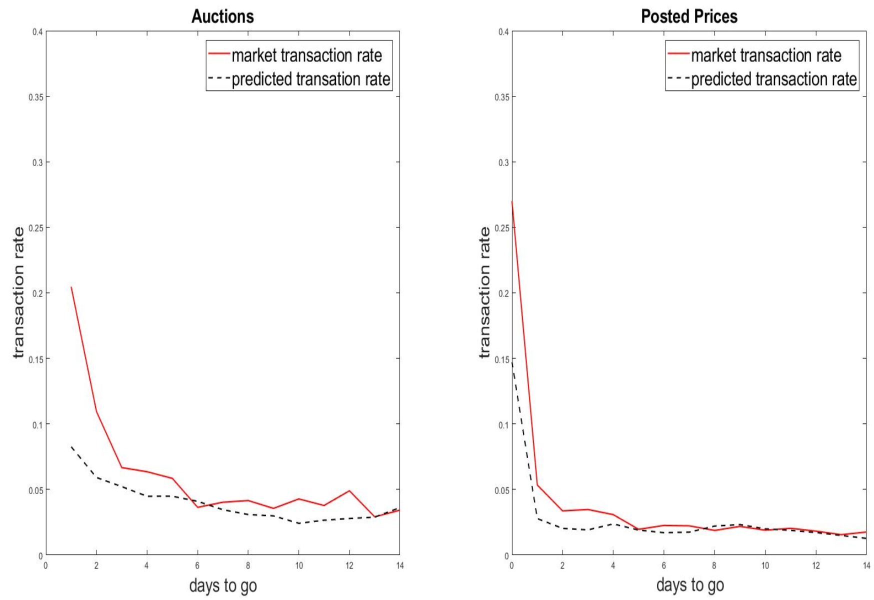

Figure 12: Market and Estimated Transaction Rates

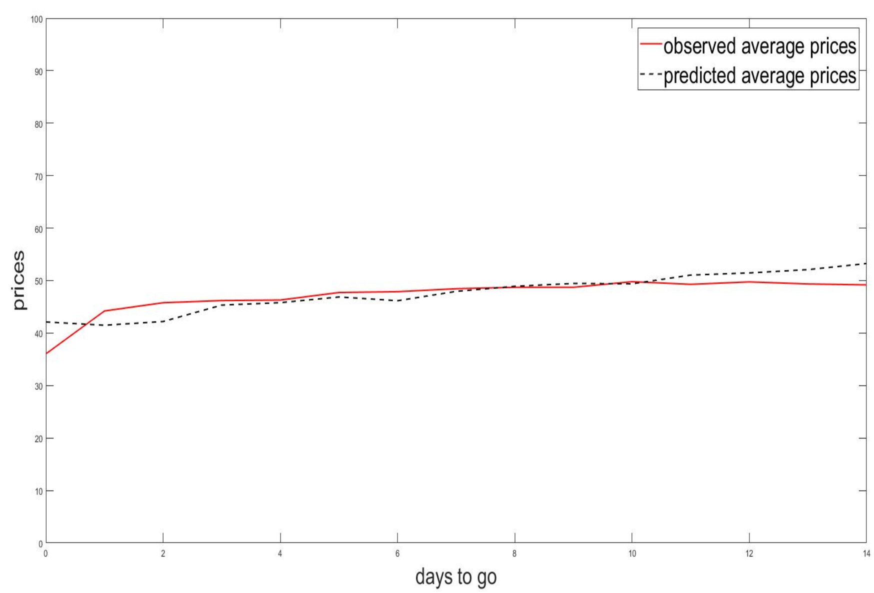

Figure 13: Observed and predicted average auction share over time

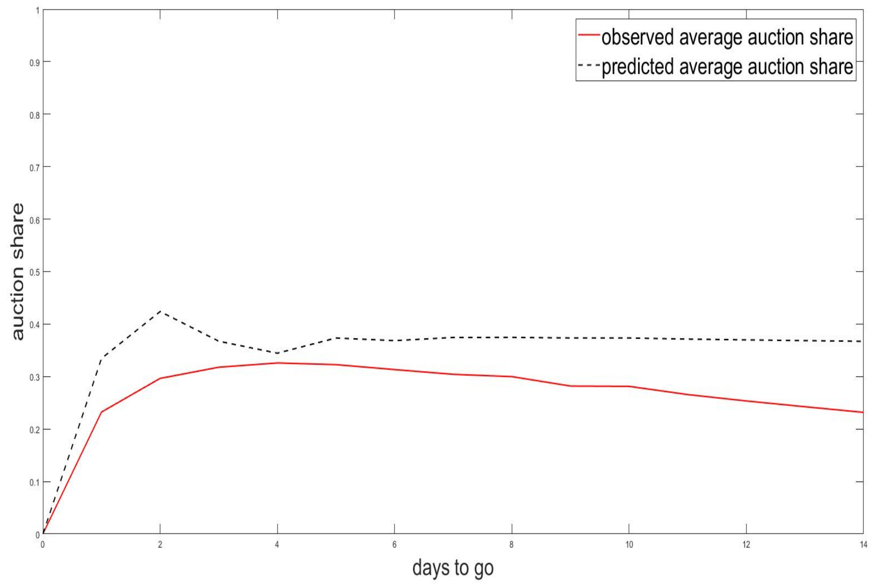

Figure 14: Observed and predicted average auction share over time

Table 3: Observed and Predict Prices Information

measurement	real market	estimated
average price overall	47.9187	48.0507
average price of auctions	41.5406	47.6728
average price of posted price	50.4079	48.2829
std of prices overall	41.5109	13.3776
std of prices of auctions	40.0594	14.0722
std of prices of posted prices	41.8010	14.7905

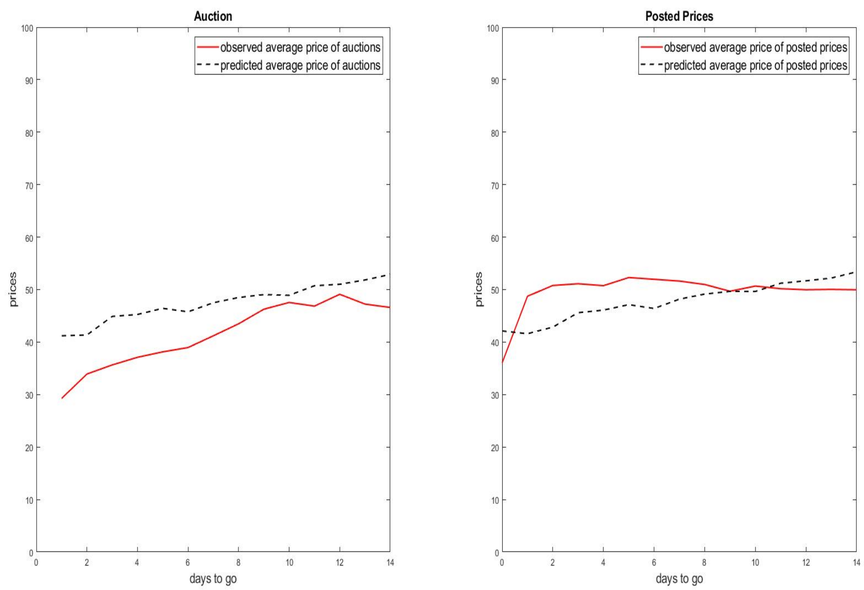

Figure 15: Observed and predicted average auction share over time

7 Counterfactual Analysis

7.1 Different Discount Rates of Auctions and Continuous Value

Given the estimated parameters above, we start the counterfactual analysis. I first do some simple analysis by changing the value distribution of buyers and changing the discount rate of auctions and continuation values. According to Wang (1993), if the value distribution of bidders is more dispersed, then the relative profit from an auction is higher. To check this, I change the $\sigma_b = \hat{\sigma_b}/2$ in the first exercise. From Table 4, we see the auction share slightly decrease in this scenario. The average price is lower and equilibrium prices are less dispersed after this change. Then I use different discount rate of auctions to check how it will affect the auction share. We see when β_1 change from 1 to 0.9, the auction share slightly decreases. The small magnitude may result from the entry rate already capture the buyer's part difference between two selling mechanisms. It may also because I have overestimate the influence of outside options. The third scenario is to check how people become less patient (β_2 from 0.99 to 0.95) will change the market equilibrium. Similar to Case 4 in the two-stage model analysis, when sellers discount their continuation value more, they have more incentive to sell their goods in the current period, so the average auction share decreases. The less continuation value also reduces the average price and the expected profit of each listing.

7.2 Different Market Characteristics

7.2.1 Price sensitivity

In this subsection, I will check how changing the characteristics of the platform affects the equilibrium auction share and prices. First, in light of the search algorithm on eBay, one counterfactual scenario is making it more related to prices. Although I have no click-through data, I will show that the change is similar to increase the price sensitivity in the buyer's arrival process. To be specific, if buyer's entry decision to a listing is related to the ranking of the listing, e.g., buyers cannot pay full attention to all the listings of a game, then a listing listed higher will be more likely to be chosen. The ranking of the listings is related to the search algorithm used by the platform. If the default ranking is not according to the best match algorithm but from lowest prices to highest prices, then buyers will be more sensitive to price. Similar to Dinerstrien et al.(2017), we can add a weight w_{jt} to represent the probability that listing j of mechanism M will be considered in period t.

$$w_{jt}^{M} = exp(-r(\frac{p_{jt} - min(p_{jt}}{std(p_{gt})}),$$

$$\text{where } r > 0.$$

Add this weight to the original arrival rate equation, we have

$$\lambda_{jt}^{MB'} = w_{jt}^{M} \lambda_{gt}^{MB} \frac{exp(\alpha_1^M p_{jt} + \alpha_2^M X_{jt}^2)}{\sum_j w_{jt}^M exp(\alpha_1^M p_{jt} + \alpha_2^M X_{jt}^2)},$$

$$= exp(\rho_0^{MB} + \rho_1^{MB} t + \rho_2^{MB} X_g^1) \frac{exp(\alpha_1^M p_{jt} - r(\frac{p_{jt} - min(p_{jt})}{std(p_{gt})}) + \alpha_2^M x_{jt})}{\sum_j exp(\alpha_1^M p_{jt} - r(\frac{p_{jt} - min(p_{jt})}{std(p_{gt})} + \alpha_2^M x_{jt}))}.$$

Therefore, we can expect that the more price related search algorithm can make the buyer's arrival rate or entry decision more sensitive to price. Considering this, for this counterfactual scenario, I change the price coefficient to $\alpha_1^M = 2\alpha_1^M$, for $M \in \{A, P\}$. We have done this simulation in a simple two-stage case in the model part. Based on that simulation, we expect the average auction share will decrease after this change. The second column in Table 5 gives the results of this counterfactual analysis. We see it follows our expectation that the average auction share is lower than before. Also, because in this case the price competition among listings in the same mechanisms is fiercer, we see the average prices for all the cases are lower and prices are also less dispersed. The corresponding profits which include continuation value also become slightly lower.

Note that in the empirical part of supply side, I have made assumptions to make the model look like a partially single-agent model. Here when I do the counterfactual analysis, I still keep these assumptions. Therefore, when I solve a seller's optimal strategy I will assume other sellers keep the same prices (observed market prices) in the dynamic model. This will generally underestimate the magnitude of price decrease results from the higher price sensitivity since in the full competition dynamic model, a seller has to take other seller's price decrease into consideration.

7.2.2 Availability of listings

Compared with other tickets platform, eBay has relative less tickets available on the market. An ideal way to construct the counterfactual scenario is to expand the number of listings for each game in each period. However, it is hard to figure out a proper way to extend these consideration sets. Here, I use a simple way to get some idea of this change. Since when the number of competitive listings becomes larger, buyer's probability to choose all listings in the original set will uniformly become less. This is equivalent to decrease the constant in λ_{gt}^{MB}. Therefore, for this exercise, I make the following change: $\lambda_{gt}^{MB} = \hat{\lambda_{gt}^{MB}}/2$, for $M \in \{A, P\}$. The third column in Table 5 shows that this change will decrease average auction share, average price level and price dispersion of these existing listings. These results are consistent with Case 3 in the model section as well.

7.2.3 Commission fees

Finally, we can try a different commission fee policy. Since eBay only collects commission fees from sellers, here, I just consider how increase the seller's commission fees from 10% to 20 % will change the market. Column 4 in Table 5 implies this change will significantly increase the equilibrium prices. However, since the commission fee is collected from sellers by the same percentage in both mechanisms, the auction share almost keeps the same after in this scenario.

7.3 Only With Posted Prices

In the end, let's see how the equilibrium prices and sellers' profits change if we only allow the sellers to use posted price mechanism. In this exercise, I will still keep the assumptions I have made before. Therefore, I haven't increase the number of competitive sellers in posted prices when solving for an individual seller's dynamic problem. Table 6 summarizes the results. When sellers are only allowed to use posted price mechanism, some sellers who prefer to use auctions have to choose posted price. This will lower the sellers' expected profits. Given the lower continuation value in the dynamic model, sellers will set lower prices than before. It will be more interesting if we can figure out how the competition change and affect the market equilibrium when sellers only allow for posted prices. However, it requires us to solve the dynamic price competition problem with some assumption about the buyer's arrival process to posted prices. This will be studied more in the future.

Note that most counterfactuals I have made above, such as change the search algorithm to be more related to price, will decrease the average equilibrium prices, price dispersion and seller's expected profit. However, all these results are given under the assumption that the other things in the buyer's entry model keep the same. This may not be true. For example, if the market prices become lower, more buyers are likely to be attracted from other platforms. This may increase the sellers' and the platform's profits in the long run. Also, one thing I haven't shown explicitly in the model but is also important is when the market prices are less dispersed, sellers will have lower cost to discover proper prices for their listings and this may mitigate sellers' incentive to use auctions.

Table 4: Summary of Counterfactual Analysis (1)-(3)

	estimated	value distribution	β_1	β_2
average auction share	0.3669	0.3664	0.3666	0.3132
average prices overall	48.0507	42.7715	48.4354	25.1901
average prices of auctions	47.6728	42.8200	47.6161	22.8645
average prices of posted prices	48.2829	42.8434	48.8412	26.4072
std prices overall	13.8792	11.9816	13.4363	11.9108
std of prices in auctions	13.3776	11.4208	12.9615	10.9844
std of prices in posted prices	14.7905	11.8233	14.3018	12.0380
average profit overall	41.1828	40.5437	41.1010	22.0903
average profit from auctions	41.1811	40.5420	41.0985	22.1647
average profit from posted prices	41.4326	40.8422	41.3589	21.9037

Table 5: Summary of Counterfactual Analysis (4)-(6)

	estimated	price sensitive	marketthickness	fee
average auction share	0.3669	0.3590	0.3589	0.3668
average prices overall	48.0507	45.6442	46.1186	53.5227
average prices of auctions	47.6728	45.2768	45.8539	53.0824
average prices of posted price	48.2829	45.8140	46.2622	53.8110
std of prices overall	13.8792	4.9098	5.1970	13.5415
std of prices in auctions	13.3776	5.4907	5.7673	12.6935
std of prices in posted prices	14.7905	5.5159	5.8811	14.9624
average profit overall	41.1828	39.3114	39.3140	40.9456
average profit from auctions	41.1811	39.3113	39.3136	40.9448
average profit from posted prices	41.4326	39.6763	39.6791	41.2067

Table 6: Only with Posted Price

	overall	auctions	posted prices	only with posted prices
average prices	48.0507	47.6728	48.2829	43.8033
std of prices	13.8792	13.3776	14.7905	6.0672
average profits	41.1828	41.1811	41.4326	37.3989

8 Conclusion

This paper tries to assess the dynamic selling mechanism choice problem in a perishable good market. As typical perishable goods, sport tickets are resold on different platforms by various selling mechanisms. Platforms are different from each other in many other dimensions, such as search algorithms, market thickness and commission fees. Whether these characteristics of a platform will affect its participants' dynamic mechanism choices and pricing strategies seems an interesting question.

Motivated by this observation, this paper analyzes buyers' and sellers' behavior on eBay's ticket resale market. By modeling and estimating buyers' decision process, I find that buyers are sensitive to price but the sensitivity has moderate magnitude. When I assume there is no value discount in auctions, their arrival rates to posted prices are always higher than the one to auctions. Given the demand model, the dynamics of a seller's mechanism choice across time can be explained by the proposed dynamic model with an outside option in the end. Combining the assumptions about sellers with the market observables, I am able to structurally estimate the seller's dynamic pricing and mechanism choice model. This model can capture the price competition to some extent. Although some of the market information, such as the price dispersion cannot be captured, the estimation results are able to correctly predict the market average prices, the dynamics of prices and the dynamics of auction share.

Given the estimation results, I check how the market average auction share, average price and sellers' profits change in different counterfactual scenarios. First, when sellers are more patient about the continuation value from future sales, they have less incentive to use auctions. In other words, forward-looking sellers are generally more likely to use dynamic posted prices than myopic sellers are. Second, the average auction share will decrease if buyers are more sensitive to price when they make entry decisions. Under this scenario, the average equilibrium price and the price dispersion are also lower than before. I show that this finding can imply how the change of search algorithm will affect the market. Specifically, when the search algorithm is more related to prices, auctions will be relative less attractive. Similar to the price sensitivity, if there are more available listings for the same game in the same period with same selling mechanism, the average auction share will be lower. In these two exercises, the average expected profits of sellers are reduced by about 5 % in my setting. All of these are consistent with the simple simulations that I conduct in the model part. Besides, the average auction share would not change significantly when increasing the commission fees from sellers. Finally, I eliminate auctions from the mechanism menu to see how the market equilibrium will change. The result indicates that the average price and average sellers' profits will decrease under this exercise. This is because the sellers who prefer to use auctions are stuck with posted prices, resulting in lower continuation value and lower average prices.

The paper can be improved in the following aspects. First, as I mentioned above, to make the model tractable, I have made several assumptions. Some of them, such as the perfect foresight assumption, may be too strong. What's worse, the assumptions may affect the results of some counterfactual analysis. For example, when eliminating auctions, I still keep the assumption that a seller will use the original market information as his opponent's information. This assumption eliminates the change of market competitiveness under the new scenario. Therefore, relaxing the assumption will be important for my future study. Second, the estimation results cannot capture some market information, such as the price dispersion. Besides, the average auction share is relative higher than the observed one. Since the estimation results show seller's decisions heavily rely on his outside option in each period, a more flexible model for the outside option may be helpful. Finally, as I mentioned before, I am not able to identify all the parameters including the discount rate of auctions well given the limited data. Current results are under the assumption that the value distribution is the same across different selling mechanisms. This will be violated if buyers do discount their value from auctions in real market. Therefore, to make the results more robust, I will do more estimation under different discount rates later.

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Appendix

A Supplement to Data and Market

Figure A1-A5 give the search page of eBay and Stubhub.

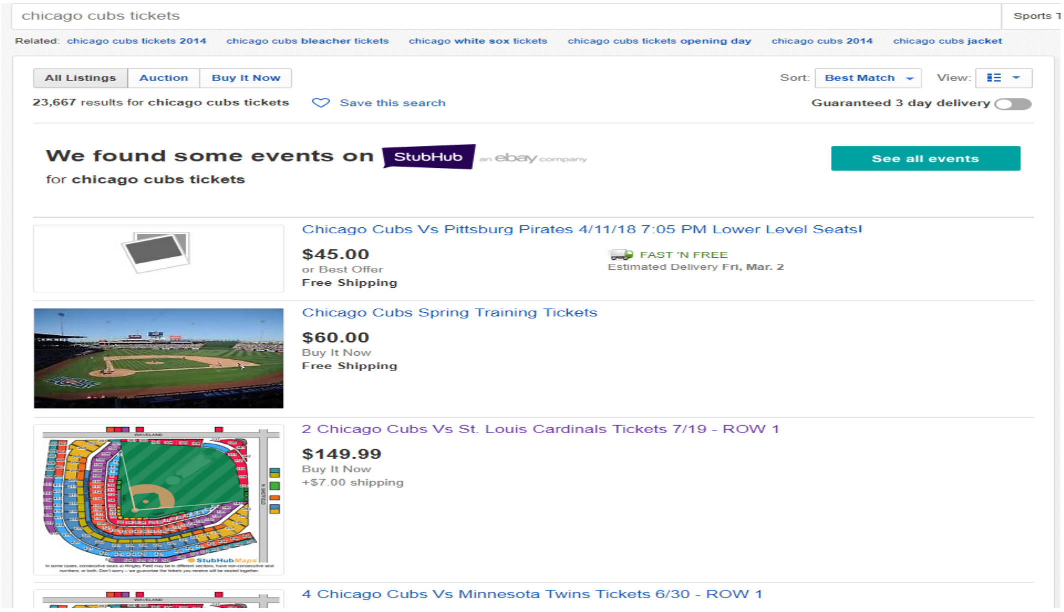


Figure A.1: Search Page 1 on eBay

Following Table A1 to Table A9 and Figure A6 and A7 supplement the summary statistics section above.

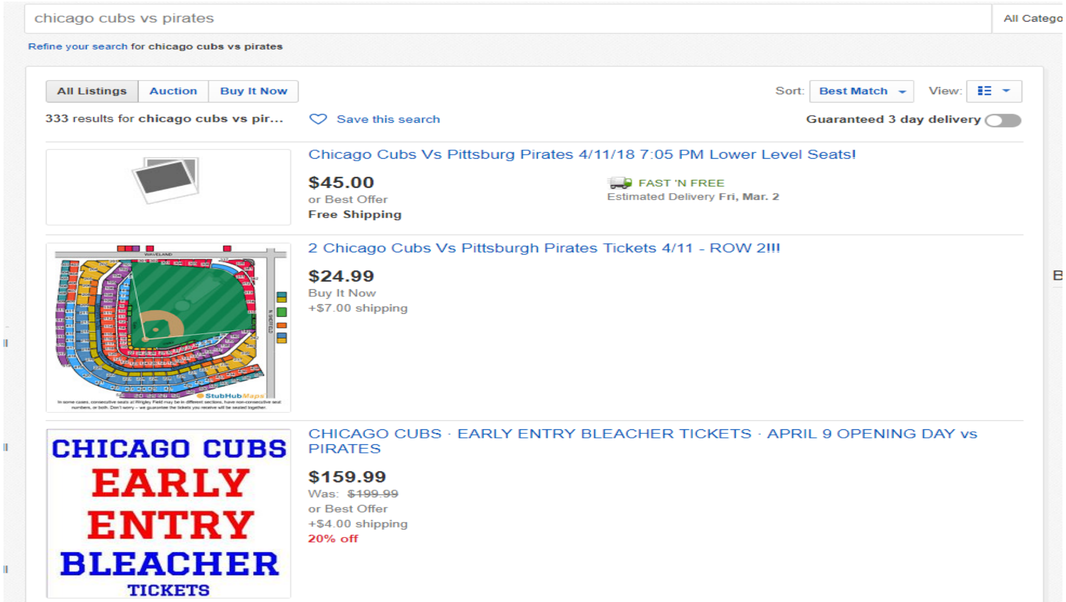


Figure A.2: Search Page 2 on eBay

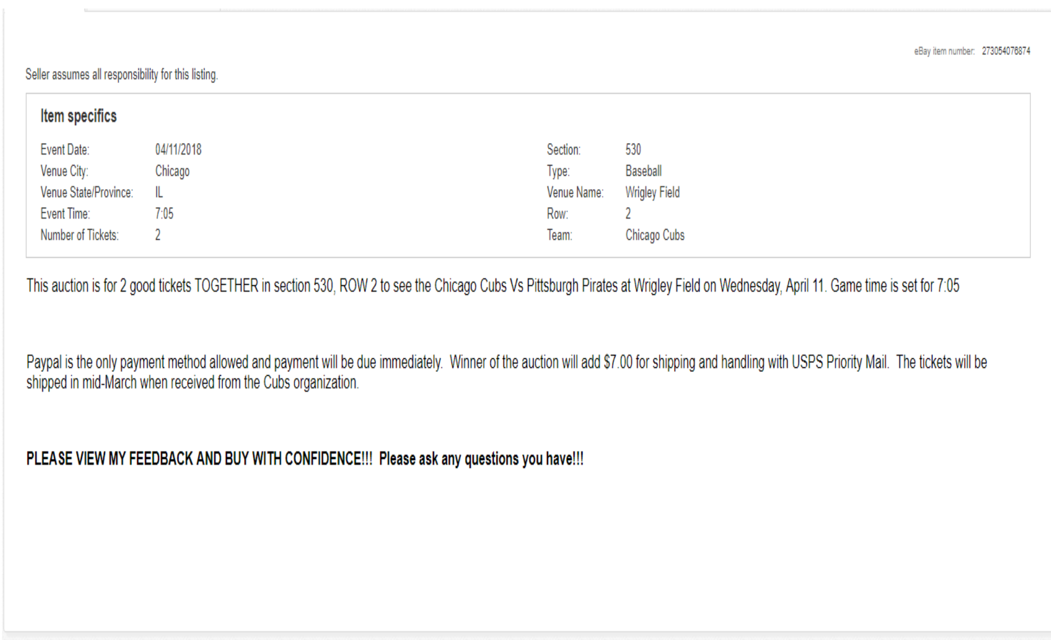


Figure A.3: Search Page 3 on eBay

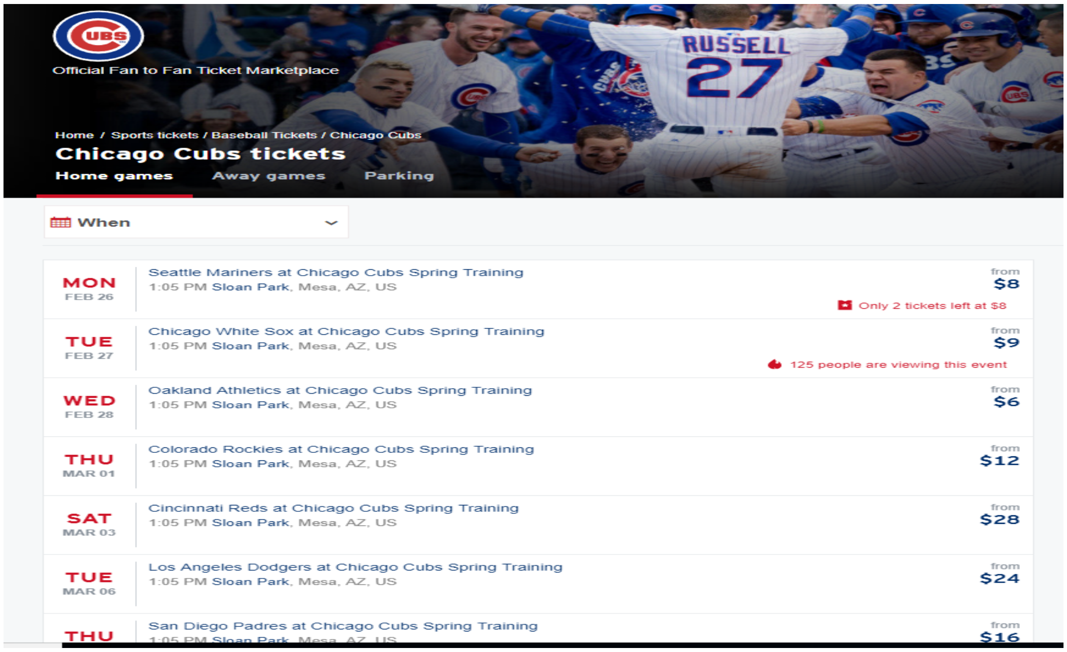


Figure A.4: Search Page 1 on Stubhub

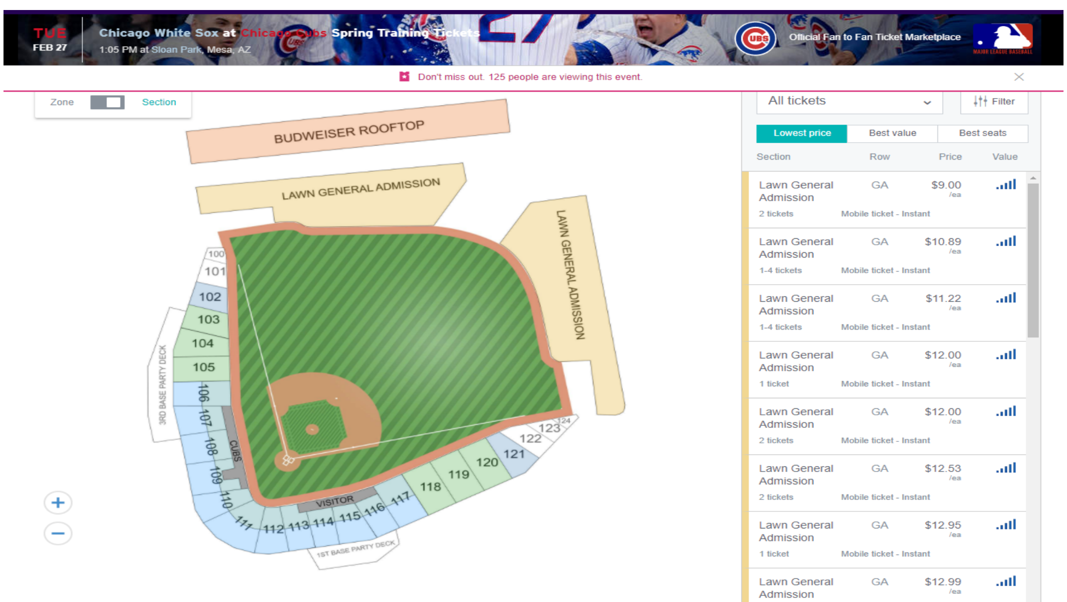


Figure A.5: Search Page 2 on Stubhub

Table A.1: Summary of Opponents

Values	Freq.	Percent	Cum.
1	9,925	12.34	12.34
2	3,822	4.75	17.10
3	7,641	9.50	26.60
4	3,708	4.61	31.21
5	4,073	5.07	36.27
6	1,558	1.94	38.21
7	2,787	3.47	41.68
8	4,563	5.67	47.35
9	2,132	2.65	50.00
10	3,615	4.50	54.50
13	8,922	11.10	65.59
14	3,827	4.76	70.35
15	1,995	2.48	72.83
16	6,486	8.07	80.90
17	8,569	10.66	91.56
18	3,695	4.60	96.15
19	3,095	3.85	100.00
Total	80,413	100.00	

Table A.2: Summary of Weekdays

days	Freq.	Percent	Cum.
1	27,264	29.50	29.50
2	14,849	16.07	45.57
3	50,298	54.43	100.00
Total	92,411	100.00	

Table A.3: Summary of Sections

section	Freq.	Percent	Cum.
1	5,858	6.34	6.34
2	7,155	7.74	14.08
3	2,751	2.98	17.06
4	9,826	10.63	27.69
5	3,633	3.93	31.62
6	11,949	12.93	44.55
7	10	0.01	44.56
9	725	0.78	45.35
10	7,265	7.86	53.21
12	10,965	11.87	65.08
13	15,724	17.02	82.09
14	10,534	11.40	93.49
15	6,016	6.51	100.00
Total	92,411	100.00	

Table A.4: Summary of Rows

Variable	Obs	Mean	Std. Dev.	Min	Max
row	92,411	8.743981	6.012439	1	124

Table A.5: Summary of Auction Duration

duration	Freq.	Percent	Cum.
0	66,239	71.68	71.68
1	2,514	2.72	74.40
2	664	0.72	75.12
3	4,380	4.74	79.86
4	782	0.85	80.70
5	4,641	5.02	85.73
6	1,762	1.91	87.63
7	8,235	8.91	96.54
8	76	0.08	96.63
9	500	0.54	97.17
10	2,618	2.83	100.00
Total	92,411	100.00	

Table A.6: Average Number of Listings for the Same Game in the Same Period

Variable	Obs	Mean	Std. Dev.	Min	%25	%75	Max
numberoflistings	1,398	66.10229	40.71524	2	39	91	245

Table A.7: Number of Bids in Auctions

numberofbids	Freq.	Percent	Cum.
0	19,577	74.12	74.12
1	2,026	7.67	81.79
2	4,810	18.21	100.00
Total	26,413	100.00	

Table A.8: Transactions and Auctions

	chosen		
auction	0	1	Total
0	64,116	1,882	65,998
1	24,929	1,484	26,413
Total	89,045	3,366	92,411

Table A.9: Relative Start Prices and Relative Transaction Prices

relative price	mechanism	Obs	Mean	Std. Dev.	Min	Max
	total	16,327	0.8357	0.6415	0.0000	4.6871
start price/face value	auction	6,181	0.5002	0.4481	0.0000	1.9227
	posted price	10,146	1.0400	0.6554	0.0000	4.6872
	total	16,327	1.0044	0.5762	0.011	6.5385
transaction price/face value	auction	6,181	0.7682	0.4200	0.011	3.125
	posted price	10,146	1.1483	0.6100	0.0658	6.5385

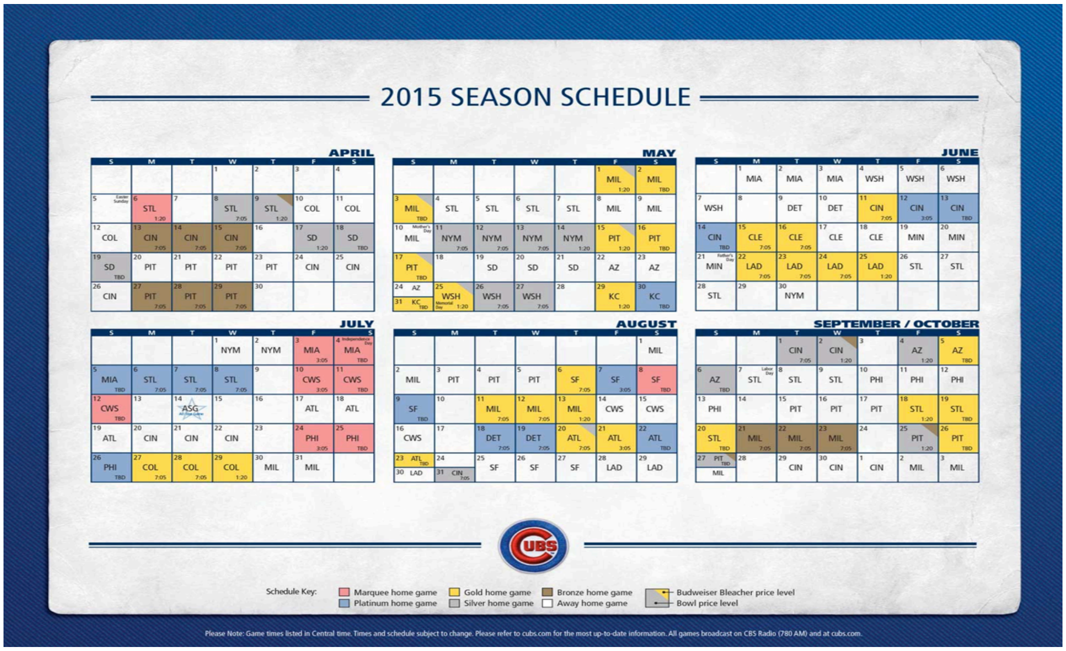
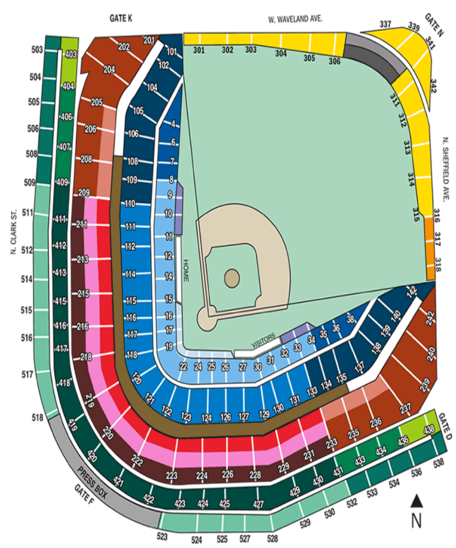
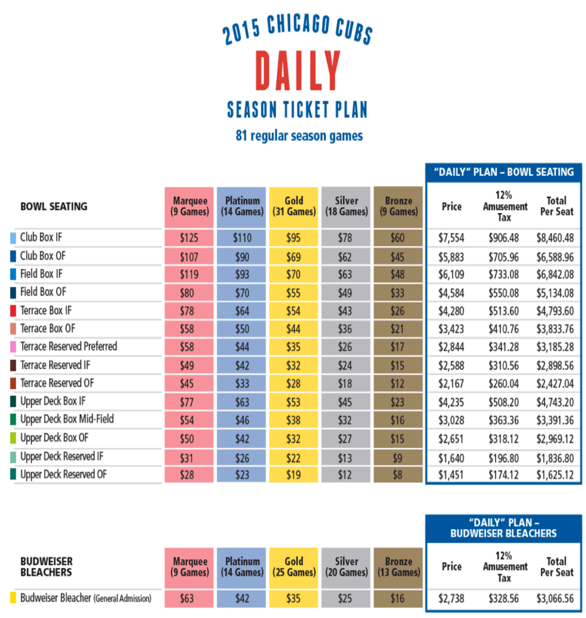


Figure A.6: 2015 Chicago Cubs Season Schedule





2015 CHICAGO CUBS

DAILY

SEASON TICKET PLAN

81 regular season games

BOWL SEATING	Marquee (9 Games)	Platinum (14 Games)	Gold (31 Games)	Silver (18 Games)	Bronze (9 Games)	"DAILY" PLAN – BOWL SEATING: Price	12% Amusement Tax	Total Per Seat
Club Box IF	$125	$110	$95	$78	$60	$7,554	$906.48	$8,460.48
Club Box OF	$107	$90	$69	$62	$45	$5,883	$705.96	$6,588.96
Field Box IF	$119	$93	$70	$63	$48	$6,109	$733.08	$6,842.08
Field Box OF	$80	$70	$55	$49	$33	$4,584	$550.08	$5,134.08
Terrace Box IF	$78	$64	$54	$43	$26	$4,280	$513.60	$4,793.60
Terrace Box OF	$58	$50	$44	$36	$21	$3,423	$410.76	$3,833.76
Terrace Reserved Preferred	$58	$44	$35	$26	$17	$2,844	$341.28	$3,185.28
Terrace Reserved IF	$49	$42	$32	$24	$15	$2,588	$310.56	$2,898.56
Terrace Reserved OF	$45	$33	$28	$18	$12	$2,167	$260.04	$2,427.04
Upper Deck Box IF	$77	$63	$53	$45	$23	$4,235	$508.20	$4,743.20
Upper Deck Box Mid-Field	$54	$46	$38	$32	$16	$3,028	$363.36	$3,391.36
Upper Deck Box OF	$50	$42	$32	$27	$15	$2,651	$318.12	$2,969.12
Upper Deck Reserved IF	$31	$26	$22	$13	$9	$1,640	$196.80	$1,836.80
Upper Deck Reserved OF	$28	$23	$19	$12	$8	$1,451	$174.12	$1,625.12

BUDWEISER BLEACHERS	Marquee (9 Games)	Platinum (14 Games)	Gold (25 Games)	Silver (20 Games)	Bronze (13 Games)	"DAILY" PLAN – BUDWEISER BLEACHERS: Price	12% Amusement Tax	Total Per Seat
Budweiser Bleacher (General Admission)	$63	$42	$35	$25	$16	$2,738	$328.56	$3,066.56

▲ ALL PRICES SUBJECT TO ADDITIONAL 12% AMUSEMENT TAX

Figure A.7: Chicago Cub's 2015 Season Ticket Plan

B Tables for Reduced Form Analysis

Table B.1: Transactions

VARIABLES	(1) chosen	(2) chosen	(3) chosen	Clogit chosen
auction	0.0178***	0.0182***	0.0195***	0.695***
	(0.00156)	(0.00156)	(0.00159)	(0.0462)
facevalue	0.000648***	0.000620***	0.000404***	0.00784***
	(4.76e-05)	(4.80e-05)	(6.91e-05)	(0.00231)
section	0.00185***	0.00206***	0.00134***	0.0532***
	(0.000222)	(0.000245)	(0.000292)	(0.0100)
row	-0.000492***	-4.29e-05	6.65e-05	-7.62e-05
	(0.000128)	(0.000159)	(0.000162)	(0.00335)
daystogo	-0.0176***	-0.0176***	-0.0175***	
	(0.000705)	(0.000705)	(0.000705)	
qdaystogo	0.000912***	0.000908***	0.000902***	
	(4.58e-05)	(4.58e-05)	(4.57e-05)	
logstartprice	-0.0236***	-0.0234***	-0.0257***	-0.348***
	(0.000640)	(0.000642)	(0.000660)	(0.0128)
shipping	-0.000869***	-0.000844***	-0.000772***	-0.0176***
	(0.000141)	(0.000143)	(0.000144)	(0.00520)
opponent	0.000212*	0.000224*	0.0232***	
	(0.000118)	(0.000118)	(0.00367)	
days	-0.00816***	-0.00827***	-0.368***	
	(0.000848)	(0.000848)	(0.0479)	
titlsection		-0.000799***	-0.00128***	
		(0.000299)	(0.000306)	
titlrow		-0.00124***	-0.00146***	
		(0.000267)	(0.000273)	
31.eventid			0.299***	
			(0.0629)	
184.eventid			0.000863	
			(0.00963)	
Constant	0.158***	0.169***	0.910***	
	(0.00562)	(0.00615)	(0.0826)	
Observations	73,163	73,163	73,163	51,601
R-squared	0.041	0.042	0.051	

Table B.2: Transaction of Auctions

VARIABLES	(1) chosen	(2) chosen	(3) chosen	Clogit chosen
facevalue	0.000602***	0.000474***	6.77e-05	-0.00290
	(0.000110)	(0.000111)	(0.000178)	(0.00397)
section	0.00173***	0.00236***	0.000874	0.0177
	(0.000547)	(0.000575)	(0.000790)	(0.0172)
row	-0.000639*	0.00138***	0.00178***	-0.00203
	(0.000330)	(0.000404)	(0.000418)	(0.00499)
daystogo	-0.0255***	-0.0251***	-0.0268***	
	(0.00175)	(0.00175)	(0.00175)	
qdaystogo	0.00134***	0.00130***	0.00137***	
	(0.000113)	(0.000113)	(0.000113)	
logstartprice	-0.0245***	-0.0236***	-0.0240***	-0.342***
	(0.00101)	(0.00101)	(0.00105)	(0.0167)
shipping	-0.000233	-0.000372	-0.000239	0.0204***
	(0.000316)	(0.000322)	(0.000331)	(0.00768)
opponent	-0.000156	-0.000164	0.0269***	
	(0.000291)	(0.000290)	(0.00796)	
days	-0.0104***	-0.0110***	-0.390***	
	(0.00207)	(0.00208)	(0.110)	
titlsection		-0.00313***	-0.00258***	
		(0.000727)	(0.000760)	
titlrow		-0.00570***	-0.00602***	
		(0.000686)	(0.000712)	
31.eventid			0.351***	
			(0.129)	
184.eventid			-0.0351	
			(0.0233)	
Constant	0.218***	0.275***	1.031***	
	(0.0136)	(0.0151)	(0.196)	
Observations	20,610	20,610	20,610	10,097
R-squared	0.051	0.055	0.068	

Table B.3: Transaction of Posted Prices

VARIABLES	(1) chosen	(2) chosen	(3) chosen	Clogit chosen
facevalue	0.000582***	0.000582***	0.000551***	0.0164***
	(5.30e-05)	(5.37e-05)	(7.45e-05)	(0.00308)
section	0.00176***	0.00178***	0.00157***	0.0559***
	(0.000229)	(0.000260)	(0.000296)	(0.0134)
row	-0.000402***	-0.000437***	-0.000591***	-0.00820
	(0.000135)	(0.000168)	(0.000173)	(0.00526)
daystogo	-0.0149***	-0.0149***	-0.0146***	
	(0.000722)	(0.000722)	(0.000723)	
qdaystogo	0.000765***	0.000765***	0.000742***	
	(4.69e-05)	(4.69e-05)	(4.69e-05)	
logstartprice	-0.0211***	-0.0212***	-0.0270***	-0.751***
	(0.000964)	(0.000967)	(0.00105)	(0.0376)
shipping	-0.00114***	-0.00114***	-0.00111***	-0.0575***
	(0.000157)	(0.000157)	(0.000160)	(0.00917)
opponent	0.000340***	0.000339***	0.0207***	
	(0.000122)	(0.000122)	(0.00411)	
days	-0.00792***	-0.00793***	-0.353***	
	(0.000880)	(0.000882)	(0.0522)	
titlsection		-3.73e-05	-0.000577*	
		(0.000316)	(0.000331)	
titlrow		9.65e-05	0.000143	
		(0.000273)	(0.000283)	
32.eventid			0.297***	
			(0.0661)	
184.eventid			0.0141	
			(0.00993)	
Constant	0.140***	0.140***	0.876***	
	(0.00608)	(0.00661)	(0.0881)	
Observations	52,553	52,553	52,553	23,103
R-squared	0.026	0.026	0.038	

Table B.4: Transaction Prices

VARIABLES	(1) transaction price	(2) transaction price	Auctions transaction price	Posted Prices transaction price
auction	-11.52***	-10.27***		
	(0.340)	(0.286)		
facevalue	1.058***	0.857***	0.923***	1.126***
	(0.0124)	(0.0149)	(0.0146)	(0.0176)
section	0.998***	0.373***	0.669***	1.030***
	(0.0579)	(0.0622)	(0.0676)	(0.0849)
row	0.198***	0.175***	-0.0740**	0.360***
	(0.0292)	(0.0252)	(0.0347)	(0.0425)
daystogo	2.052***	1.860***	1.609***	2.229***
	(0.162)	(0.129)	(0.196)	(0.226)
qdaystogo	-0.0764***	-0.0712***	-0.0418***	-0.0928***
	(0.0106)	(0.00845)	(0.0127)	(0.0148)
shipping	-0.720***	-0.568***	-0.769***	-0.653***
	(0.0646)	(0.0539)	(0.0663)	(0.101)
opponent	0.205***	-38.75***	0.234***	0.164***
	(0.0280)	(0.873)	(0.0326)	(0.0402)
days	-2.413***	416.5***	-3.374***	-1.906***
	(0.195)	(10.15)	(0.226)	(0.280)
31.eventid		-670.4***		
		(15.74)		
184.eventid		0.831		
		(1.470)		
Constant	-16.30***	-590.6***	-14.75***	-21.51***
	(1.362)	(15.74)	(1.629)	(1.924)
Observations	14,410	14,410	5,443	8,967
R-squared	0.579	0.737	0.714	0.499

Table B.5: Start Prices

	(1)	(2)	Auctions	Posted Prices
VARIABLES	start price	start price	start price	start price
auction	-11.76***	-12.59***		
	(0.422)	(0.416)		
facevalue	1.421***	1.384***	1.234***	1.500***
	(0.0126)	(0.0179)	(0.0192)	(0.0161)
section	1.247***	1.383***	0.969***	1.404***
	(0.0618)	(0.0750)	(0.0965)	(0.0770)
row	-0.506***	-0.422***	0.127**	-0.683***
	(0.0357)	(0.0350)	(0.0583)	(0.0444)
daystogo	0.656***	0.787***	1.345***	0.455*
	(0.197)	(0.190)	(0.309)	(0.243)
qdaystogo	-0.0191	-0.0295**	-0.0268	-0.0189
	(0.0128)	(0.0123)	(0.0200)	(0.0158)
shipping	-0.201***	-0.135***	-0.111**	-0.196***
	(0.0394)	(0.0386)	(0.0559)	(0.0527)
opponent	0.217***	-34.76***	0.232***	0.195***
	(0.0329)	(0.985)	(0.0514)	(0.0409)
days	0.671***	371.0***	-0.502	1.179***
	(0.237)	(12.88)	(0.366)	(0.296)
31.eventid		-632.4***		
		(16.91)		
184.eventid		0.414		
		(2.595)		
Constant	-19.15***	-524.6***	-27.68***	-21.60***
	(1.497)	(22.25)	(2.373)	(1.859)
Observations	73,163	73,163	20,610	52,553
R-squared	0.258	0.314	0.342	0.236

Table B.6: Auction Choice

VARIABLES	(1) auction	(2) auction	clogit auction
facevalue	0.000785***	0.00123***	0.0377***
	(0.000101)	(0.000111)	(0.000944)
section	0.000490	0.00299***	0.0800***
	(0.000514)	(0.000542)	(0.00393)
row	-0.00679***	-0.00733***	-0.0436***
	(0.000310)	(0.000312)	(0.00182)
daystogo	-0.00307***	0.0221***	
	(0.000411)	(0.00172)	
qdaystogo		-0.00169***	
		(0.000112)	
shipping		0.00538***	0.0241***
		(0.000345)	(0.00185)
opponent		-0.000157	
		(0.000288)	
weekdays		0.0135***	
		(0.00207)	
logstartprice			-0.647***
			(0.0115)
Constant	0.325***	0.185***	
	(0.00885)	(0.0131)	
Observations	73,168	73,168	72,599
R-squared	0.009	0.016	

C New Model with Change of Seller's Arrival Process

C.0.1 Model

Assumption 3 *When sellers set prices and make mechanism choices, the only information they can get is* λ_t^{MB} *and* λ_t^{MS}*. Then the arrival rate of buyers in each good as*

$$log(\lambda_{jt}^{MB}) = log(\frac{\lambda_t^{MB}}{\lambda_t^S}) + \alpha_1^M(p_{jt} - \overline{p}) + \alpha_2^M(X_{jt}^2 - \overline{X^2})$$

$$= (\rho_0^{MB} - \rho_0^{MS}) + (\rho_1^{MB} - \rho_1^{MS})t + (\rho_2^{MB} - \rho_2^{MS})X_g^1 + \alpha_1^M(p_{jt} - \overline{p}) + \alpha_2^M(X_{jt}^2 - \overline{X^2})$$

$$\lambda_{jt}^B = exp(\rho_0 + \rho_1 t + \rho_2 X_g^1 + \alpha_1^M(p_{jt} - \overline{p}) + \alpha_2^M(X_{jt}^2 - \overline{X^2})).$$

X_{jt}^2 include the section and row information on the first page,

$\overline{X}^2$ and $\overline{P}$ are the average value of characteristics and average price of listings for the same game in the same period and selling mechanism. Also, when I do estimation, in the exercise, I use log-price instead of price in the arrival process.

Here, I estimate the parameters in value distribution and arrival process simultaneous using sale information for both auctions and posted prices respectively. We can put some restrictions. For example, consider the linear part interpolation in the seller's problem, we can restrict the linear part in the value distribution is the same across different selling mechanisms, but allow mean and variance of the distribution to be different. There are some disadvantages of this method:1) we cannot estimate fixed effect in the value distribution part; 2) the bids information is not used;3) many parameters are estimated simultaneously which may increase the computation burden and make the identification more relies on the function form. However, it can also make the value distribution more flexible and reduce the sample selection problem we mentioned above.

$$Prob(sell_{jt}^M) = \sum_{n=1}^{\infty} Prob(N_{jt} = n)(1 - Prob(log(b) < log((1 + \tau_1)p_{jt}))^n)$$

$$= \sum_{n=1}^{\infty} \frac{e^{-\lambda_{jt}}(\lambda_{jt})^n}{n!}(1 - F^b(log(p_{jt}))^n)$$

and

$$log(\lambda_{jt}^{MB}) = (\rho_0^{MB} - \rho_0^{MS}) + (\rho_1^{MB} - \rho_1^{MS})t + (\rho_2^{MB} - \rho_2^{MS})X_g^1 + \alpha_1^M(p_{jt} - \overline{p}) + \alpha_2^M(X_{jt}^2 - \overline{X^2})$$

C.0.2 Data

For this exercise, I randomly choose 18 games to do the estimation. Following Table C1 and Figure C1-C2 summarize relative prices of the subsample data.

Table C.1: Relative Start Prices and Relative Transaction Prices of Subsample

relative price	mechanism	Obs	Mean	Std. Dev.	Min	Max
	total	3,963	0.9223001	0.7214884	0.0000269	3.69318
start price/face value	auction	1,616	0.6777	0.5184904	0.0000269	2.678393
	posted price	2,347	1.090727	0.790222	0.004717	3.693182
	total	3,963	1.208957	0.6192162	0.1090909	4
transaction price/face value	auction	1,616	1.002251	0.569532	0.1475	3.125
	posted price	2,347	1.351282	0.6120078	0.1090909	4

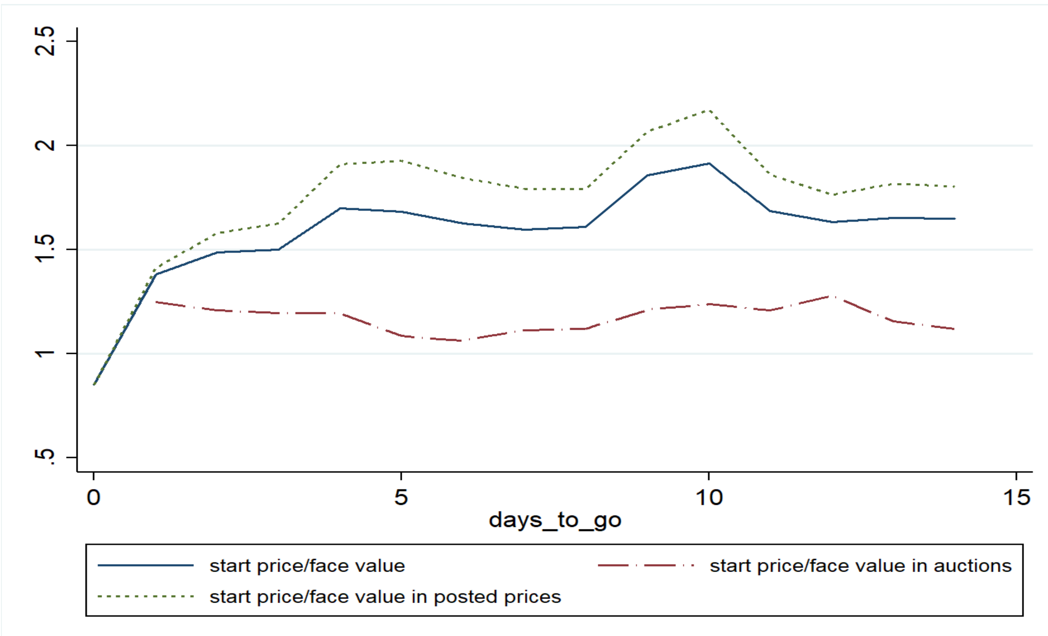


Figure C.1: Start Price/Face Value over Time of Subsample

C.0.3 Results

Results for demand part are shown in Table C2. Notice I haven't use IV in these practices. Figure C3 depicts the predicted arrival rates. Figure C4 shows the average value of buyers of different selling mechanisms. From Figure C5, we see the estimation results can capture the dynamics of transaction rates well.

With the estimation results from demand side, I continue estimate the parameter in the supply side. Here I restrict $\gamma_2^0 = 0$.

Without last period change:outside option=0.6013*facevalue, $\beta_2 = 0.99$

With last period change: outside option=0.6029*facevalue, $\beta_2 = 0.9$.

Further, I divide sellers to be experienced and inexperienced by start price/face value smaller than 2 or not with last period change. The estimation results are as follows

Experienced: outside option=3.8344*facevalue, $\beta_2 = 0.99$.

Inexperienced: outside option=3.8344*facevalue, $\beta_2 = 0.99$.

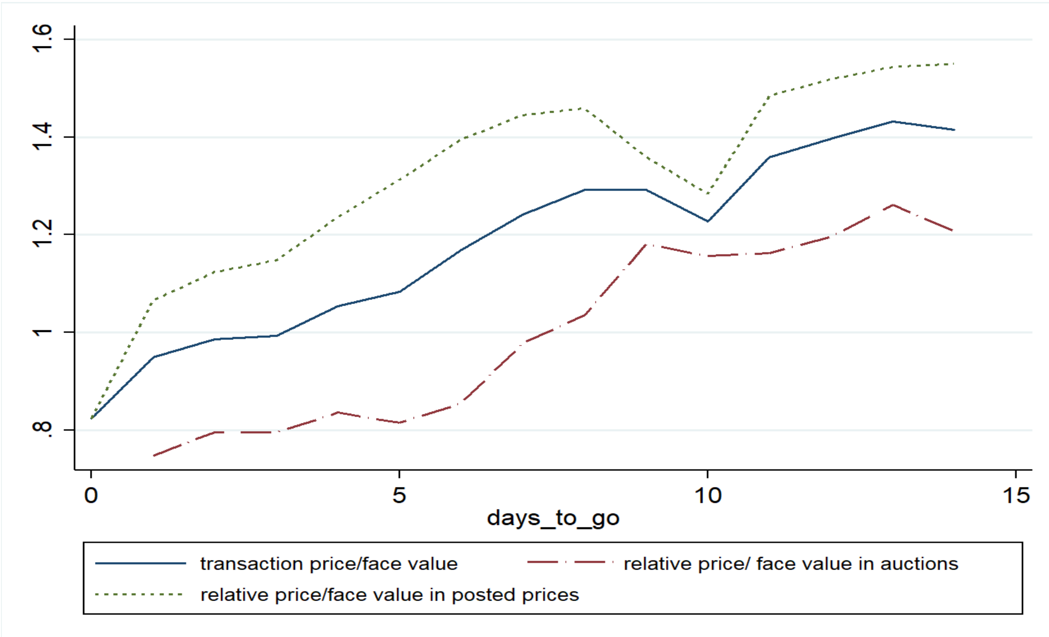


Figure C.2: Transaction Price/Face Value over Time of Subsample

Table C.2: With Expanding the Data According to Their Number of Tickets

		no change of last period		change last period	
		Auction	Posted Price	Auction	Posted Price
	constant	0.9440	0.4231	1.0108	0.1162
	opponent	-0.0583	-0.0604	-0.0592	-0.0567
	weekdays	-0.5431	-0.5876	-0.5474	-0.5932
Arrival	time left	-0.1632	-0.1244	-0.1613	-0.1253
	titlsection	0.0291	0.0021	0.0024	0.0091
	titlrow	-0.0661	-0.0085	-0.0666	-0.0111
	log(price)	0.0003	-0.3087	-0.0045	-0.3671
	shipping	0.0520	-0.0319	0.0410	-0.0368
	correction	No	Yes	No	Yes
	face value	0.0156	0.0156	0.0162	0.0162
	section	0.0073	0.0073	-0.0024	-0.0024
	row	-0.0167	-0.0167	-0.0038	-0.0038
Value	prob				
Distribution	σ_b	0.6970	0.8592	0.7758	0.7426
	μ	2.8313	2.7747	2.6813	2.9862
	β				

Similar to the original model, this estimation results can predict the level of prices, dynamics of prices and auction shares well. However, the auction share is higher than the observed market auction share and the price dispersion is much less than the observed one.

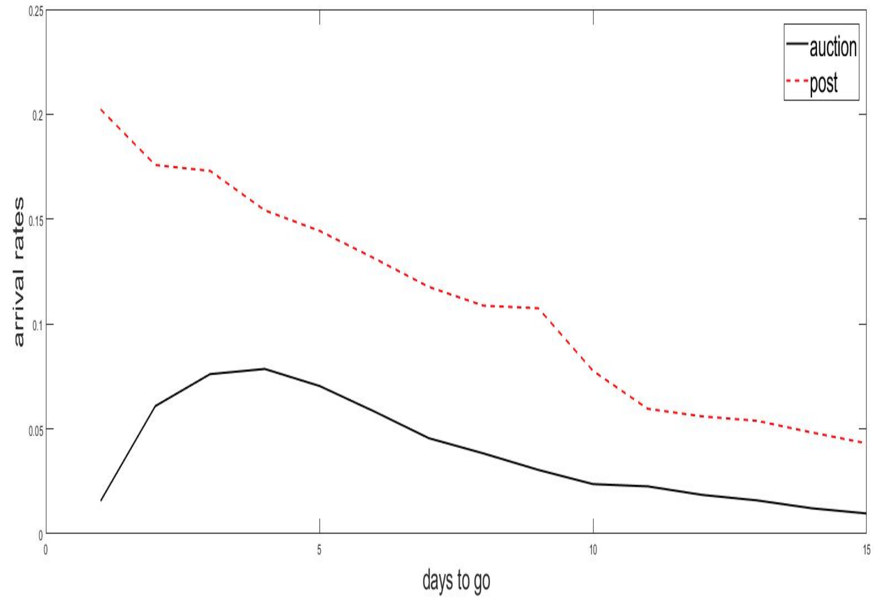


Figure C.3: Estimated Arrival Rates without Last Period Change in One-step Model

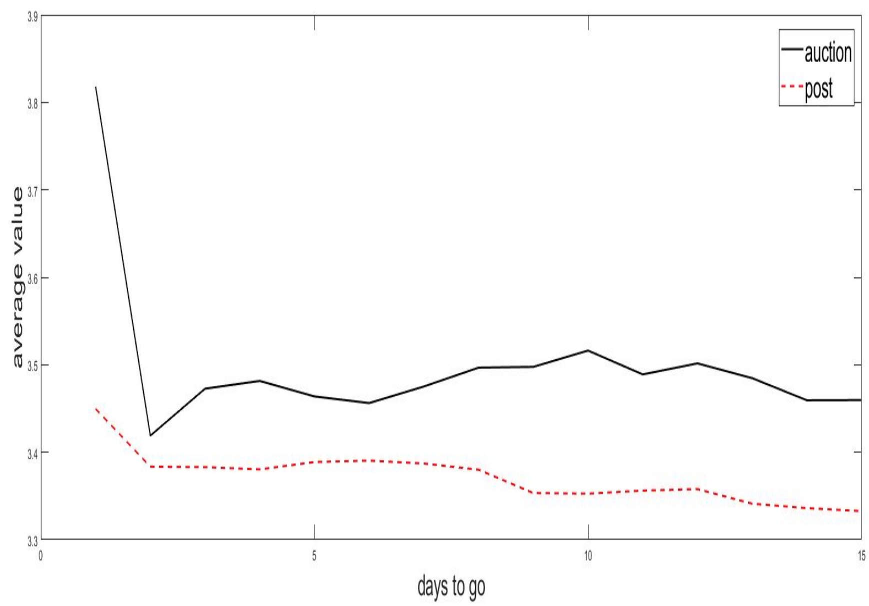


Figure C.4: Estimated Value Distribution Without Last Period Change in One-step Model

C.0.4 Counterfactual Analysis

Finally, I also do three parts counterfactual analysis for the new model. Results are shown in Table C3-C5.

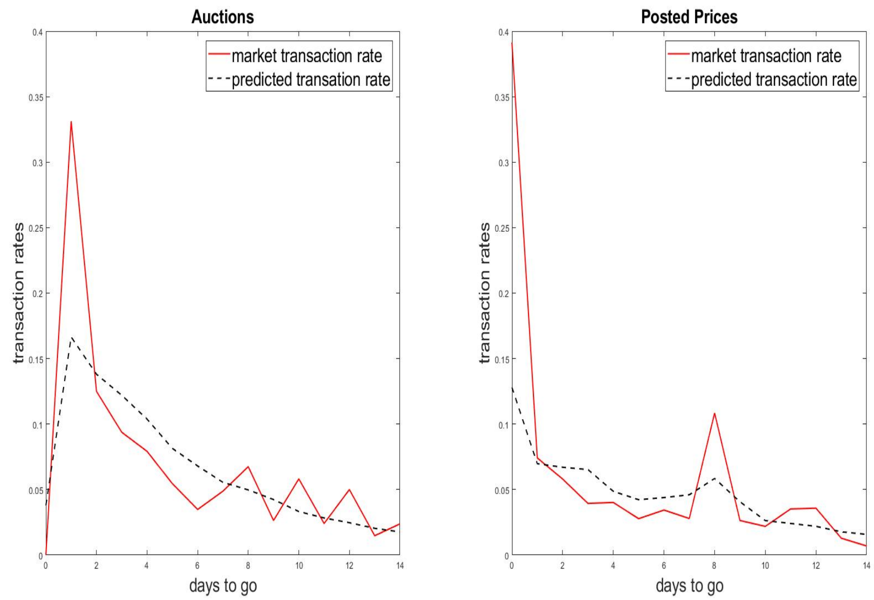


Figure C.5: Estimated Transaction Rates without Last Period Change in One-step Model

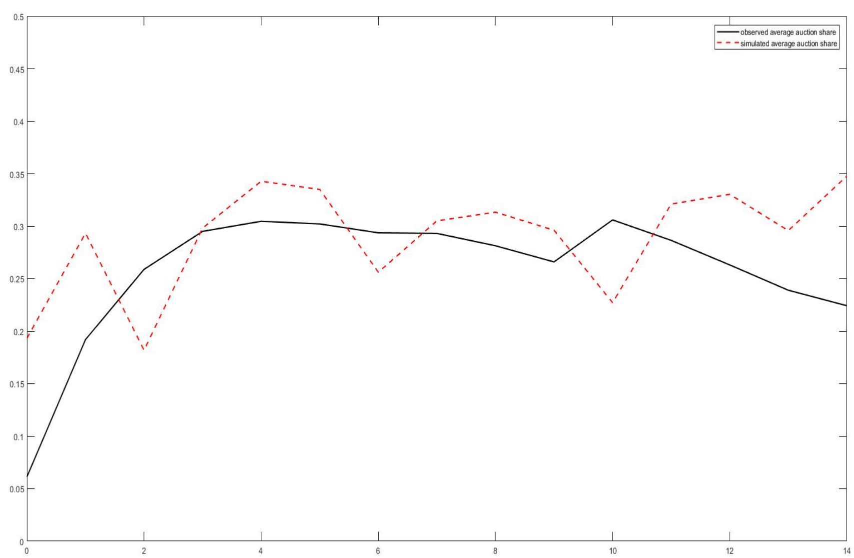


Figure C.6: Auction Share over Time in One-step Model

Table C.3: Summary of Counterfactual Analysis (1)-(3) without Last Period Change

	real market	estimated	value distribution	β_1	β_2
mean auction share	0.2719	0.2969	0.281	0.2061	0.3265
mean prices	70.5098	74.941	51.3441	67.3479	28.7062

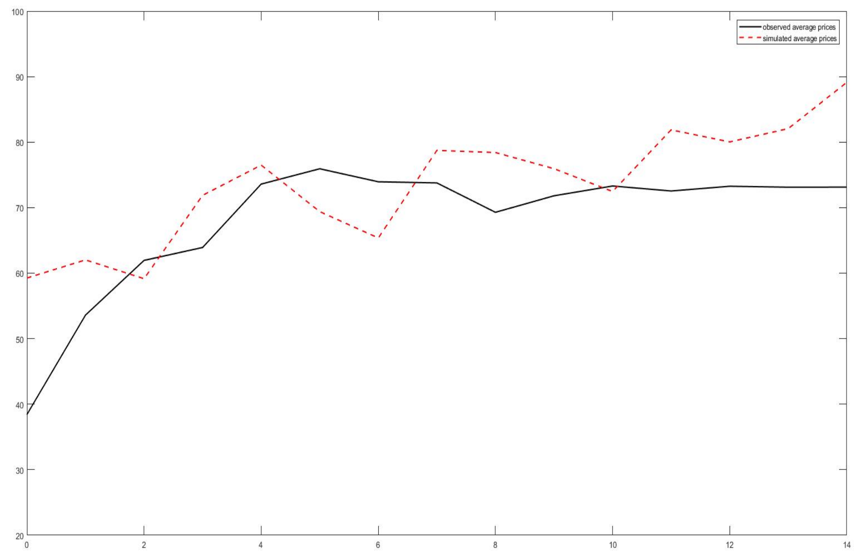


Figure C.7: Start Price over Time in One-step Model

Table C.4: Summary of Counterfactual Analysis (4)-(6) with Last Period Change

	real market	estimated	price sensitive	obfuscation	commission fee
mean auction share	0.2719	0.2969	0.295	0.2932	0.3365
mean prices	70.5098	74.941	69.9654	74.9357	77.4787

Table C.5: Only with Posted Price with Last Period Change

	real market	estimated	auctions	posted prices	only with posted prices
mean prices	70.5098			74.941	71.2628
std prices	70.0054			18.8465	18.1884