Selling Mechanisms for Perishable Goods:

An Empirical Analysis of an Online Resale Market for Event Tickets

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Abstract

Which selling mechanisms should sellers use to sell their goods? Even though this is one of the most fundamental decisions a seller can make, there is little empirical research on mechanism choice. This paper takes a step in this direction by analyzing the choice between auctions and posted prices in the context of a scarce perishable good: National Football League (NFL) tickets. Using data from eBay, this study estimates a structural model in which heterogeneous, forward-looking sellers optimally choose which selling mechanism they use. Counterfactual results suggest that sellers would experience an average 11.45% increase in expected revenues if auctions were removed and an almost 26% decrease if posted prices were. In turn, consumers would be unambiguously harmed if the platform specialized in either mechanism. These results can be useful not only in the context of perishable goods but also to improve general platform design.

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1 Introduction

The choice of which selling mechanism to use is one of the most fundamental decisions a seller can make. While the determination of optimal pricing and other considerations given a chosen mechanism has received significant attention in both the empirical marketing and economics literatures, the choice of which mechanism to use has received scarce attention. The advent of modern technology-based marketplaces which bring buyers and sellers together to facilitate trade has made it easier for platforms to offer a variety of selling mechanisms, and for sellers to choose which of these mechanisms to trade their products. These platforms have used a wide array of different mechanisms, most notably auctions and posted prices: TaskRabbit and Prosper.com, which began their operations as auction-based platforms, have now abandoned auctions and focused on better matching procedures, eBay began as an auction market but now hosts several mechanisms, and Upwork and Freelancer still rely heavily on procurement-like mechanisms to match workers to employers for specific tasks. Against this background, it is increasingly becoming important to develop a deeper understanding of the relative efficacy of various selling formats as well as of the forces which drive buyers' and sellers' choices between mechanisms in real markets. This paper takes a step in this direction by analyzing the choice between auctions and posted prices in the context of National Football League (NFL) tickets offered at eBay.

Event tickets, as well as airline seats, hotel rooms, and online advertising spots, are examples of perishable goods. Such goods are ubiquitous. The fact that these goods need to be consumed before or at a deadline introduces several layers of complexity to the problem of how to sell them because the environment in which they are traded is inherently nonstationary. As a consequence, the improvement of markets for perishable goods is a continuing effort, and the use of different selling mechanisms is frequently suggested as a way to achieve this goal. However, there is little empirical evaluation of individuals' behavior in a perishable good market in which several mechanisms are actually available to sellers, which is necessary to assess the efficacy and best way to implement this policy.

This setting which I consider in this study is a favorable one to conduct this exercise for several reasons. First, event tickets are a traditional example of a perishable good since they lose their value after the event takes place. In addition, NFL tickets are particularly scarce, with teams playing only eight regular season home games per year, which intensifies the importance of deadlines as the substitution of these goods becomes infeasible. Second, eBay offers a menu of different selling mechanisms from which sellers can choose when listing a good, and these different mechanisms are used at the same time to offer comparable items. This is attractive because it allows me to model how the market splits across the different formats and perform counterfactual exercises in which the set of mechanisms available to sellers changes while accounting for the redistributive effects of these changes. On the other hand, explicitly measuring this mechanism substitution pattern would not be possible in settings in which only one mechanism is available. A further advantage is that the existence of a deadline shifts the incentives of sellers to choose their selling mechanism, so variation in mechanism choice is observed within the same seller-tickets pair over time. Finally, the market for NFL tickets is arguably not as complex as that of other relevant perishable goods such as airline seats or hotel rooms, which facilitates the analysis.[1]

This paper first documents how individuals behave across time in a perishable good market where several mechanisms are available. Since the data used in this study come from eBay the focus is on the tradeoff between auctions and posted prices as these are the main mechanisms available at this platform. Most tickets enter the market within one week of the game, with very little activity on game day. Furthermore, as predicted by several revenue management models and previously documented by other studies, both posted prices and auction start prices decrease with respect to face values (i.e. prices on the primary market) as the deadline approaches. This pattern of decreasing prices is to be expected in light of both the proximity to the deadline and the increase in supply. However, while supply expands considerably as the deadline approaches, the increase in demand more than compensates it. This apparent contradiction between higher demand and lower prices can be explained with forward-looking behavior: sellers anticipate future market conditions and take them into account when making mechanism choices and pricing decisions.

If sufficiently far from or close to the deadline, sellers are relatively more likely to choose posted prices, with auctions being overwhelmingly favored around two weeks before the game. Most sellers are casual, offering tickets for only one game and never relisting their tickets when the first attempt of selling them was unsuccessful. Moreover, most sellers that do relist seem to have persistent preferences towards specific selling mechanisms as they do not switch between auctions and posted prices at any point in time.

[1] In the case of airline seats and hotel rooms there are several, vertically differentiated firms competing in the market. In addition, there is more scope for consumers to intertemporally substitute consumption. On the other hand, there is a unique provider of NFL tickets in the primary market, and different games are not as close substitutes as, for instance, the same hotel room at two points in time.

However, the data also display substantial heterogeneity *across* sellers: similar sellers offering comparable tickets at the same time systematically make different choices. Finally, buyers seem to become less prone to participate in auctions when the deadline is close, possibly because they become less willing to wait to find out whether they will obtain the tickets.

The main goal of this paper is to analyze and quantify the impacts of changes in the menu of selling mechanisms on market outcomes. To achieve this goal, I propose an empirical structural model of dynamic mechanism choice which is specified to capture the aforementioned empirical patterns as well as institutional details of eBay. A structural model is required because counterfactual scenarios in which, for instance, only posted prices are available, are not observed. Thus, it is necessary to account for how such changes impact the functioning of this market, including how each mechanism's market interacts with the others. In this model, sellers are assumed to have perfect foresight over future market conditions and can choose between auctions and posted prices as well as alter their choices as the deadline approaches. Their choice of mechanism as well as its features – starting prices and length of auctions or posted prices – are the result of a finite-horizon, dynamic optimization problem. Buyers randomly arrive to sellers' listing and make optimal decisions based on their willingness-to-pay to acquire the tickets with which they were matched at specific days.

I estimate this model in three steps. The first difficulty in this exercise is that the number of potential buyers that arrive to each listing is not observed. In the first step, in which I recover the distribution buyers' willingness-to-pay and how it changes over time, I circumvent this issue by leveraging existing tools from the literature on empirical auctions with an unknown number of bidders. These tools along with the theoretical prediction that the submitted bids equals buyers' valuations allow me to recover the distribution of buyers' willingness-to-pay in a flexible and yet parsimonious time-varying fashion.

The second step infers the random process through which potential buyers arrive to sellers' listings. Since the realizations of this process are not observed, I make use of sales outcomes to estimate the parameters of these arrival processes. In particular, given the listing's price and the estimated distributions of valuations the estimation procedure aims to rationalize whether the good was sold by varying these arrival parameters based on observable market and seller characteristics.

After recovering the demand side primitives, the third step recovers the supply side parameters, which were taken as given in the previous two steps. It is necessary to rationalize two sets of decisions by sellers: mechanism choice and exit. Thus, I propose two sets of parameters to be estimated, namely risk aversion and outside option parameters. Depending on how risk averse a seller is she will react differently to a set of demand conditions, while the level of her outside option will guide her decision to exit the market. To accommodate the heterogeneity in sellers' choices, I allow these parameters to be seller-specific and estimate the parameters of the distribution of risk aversion and outside option parameters. The estimation is based on the solution to the sellers' optimization problem, which can be solved by backward induction since the time horizon is finite. This solution gives rise to mechanism-specific conditional choice probabilities, which are matched to the observed decisions via simulated maximum likelihood.

Based on these estimates I conduct counterfactual studies in which the menu of mechanisms is altered. In particular, I assess what would be the impact on market outcomes (i.e. sales and transaction prices) when only posted prices or only auctions were available to sellers. I find that sellers would benefit from a platform specialized in posted prices, with unconditional expected revenues accrued by them on average increasing by 11.45%. On the other hand, an auction-only platform would reduce expected revenues by almost 26%. In turn, buyers would always be harmed when if only one type of selling mechanism was available, as not only the probability of making a purchase would decrease, but the expected sale prices would increase. Thus, allowing for different mechanisms to be used has opposite effects for the two sides of this market. These findings can potentially be useful to guide general platform design. By shedding light on the drivers of mechanism choice and how users respond to changes in the menu of mechanisms available on a platform, this paper can aid in deciding which mechanisms a platform should offer.

It is important to mention what this model does not capture. In particular, it does not account for the entry decisions of sellers and buyers, that is, it does not explicitly model how sellers' and buyers' decide whether and when to enter the market. Instead, for the purposes of the counterfactual exercises I assume that sellers would still have entered the market with the same tickets at the same point in time, with demand evolving proportionally to existing supply in the same way as it did in the data. That is, if existing supply at a point in time implied in the counterfactual is different from what was observed in the data, I assume that the number of potential buyers adjusts so that the relative number of buyers to listings is the same as what is observed. Furthermore, it does not model buyers' search process and decision to participate in a given listing. Rather, it associates to each mechanism a random buyer arrival process, which can be interpreted as a reduced-form way to capture these buyers' choices. For instance, if in this market equilibrium buyers' face the same expected payoffs in auction and posted price markets, these processes can be seen as an approximation to the mixed strategy probabilities of a given buyer joining a particular market.

The remainder of the paper proceeds as follows. First, I briefly review the existing literature to which this paper is related. I then describe the empirical setting in more detail, focusing on the market for NFL tickets and the eBay marketplace. Next I describe the sample used in this study and document the main empirical patterns it displays. Motivated by such patterns, I propose an empirical model which aims to rationalize sellers' choices and discuss how this model's primitives can be estimated. I then present the model's estimates and counterfactual results. Finally, I conclude the paper by summarizing the key findings and outlining directions for future research.

2 Literature review

This paper is primarily related to the literatures on mechanism choice, perishable goods, and online markets. In the sections below I summarize both the existing theoretical and empirical work in these areas and how it relates to my research.

2.1 Theory

The literature on mechanism choice is closely related to the one on mechanism design. I will focus on the choice between auctions and posted prices as this is the tradeoff studied not only in this paper, but also in several theoretical models. In static models, it is often the case that, all else constant, auctions weakly dominate posted prices from a seller's perspective, that is, in terms of expected revenue. Perhaps the first comparison between these two mechanisms in a dynamic setting was made by Wang (1993), who showed that when buyers arrive randomly and auctions are costless posted prices are indeed dominated by auctions. For auctions not to be optimal, it is required that auctioning costs exist and the distribution of buyers' valuations is not too steep.[2] Ziegler and Lazear (2003) modeled such costs as impatience and found that posted prices will be chosen if the seller is sufficiently impatient because they yield immediate transactions, whereas auctions need to last for a specified amount of time regardless of whether a willing buyer arrives.

Within marketing, the topic of mechanism choice was mostly addressed in more constrained environments: instead of comparing different mechanisms, researchers addressed different policies within a given mechanism. One example of such approach is the choice between EDLP and HiLo, as in, for instance, Ho et al. (1998). Another example is the literature on life-cycle pricing of durables goods that focuses on the choice between commitment and price-cutting, of which a recent example is Öry (2016).

Theoretical work on how to sell a perishable good is vast, particularly in the field of revenue management, as the textbook by Talluri and van Ryzin (2004) attests. While most of this work concerned optimal pricing, of which a seminal example is Gallego and van Ryzin (1994), more recently researchers have also focused on optimal dynamic auctions for perishable goods as in Vulcano et al. (2002) and Pai and Vohra (2013). However, this literature has traditionally focused on deriving the optimal policy given a selling mechanism instead of on the optimal choice of mechanism.

More recent work has merged mechanism design with revenue management, relating directly to the question of optimal selling mechanisms for perishable goods. Board and Skrzypacz (2016) showed that when the seller can commit to a selling strategy the optimal policy is to post a sequence of prices which evolve optimally according to observed outcomes and then run an auction at the deadline in case there are any units of the good left. When the seller cannot commit, Dilme and Li (2016) find that it is optimal for the seller to hold sporadic fire sales. However, these papers require strong assumptions about consumer knowledge and rationality. Contributions have also been made on general mechanism design problems with deadlines, of which an example is Mierendorff (2016), and on dynamic mechanism design specifically for online commerce, which was studied by Gallien (2006).

Motivated in part by the advent of online markets, recent studies have also addressed the concurrent use of different mechanisms to sell comparable goods. Similarly to this paper, most of these studies focused on the tradeoff between auctions and posted prices. Kultti (1999) showed that if buyers choose whether to join an auctions market or

[2] Intuitively, if the dispersions of buyers' valuations is low, an informed seller would benefit less from an auction as this mechanism performs relatively better under high demand uncertainty.

a posted prices market then the markets reach an equilibrium in which the two mechanisms become equivalent, while Etzion et al. (2006), Caldentey and Vulcano (2007), Etzion and Moore (2013), Hummel (2015), and Selcuk (2017) allowed buyers to participate in both markets and derived conditions under which sellers are better off using both mechanisms. Given this tension in the theoretical literature, more empirical work on this topic could be useful. Recent contributions such as Anwar and Zheng (2015) and Chen et al. (2016) have also incorporated the possibility of using auctions with buy-it-now prices.

This study follows the modeling approach of majority of the aforementioned papers in that it does not explicitly model competition. In particular, it specifies the sellers' optimization problem as a single-agent problem, in which competing sellers only interact in a stylized way in the spirit of monopolistic competition. While there are several studies which explicitly account for dynamic price competition in a perishable goods setting, to my knowledge a model which allows competing sellers to choose different mechanisms in such environment is yet to be developed.

2.2 Empirics

Mechanism choice has proven to be a fruitful field of empirical research in recent years. This is in part due to the advent of online markets, which facilitated the access to certain mechanisms by sellers, particularly auctions (see Farronato (2017) for a survey on research regarding selling mechanisms in online markets). An early contribution was made by Hammond (2010), who documented a pattern also found in this study and in several others: posted prices are less likely to be successful, but yield higher payments conditional on a sale. Furthermore, both mechanisms are concurrently used to sell identical or similar goods, despite the usual revenue-dominance property of auctions. Several possible explanations for these patterns have been suggested: Zeithammer and Liu (2006) found that both observable and unobservable seller heterogeneity are the most likely driver of mechanism choice. In this paper, observed seller heterogeneity plays a role in how many potential buyers a seller attracts, while unobserved heterogeneity takes the form of risk aversion and outside option parameters. Einav et al. (2015) suggested that seller experimentation could be a factor into mechanism choice. Einav et al. (2017) explained the decline in the use of auctions with changes in seller incentives as consequence of changes on the eBay platform and on buyers' preferences for each mechanism. There were no such changes in the platform during the time period of my data, and buyer heterogeneity is captured flexibly in my model. Coey et al. (2016) explained the use of different mechanisms through private buyer deadlines, with auctions acting as discount opportunities. In my setting not only buyers' deadlines are public, but they also apply to sellers. A different stream of the literature analyzes mechanism choice by the platforms themselves rather than users. Examples include Huang (2016) and Wei and Lin (2017), who studied the decision of abandoning auctions in favor of centralized price setting by Prosper.com, finding mixed evidence on whether this decision was beneficial. However, none of these studies have addressed this tradeoff in the context of a perishable good market.

Within marketing, empirical studies also focused more on addressing different policies within a mechanism rather than on comparing mechanisms. In the context of the tradeoff between EDLP and HiLo, examples of studies include Hoch et al. (1994), Lal and Rao (1997), Bell and Lattin (1998), Pesendorfer (2002), Bell and Hilber (2006), Ellickson and Misra (2008), and Ellickson et al. (2012). In turn, the topic of life-cycle pricing of durable goods has recently been empirically studied by, for example, Nair (2007), Daljord (2014), and Rao (2015). Nevertheless, despite the similarities between these topics and the one addressed here it is important to emphasize that such themes are not directly concerned with mechanism choice itself.

The studies to which this article is most closely related display structural estimation of models in which sellers choose between auctions and posted prices. Hammond (2013) proposed a static model of competing sellers offering compact-discs, and found that seller outside options are a key force behind which mechanism they choose, with high outside option sellers tending to favor posted prices. Sweeting (2013) and Bauner (2015) are the papers to which this study is most closely related, studying mechanism choice in the context of Major League Baseball (MLB) tickets on eBay. However, both these studies incorporated the sellers' choice of hybrid auctions, from which I abstract. On the other hand, Hammond (2013), Sweeting (2013), and Bauner (2015) follow an essentially static approach, while this study attempts to take into account the inherent dynamic nature of selling perishable goods such as event tickets. Furthermore, these three papers relied on heterogeneous mechanism-specific costs to explain sellers' choices. In this paper, this essential seller heterogeneity is introduced as seller-specific risk aversion parameters.

This paper also relates to others that empirically studied event tickets. Sainam et al. (2010) studied the effects of consumer options on both consumer surplus and sellers' profits, indicating that resale can be beneficial to both. On the other hand, the analysis of resale opportunities has been controversial as it can incentivize rent-seeking behavior.

Leslie and Sorensen (2014) structurally estimated a model of rent-seeking applied to concert tickets, while Bhave and Budish (2014) compare outcomes with and without auctions in the primary market for tickets and found that the use of auctions can mitigate arbitrage. Finally, Sweeting (2012) not only documented empirical regularities consistent with most dynamic pricing models (e.g. prices decrease as the deadline approaches) but also estimated a structural model of forward-looking sellers. However, his analysis was confined to posted prices, while here I explore the topic of mechanism choice.

3 Empirical setting

This section describes the empirical setting studied in this paper. First, it briefly describes the overall market for NFL tickets and the main platforms for ticket resale, StubHub and Ticketmaster. Then it describes in more detail the platform eBay, whose data are used in this paper.

3.1 NFL and the market for NFL tickets

The NFL is the American professional football league, which is arguably the most popular sport in the United States. According to Statista (2016), between 2009 and 2015 on average one third of survey respondents picked pro football as their favorite sport.[3] This popularity is also reflected in ticket prices and attendance, as shown in Table 1: as of 2015-16, the NFL had the most expensive average ticket as well as the highest absolute and relative average attendances per game. However, this is likely due not only to football's popularity but also because opportunities to go to an NFL game are much more scarce than for other American sports leagues, as in each season NFL teams play only two preseason and eight regular season home games, while MLB teams play 81 regular season home games alone, and National Hockey League (NHL) and National Basketball Association (NBA) teams play 41 such games.

In the last 15 years the financial performance of the NFL displayed constant improvement. Total revenue accrued by NFL teams increased steadily, going from 4.28 in 2001 to 12.16 billion dollars in 2015. Ticket prices also grew in the last decade, rising from

[3]College football was the fourth most picked sport with an average on 11.29% behind pro football, pro baseball (15%), and other answers (15%).

an average of 62.38 in 2006 to 92.98 dollars in 2016. A back-of-the-envelope calculation reveals that game tickets still comprise a relevant share of teams' revenues. In 2015, the average ticket price was 85.83 dollars, with an average total regular season attendance of 539,333 per team, and an average revenue of 380 million dollars per team. Hence, ticket revenue constituted on average 12.18% of total revenues accrued by teams.

The primary source of tickets for NFL games is through the teams themselves via the platform Ticketmaster, with which the NFL has had a long agreement. Teams offer season packages that entail tickets for the aforementioned ten games as well as rights and advantages in case the team reaches the playoffs. It is also common for these packages to include parking and party passes. While most teams have waitlists to acquire these packages, they also offer tickets for individual games, which are limited and more expensive than a season package ticket, and prices might vary across games. More recently teams have started to offer specific packages for subsets of games (e.g. versus conference rivals only), possibly as a price discrimination tool.

Tickets can also be acquired in the secondary market through several sources. The largest player in the American ticket resale market is StubHub, with an estimated market share of 50% according to Satariano (2015). StubHub, which was acquired by eBay in 2007, specializes in ticket resale and allows sellers to list their tickets through posted prices only, charging average commission fees of 25% over transaction prices (roughly 10% from buyers and 15% from sellers). Nevertheless, activities on StubHub and eBay are kept separate, which means that sellers are not precluded from listing their tickets on both platforms at the same time.

Ticketmaster is the second largest platform in the American ticket resale market with an estimated market share of 11%. In the context of NFL tickets, it has a specific resale platform, Ticket Exchange, which is promoted as the official secondary market for NFL tickets. This platform has had a long and controversial policy of price floors which effectively prevented sellers from choosing prices below the face value of the tickets, and was subject to antitrust investigations and eventually abandoned in November of 2016.[4] Furthermore, Ticket Exchange charges buyers a 15% commission fee applied to the transaction amount, and either 10% (for season ticket holders) or 15% (others) from sellers.

[4]See Pociask (2014) and Belson (2016) for examples of news coverage of this issue.

3.2 eBay marketplace

Unlike Ticketmaster and StubHub, eBay is not specialized in ticket resale, offering a wide variety of goods. Sellers can choose from a standardized menu of mechanisms: ascending-like auctions, hybrid auctions with a buy-it-now option, posted prices, and posted prices with an option for buyers to make offers to sellers, who can then engage in bargaining. These choices can be changed over the duration of a listing, and even though posted price listings have a specified duration, in practice they can be extended and reviewed at the seller's discretion. On the other hand, auctions need to last for a specified number of days, which is chosen by the seller. The options offered by eBay are one, three, five, seven, or ten days. While a seller in principle can end an auction prematurely this is rarely seen in the data.[5] This can be in part explained by a fee that a seller needs to pay in case the auction is ended after bids were submitted and without a sale being made. Another possible explanation is that ending the auction in this fashion could potentially yield negative feedback to the seller, which is of crucial importance in online markets (see Tadelis (2016) for a review of the existing research on this topic).

Multiple units cannot be offered through auctions: for instance, if a seller creates an auction offering two tickets, then this listing effectively is for the pair as a bundle. On the other hand, if this seller creates a posted price listing for these two tickets then nothing prevents the sale of them separately. Consequently, eBay has a limited policy that allows sellers to offer the same item in two different formats at the same time. However, it does not allow sellers to have two concurrent posted price listings for the same item. In the data, few sellers choose to use both mechanisms at the same time. This may be because it is costly for sellers to monitor multiple listings and some might prefer not to run the risk of selling the same set of tickets twice as at least one of these transactions will not be completed, potentially yielding negative reviews for the seller as a consequence.

The focus of this paper is on the tradeoff between posted prices and auctions. Consequently, the choices of hybrid auctions and bargaining-enabled listings will not be considered, which is in accordance with the data: while many sellers choose hybrid auctions, the buy-it-now option is rarely used by buyers. On the other hand, negotiations do play a more substantial role among posted price sales. This will be captured in a stylized way in the model through daily price choices by sellers. A more thorough discussion will be given in the description of the data and of the model itself.

[5]Out of 27,040 auctions in the final sample only 475 (less than 1.76%) were ended prematurely.

Finally, fees charged on eBay are considerably lower than on Ticket Exchange and StubHub. Sellers are charged a 9% commission fee over the transaction amount, and this fee is capped above at $250. Listing fees of less than one dollar are only applied to listings in excess of 50 in a month, and are reimbursed in case the item listing ends in a sale.

4 Data and descriptive analysis

This section describes and summarizes the data and presents the main empirical patterns which the empirical model needs to take into account. I first describe what variables the data contain, followed by a brief summary of the final sample used in this exercise. Then I proceed to document the market evolution and outcomes. Finally, I report sellers' choices, focusing on how mechanism choice changes as the deadline approaches.

4.1 Observed variables

The bulk of the data used in this study comes from eBay. For all listings of NFL tickets created on eBay between January of 2013 and February of 2014, I observe: when the listing was created and when it ended, its format (auction, hybrid auction, or posted price with or without a bargaining option), the start, posted, reserve, or buy-it-now prices,[6] the duration of auctions, the title and subtitle chosen by sellers, the product category, whether the list was sold and for what price, the number of bundles and tickets per bundle, the location of the seats and the game to which they corresponded, the identity of sellers and potential buyers, all bids submitted, and all offers made in negotiations.

Regarding sellers, I further observe their title and their feedback score and percentage rating. The score is computed in the following way: a seller receives one point for each positive rating, no points for each neutral rating, and loses one point for each negative way. Naturally, the higher the score, the "better" the seller. The percentage rating is simply the fraction of all ratings received by a seller that were positive. In addition, I compute two measures of user experience in selling tickets: the total number of tickets sold by each format and the number of listings offered. Finally, I use the seller's title to

[6]On eBay, start prices are the price at which bidding starts, acting effectively as a public reserve price, while reserve prices are private and only disclosed if bids are submitted. Since reserve prices are rarely biding in my data I will ignore them and use only start prices, referring to them as reserve prices.

classify them into being specialized in selling tickets or not: sellers whose title contained words such as "sports" or "tickets" were defined as specialized.

In addition to observables regarding supply and demand outcomes such as transaction prices, offers, and bids, I also observe a measure of potential demand. For each listing-day pair, I observe all users who clicked to see the listing's web page and how many times each user clicked.[7] Based on this variable, I am able to compute a measure of relative scarcity which I refer to as demand-to-supply (DTS) ratio. For each game-day pair, it consists of the total number of different users who were observed clicking on at least one listing for tickets divided by the number of total available listings of tickets. Despite being admittedly endogenous and noisy, this measure is used to describe how the market evolves over time, particularly as the game approaches.

Finally, I use the face value of the tickets, that is, their original prices in the primary market to compare and interpret monetary amounts. To recover tickets prices for the 2013 NFL season, which is the one my data encompass, I first made use of the Wayback Machine through the Internet Archive website to access each team's web page in mid-2013. When pricing schedules were not available through this resource I contacted each team separately to try to obtain past prices directly from them. At the end of this process I was able to recover prices for 31 out of the 32 teams, the exception being the Washington Redskins. These prices referred to the individual ticket price charged in season passes, and were matched to each listing based on the location of the tickets.

4.2 Overview of final sample

To perform the exercise proposed in this paper it is necessary to have data that track the *same set of tickets* across time. This means that identifying the listings of NFL tickets on eBay does not suffice. Rather, listings for the same set of tickets need to be linked to assess not only differences across sellers, but also if and how a given seller changes the selling mechanism as the deadline approaches. These *chains* of listings are not directly available, and were created through a lengthy and manual process which is described in detail in Appendix A. This subsection gives just an overview of this method and of the sample resulting from it.

[7]Users are classified based on their IP number. Since it is not possible to know whether the same individual clicked on a given listing with different IP numbers, each number is treated as a different potential buyer.

To restrict the number of observations I only consider tickets for the 2013 NFL season made available in the United States eBay website. I choose this season so that the data have as many observations as possible with key information on the tickets so that I could link them across different listings. This information is the game to which the tickets corresponded, the number of tickets offered, and the section and row in which the tickets were located. This information was sparse for the previous seasons, while the number of ticket listings decreased substantially after 2014, which justifies the choice of the 2013 season. I further restrict attention to regular season games which took place in the continental United States.[8] I also only consider listings of tickets for specific games, which leaves out listings just for parking passes and other special events as well as listings for several games, and exclude tickets for the Washington Redskins home games because it was the only team for which I could not obtain ticket prices in the primary market. Finally, I focus on activity within four weeks of the game. This restriction is not strong: in this period, almost 61% of tickets were introduced to the market, more than 70% of all tickets were offered at least once, and more than 73% of the transactions observed in the data took place.

The key quantities are displayed in Table 2. The final sample has tickets for 245 regular season games,[9] with 43,221 listings across 27,047 chains, offered by 10,799 different sellers. Thus, each set of tickets is listed on average 1.6 times, and each seller offers on average 2.5 sets of tickets.

Table 3 shows the overall distribution of listings across mechanisms. Since the focus of this paper is on the tradeoff between auctions and posted prices, hybrid auctions are treated as simple auctions unless the buy price was accepted, in which case the listing was considered a posted price, and bargaining-enabled listings are always treated as posted prices. A more detailed analysis incorporating these four possible mechanisms is given in Appendix B, where I argue that this simplification is inconsequential. The majority of listings are offered through auctions, which are disproportionately more likely to be successful than posted prices.[10]

However, the analysis at the listing level can be misleading. Table 4 further char-

[8] This excludes games of the NFL International Series, which took place in London, England, between the Minnesota Vikings and the Pittsburgh Steelers and between the Jacksonville Jaguars and San Francisco 49ers, as well as the game hosted by the Buffalo Bills against the Atlanta Falcons in Toronto, Canada.

[9] These are all eligible games because there are 256 regular season games in total, but Washington Redskins (8) and International Series (3) games were excluded.

[10] Multi-bundle posted price listings (e.g. for two pairs) are considered to be successful if at least one of the bundles is sold.

acterizes the types of chains of tickets regarding whether and how they were relisted. A little less than two thirds of all sets of tickets are only made available once, in part due to a higher conversion rate: almost 58% of these tickets are sold, while less than 41% of relisted tickets were ever sold. Among the sets that get relisted, the majority are always made available through the same format, which is a first suggestion that sellers have preferences towards specific mechanisms, and once more there is some indication that auctions are more likely to be successful by comparing the second and third rows. Further evidence of this is shown in Table 5, which details what mechanisms are chosen for the single-listing chains. Not only are the majority of these chains offered as auctions, but these are also more likely to be successful.

Table 6 exhibits the overall transition patterns between mechanisms when tickets fail to sell and are relisted. The rows show which format was chosen before and the columns indicate the sellers' new choice conditional on the ticket being offered again (i.e. relisted). As expected, there is considerable persistence in sellers' mechanism choice. However, it is also interesting to note that posted prices are relatively more likely to be relisted as auctions than the converse: 85.12% of relisted auctions re-entered the market as auctions, but only 81.83% of relisted posted prices re-entered the market as such.

Finally, Table 7 illustrates the heterogeneous types of and choices across sellers. Most sellers are casual: almost 60% offer only one set of tickets in the sample, more than 62% never relist, and over 63% offer tickets for a single game. Moreover, almost all sellers offer tickets for games of only one team. Rigid preferences for specific mechanisms are once again seen since more than two thirds of the sellers that relist at some point always use the same mechanism. Further description of seller heterogeneity and how it affects sellers' decisions is provided in Appendix D.

4.3 Market evolution

While the analysis in the previous section was essentially cross-sectional, this subsection presents the main empirical patterns of the market over time. The analysis focuses on the raw patterns without accounting for heterogeneity for ease of interpretation. Results which account for heterogeneity are presented in Appendix E and are qualitatively equivalent to the ones which I describe below. Game day is normalized to be day 0 throughout this analysis and the model.

Figure 1 presents the evolution of supply: it displays the number of available listings at each day before the deadline pooled across all games in the sample. A few interesting patterns emerge. First, there is a weekly expansion in supply: the number increases by around 800 listings seven days prior to the game, by roughly 500 fourteen days before, and 300 three weeks before. This is likely due to the weekly pattern of NFL games, which take place mostly on Sundays. Thus, it is possible that fans watch games, update their beliefs about the value of a game, and then decide whether to participate in the market. Second, most of the activity takes place within one week of the game. For instance, the average number of listings increases from 1,008 fifteen days before the game to more than three times this number with just six days before the game. Finally, the market vanishes quickly, with supply going from 1,585 listings one day before the game to 308 on game day, the lowest level during the four weeks prior to the game.

The expansion in supply is accompanied by an increased in demand as displayed in Figure 2. The histogram shows the number of potential buyers looking for tickets on the website averaged across all games for each day.[11] Once again a weekly pattern can be seen, with the average level of demand increasing and then falling noticeably on game day. This Figure also shows a steady inflow of new consumers to the market, which suggests that the pool of consumers is changing as well.

Given that both demand and supply increase as game day approaches it is useful to understand how the market evolves in relative terms, which is displayed in Figure 3. It displays the average demand-to-supply (DTS) ratio across games, that is, the average ratio between the number of distinct potential buyers and the number of existing listings.[12] Once again a weekly pattern can be seen, with the mean DTS ratio noticeably increasing one, two, and three weeks before the deadline. Furthermore, the average DTS ratio increases as game day approaches: the number of potential buyers for each listing goes from around two fourteen days before the game to more than four on the day before the game.

Since demand seems to grow faster than supply, the pattern presented in Figure 4 is somewhat surprising: both auction start prices and buy-it-now prices decrease relative

[11] I consider a potential buyer to be an user, identified by the user's IP address, who viewed (i.e. clicked on) at least one listing page for a particular game.

[12] The DTS ratio is related to the concept of "queue length" from the competitive search literature, which is defined as the number of vacancies posted by firms divided by the number of unemployed workers in the labor market. In this paper's context, sellers listing tickets can be seen as firms positing jobs, and potential buyers correspond to the unemployed workers. See Rogerson et al. (2005) for an overview of search-theoretic models of the labor market, including directed search.

to the face value of the tickets, even though conditions are arguably more favorable to sellers. This pattern was also reported by Sweeting (2012) in the context of MLB tickets. Interestingly not only the patterns but also the magnitudes of the average ratios between the prices chosen by sellers and the face values are comparable. These patterns will be rationalized in the model through forward-looking behavior: sellers anticipate favorable conditions in the future when making their decisions further away from the game.

4.4 Sellers' mechanism choice and performance

In this subsection, I show how mechanism choice evolves as the deadline approaches. For this subsection and for the estimation of buyer arrival and sellers' parameters I will focus on a more homogeneous subsample, which contains only pairs of tickets that were never offered simultaneously across two or more listings (i.e. doublelisted) and which were always offered as a pair (i.e. were never rebundled). Just a little more than 5% of sets of tickets are doublelisted or rebundled, and of the remaining chains almost 75% consisted of pairs. Therefore, this restriction still maintains the majority and most common sets of tickets in the data.

Figure 5 shows the number of listings created on each day before the game and the fraction of these listings that entered the market as auctions. The creation of listings mirrors the pattern seen in Figure 1 for the entire sample, but the mechanism choice is already somewhat reflective of forward-looking behavior. Auctions are the most common choice until one day before the game, when there is a huge decrease in the likelihood of a seller creating an auction. This is reasonable: since auctions need to last for at least one day, the incentives for creatingq one when the deadline is extremely close are weak. However, even before the final day there are movements in this probability. A month away from the game, the probability of creating an auction is around 64% and increases to almost 75% ten days before the game, when it starts decreasing. Another indication of forward-looking behavior is displayed in Figure 6, which shows the duration chosen for the created auctions. While it is expected that sellers do not choose a duration which would make the auction be over only after the game took place, these options start being disregarded even before this is the case. This variation is indicative of the tradeoffs sellers face, and will play a big role in identifying the parameters of the model.

Having described overall seller behavior, I now show how sellers switch between mechanisms. Figures 7 and 8 show the probability of choosing each mechanism conditional on relisting, which admittedly is a very selected sample. Auctions are very persistent, being substituted for posted prices only in the last two days. However, posted prices display a different pattern: they become more likely to switch from posted price listings to auctions, but then become more persistent once more.[13]

Turning to the performance of each mechanism, Figures 9 and 10 make this comparison in two dimensions: the probability of a sale and the expected price conditional on a sale (with respect to the face value). They display the probability of a sale and average prices of listings by the day of their creation. Auctions are almost always more likely to be successful, the exception being game day and the day before. However, posted prices almost always yield higher expected prices. Thus, the tradeoff between these two mechanisms is actually a tradeoff between these two quantities. It is important to note that several studies have documented this same fact in other contexts.[14] However, it is interesting to note that this tradeoff is found even in a nonstationary environment at almost each point in time instead of only at the cross-sectional level.

4.5 Buyers' mechanism choice

Finally, even though the focus of this paper is on sellers' behavior and how it changes as a function of the distance to the deadline it is also important to document that buyers' behavior also changes. To do so, I make use of the entire final sample as in subsection 4.2 and 4.3 to illustrate how potential buyer split between auctions and posted prices over time. First, Figure 11 displays the average number of consumers on each day that clicked on at least one listing across auctions and posted prices.

The overall levels of consumers in the auction market are always higher and once again the weekly pattern presents itself. However, a notable difference is that the number of consumers in the posted price is increasing during the entire week of the game, while the number of potential buyers in the auction market starts falling four days before the game. This trajectory somewhat mirrors that of the creation of auctions shown in Figure 5, which explains why once the demand-to-supply ration shown in Figure 3 is broken down across markets the two curves evolve similarly, as shown in Figure 12.

To better understand consumers switching behavior, for each listing-day pair I cal-

[13]The only exception is the 27th day, mainly due to the small number of observations (relistings).

[14]Examples include Hammond (2010), Bauner (2015), Einav et al. (2017), and Coey et al. (2016).

culate the number of different users who click to access the listing's page. I proceed to average this quantity separately across days for each mechanism. Then, I compute the ratio between the average daily number of clicks auctions received and the average daily number of clicks on posted prices. The evolution of this variable, which I simply call "buyers' relative interest", is presented in Figure 13. Despite being noisy, this measure shows that buyers become relatively more attracted to posted prices as the deadline approaches. This is possibly because buyers want to make sure they acquire the tickets and therefore become less willing to wait for the end of an auction to find out whether they won when the deadline is near, even though the expected payment is lower. Further evidence of how buyers' behavior changes across days is provided in Appendix C.

5 Empirical model

This section presents the empirical model which is estimated using the data described above. I first describe the demand side of the model. Then, I present the supply side separately, emphasizing the assumptions made regarding individuals' behavior.

5.1 Demand

Since the focus of this paper is on sellers' dynamic behavior, the demand side of the model is relatively more stylized than the supply side will be. I make the following assumptions regarding buyers' behavior and willingness-to-pay, which I will refer to interchangeably as valuations or values.

Assumption 1. *Valuations are private, independent, and follow day-specific distributions.*

More specifically, buyer i's willingness-to-pay for tickets j t days before the game, denoted v_{ijt}, is drawn from a distribution $F_{V,t}(\cdot|X_{jt})$, in which X_{jt} is a vector of listing j's characteristics. These valuations are independent across buyers and taken from the same distribution, and each buyer knows perfectly her willingness-to-pay. In other words, this is a symmetric independent private value (IPV) model. The distributions characterize buyers' willingness-to-pay to acquire the good on day t, and are allowed to vary across time to capture several possible features of buyers' behavior. For instance, if buyers are forward-looking, as in Zeithammer (2006), then their willingness-to-pay at a given point in time will reflect their expectations about future market conditions. In other words, bidders will take into account their continuation value of staying in the market and adjust their bids accordingly. Another justification for Assumption 1 is that buyers with different valuations might arrive at different points in time. For example, Sweeting (2012) documented that the travel distance between a buyer and the location of the event affects the timing of purchases, with people living farther buying tickets earlier. Rather than modeling all these possibilities, I choose to take the resulting distributions as given and known by sellers, who cannot unilaterally alter them. For the purposes of the counterfactuals, the underlying assumption is that these distributions are also not affected by changes in the marketplace. Because eBay is a small player in the secondary market for event tickets I believe this assumption not to be strong as changes in this platform should have no overall impact on the entire market.

Assumption 2. *A buyer accepts a posted price if and only if the posted price is no greater than the buyer's valuation. If a buyer submits a bid, then the bid equals the buyer's valuation.*

The first part of Assumption 2 simply states that buyers are individually rational as it prevents them from accepting prices which exceed their willingness-to-pay. However, the second part is stronger. It effectively treats auctions as being sealed-bid second-price, in which bidders' weakly dominant strategy is to bid their own valuations. While it has been argued that tools such as proxy bidding make this sealed-bid abstraction more believable, Zeithammer and Adams (2010) argued that bidders' behavior in online auctions is not consistent with what theory predicts in such case. Nevertheless, this assumption is maintained for tractability and estimation of the model.

5.2 Supply

The following assumption is made regarding seller entry and supply.

Assumption 3. *Sellers enter the market randomly and have one pair of tickets to sell by day 0 (game day).*

Thus, the subscript j is used to denote both sellers and tickets interchangeably.[15] Sellers can choose between two mechanisms, auctions (A_ℓ), where ℓ denotes the auction's duration, and posted prices (P). Mechanisms will be denoted with k, so that $k \in$

[15] Since there are sellers in the data who offer multiple sets of tickets for the same game, this assumption can be interpreted as sellers independently making decisions for each set separately.

$\{(A_\ell)_{\ell \in \mathbb{L}}, P\}$, where $\mathbb{L}$ is an exogenous and finite set from which sellers can choose the auction duration.[16] Each k entails a choice of price, p_k, which is the reserve price for auctions or simply the posted price. The following assumption is made on sellers' mechanism choice.

Assumption 4. *The choice of posted prices is made daily. If seller j chooses an auction, the seller stays locked into this auction until it ends.*

The first part of Assumption 4 is unlikely to be true in the data because prices rarely change every day. Rather, it can be seen as implicitly capturing the possibility of negotiations: while the model would predict falling prices, this is in a sense observationally equivalent to deals being reached at an amount lower than the posted price as a result of bargaining. In turn, even though the second of part of Assumption 4 is made for simplicity it does have support from the data as sellers rarely end auctions prematurely.

From each individual seller j's perspective, the number of potential buyers who randomly arrive to j's listing on day t is N_{jt}. From the sellers' perspective this is a random variable drawn from probability mass functions $Pr_t^k(\cdot|Z_{jt}, M_{jt})$, which vary across time and mechanisms. Thus, when convenient I will use N_{jt}^k to indicate the random number of arriving potential buyers on day t when j picks mechanism k. The probability mass functions depend on characteristics of the listing, Z_{jt}, which are not necessarily the same as the ones that affect bidders' valuations above, and a vector of variables summarizing the state of the market at day t, M_{jt}. The state of the market is also indexed by j because it refers to the specific game associated with j's tickets. The following assumption is made regarding sellers' knowledge of the evolution of market conditions.

Assumption 5. *Sellers have perfect foresight of the market evolution process.*

Assumptions 5 is clearly strong: it states that sellers perfectly know the vector of market conditions at every point in time. An alternative and perhaps more common approach would be to assume that M_{jt} follows a Markov process and that sellers have rational expectations about future market conditions, that is, they know the parameters of such process. However, consider a seller assessing the expected payoff from holding a 5-day auction. This seller needs to have expectations regarding how many potential buyers will arrive during these five days. If future market conditions were unknown, this seller would need to have expectations regarding not only the state of the market on the next day, but

[16] This set is the same as the one offered by eBay, so that $\mathbb{L} = \{1, 3, 5, 7, 10\}$.

on the next four days as well, which would make the the seller's optimization problem considerably more complex. Hence, I maintain the assumption of perfect foresight. I now present the choice-specific value functions (CSVF) and sellers' final choices.

5.2.1 Auctions

If t days before the game seller j chooses an auction of length ℓ, the random number of potential buyers who arrive is denoted as $N_{jt}^{A_\ell} = \sum_{d=0}^{\ell-1} N_{j,t-d}^{A}$, which follows a distribution denoted as $Pr_{t,\ell}^{A}\left(\cdot|\{Z_{j\tau}, M_{j\tau}\}_{\tau=t}^{t-\ell+1}\right)$. Notice that I assume that different auction lengths do not attract potential buyers differently in any other way rather than the duration itself. That is, all auctions on a given day attract buyers according to the same distribution. Omitting the conditioning variables to ease notation, the CSVF for such an auction is given by:

$$\pi_{jt}^{A_\ell} = \max_{p_A} \mathbb{E}_{N_{jt}^{A_\ell}}\left[\Pr\left(V_{j,t-\ell+1}^{(n:n)} \geq p_A\right)\mathbb{E}\left[u_j\left(\max\{V_{j,t-\ell+1}^{(n-1:n)}, p_A\}\right)\middle|V_{j,t-\ell+1}^{(n:n)} > p_A\right]\right.$$
$$\left.+\Pr\left(V_{j,t-\ell+1}^{(n:n)} < p_A\right)\Pi_{j,t-\ell}\middle|N_{jt}^{A_\ell} = n\right] + \epsilon_{jt}^{A_\ell} \equiv \tilde{\pi}_{jt}^{A_\ell} + \epsilon_{jt}^{A_\ell}. \tag{1}$$

The first term in (1) states that a purchase will be made if the highest valuation buyer that arrives to j's listing values it more than the reserve price chosen by j; since it is assumed that the auctions are sealed-bid second-price and that bidders play their weakly dominant strategy, the expected payoff is simply the greater of the second highest valuation and the reserve price. I assume that sellers are weakly risk-averse with specific utility functions, $u_j(\cdot)$. In case the item is not sold, the seller has a continuation value, $\Pi_{j,t-\ell}$, which denotes the expected payoff of keeping the item. Finally, $\epsilon_{jt}^{A_\ell}$ is a seller- and choice-specific idiosyncratic shock, which is assumed to be drawn independently across choices, sellers, and time. These shocks are privately observed by the seller and unknown to the econometrician.

The optimal auction for seller j at time t is simply given by $\pi_{jt}^{A} = \max_{\ell\in\mathbb{L}_t} \pi_{jt}^{A_\ell}$. Notice that the seller's choice set is time-dependent since some auction lengths are not available if the deadline is sufficiently close.

5.2.2 Posted prices

The CSVF from creating a posted price listing on day t for seller j is given by:

$$\begin{aligned}\pi_{jt}^{P} &= \max_{p_P} \mathbb{E}_{N_{jt}^P}\left[u_j\left(p_P\right)\Pr\left(V_{jt}^{(n:n)} \geq p_P\right) + \Pr\left(V_{jt}^{(n:n)} < p_P\right)\Pi_{j,t-1}\middle| N_{jt}^P = n\right] + \epsilon_{jt}^P \\ &\equiv \tilde{\pi}_{jt}^P + \epsilon_{jt}^P.\end{aligned} \tag{2}$$

The choice of posted prices is assumed to be made daily. While prices do not change every day in the data, in the context of the model they effectively can, because the distributions of valuations are day-specific. This postulated daily choice in part captures the possibility of bargaining, which is neglected from the model, as it potentially implies decreasing prices even though the data display price rigidity.

Finally, seller j has a daily outside option given by $\pi_{jt}^O = \tilde{\pi}_{jt}^O + \epsilon_{jt}^O$ which, if chosen, means that the seller leaves the platform and does not return. Therefore, j's continuation value at time t is $\Pi_{jt} = \mathbb{E}_{\epsilon_{jt}}\left[\max\left\{\pi_{jt}^A, \pi_{jt}^P, \pi_{jt}^O\right\}\right]$, and j's choice at time t is given by $\max\{\pi_{jt}^A, \pi_{jt}^P, \pi_{jt}^O\}$.

6 Estimation

In this section I describe the estimation procedure to recover the model's primitives. The procedure has three steps: first, the distributions of valuations are recovered from bidding data. Second, given these distributions, the parameters of buyer arrival processes are estimated separately for each selling mechanism. Third, given the aforementioned estimates the risk aversion and outside option parameters are estimated by solving the sellers' problem by backward induction. All steps involve parametric assumptions which are explicitly stated. I conclude by providing a brief discussion of identification.

6.1 Distributions of valuations

Distributions of valuations are recovered from bidding data. A well-known difficulty with the empirical analysis of online auctions is that the number of potential bidders is not observed by the econometrician, which prevents the use of order statistic inversion techniques discussed in, for example, Athey and Haile (2002). Thus, I follow the approach pioneered by Song (2004) and make use of multiple bids to recover the underlying distribution of valuations.

The identification argument is as follows: under the assumption of second-price sealed-bid auction, symmetric IPV, and weakly dominant bidding, the two highest bids can be treated as the two highest valuations among buyers who arrived at the listing. Properties of order statistics imply that the joint density of these two highest valuations out of n such valuations is given by:

$$g^{(n-1,n:n)}(v_2, v_1) = n(n-1)F(v_2)^{n-2}f(v_2)f(v_1)\mathbb{1}\{v_1 \geq v_2\},$$

and the marginal density of the second highest order statistic is

$$g^{(n-1:n)}(v_2) = n(n-1)F(v_2)^{n-2}[1 - F(v_2)]f(v_2),$$

where subscripts were omitted to ease notation. Therefore, the conditional density of the highest order statistic given the second highest is just:

$$g(v_1|v_2) = \frac{f(v_1)}{1 - F(v_2)}, \tag{3}$$

where $f(\cdot)$ and $F(\cdot)$ denote the pdf and cdf of the parent distribution, respectively. Importantly, this expression does not depend on n. Furthermore, the distribution $F(\cdot)$ is nonparametrically identified from this relation. Evaluating it at $v_2 = v_1 = v$ and rearranging yields:

$$f(v) = F'(v) = g(v|v) - g(v|v)F(v),$$

which is a linear, first-order differential equation. Since $F(0) = 0$, the solution to this equation is given by:

$$F(v) = \frac{\int_0^v e^{\int_0^t g(s|s)ds} g(t|t)dt}{e^{\int_0^v g(t|t)dt}}.$$

Thus, because the function $g(\cdot|\cdot)$ can be nonparametrically estimated from the data the distribution $F(\cdot)$ can also be nonparametrically obtained by simply plugging in the estimator $\hat{g}(\cdot|\cdot)$ on the expression above. Ideally I would estimate $F_{V,t}(\cdot|X_{jt})$ separately for each day t. However, this approach entails several practical difficulties. First, the limited number of observations on each day compounded with the curse of dimensionality with respect to the dimension of X_{jt} imply that a nonparametric estimator would likely be noisy and therefore unreliable. Furthermore, the estimated distributions are a key input to recover the remaining primitives of the model, and a nonparametric estimator used as an input could possibly require non-trivial inference procedures.

Therefore, in practice I adopt a parametric approach. I assume that valuations follow a log-logistic distribution, with scale parameter $\alpha_{jt} = \exp(X'_{jt}\mu)$ and shape parameter $\beta_t = \exp(-\sigma_t)$.[17] I include in X_{jt} weekly intercepts and game indicators. I also categorize tickets into ten levels of quality and account for them using dummies.[18] Finally, I include weekly linear trends for the number of days left until the game by the time the auction ended, and the shape parameters σ_t are also allowed to vary by the week until the game when the auction ended. This choice was motivated by the empirical patterns documented in the previous section, which showed that the market drastically changes each week before the games. Finally, it is important to mention that the choice of the log-logistic distribution was made solely for computational convenience, and not due to specific properties of this distribution.

While all parameters could be jointly estimated via partial maximum likelihood (PMLE), I further leverage the distributional assumption in the following way: since valuations follow a log-logistic distribution, they can be expressed as

$$\begin{aligned}\log(V_{ijt}) &= X'_{jt}\mu + \sigma_t\epsilon_{ijt} \\ &= \mu_0 + \tilde{X}'_{jt}\mu_1 + \sigma_t\epsilon_{ijt},\end{aligned}$$

where ϵ_{ijt} follows a standard logistic distribution and is independent from X_{jt}, while $\tilde{X}_{jt}$ simply contains all the elements in X_{jt} except for the intercept. However, remember that only the two highest valuations are observed, which implies that the error terms from such observations do not have mean 0 or scale 1. Nevertheless, these shocks are still independent from the covariates X_{jt}.

[17] A random variable, V, follows a log-logistic distribution with parameters α and β if $\log(V)$ follows a logistic distribution with parameters $\log(\alpha)$ and $\frac{1}{\beta}$. Thus, the probability density function of V is $f(v) = \frac{\alpha^\beta \beta v^{\beta-1}}{(\alpha^\beta + v^\beta)^2}$ and its cumulative distribution function is $F(v) = \frac{v^\beta}{\alpha^\beta + v^\beta}$. I choose the aforementioned parametrization because it allows me to perform estimation based on the logistic distribution instead, which is computationally more attractive.

[18] These levels are interactions between upper, club, and lower levels with sideline, corner, or end zone seats, as well as a VIP category.

The approach I employ has two steps. First, I run a regression of the log of the two highest bids on the vector X_{jt}. Since the structural error terms in such regressions have non-zero mean but are independent from X_{jt}, the vector of parameters μ_1 is consistently recovered with this regression. Denote these estimates by $\hat{\mu}_1$. The second step consists of applying the PMLE procedure described above on the residuals $\hat{\log}(V_{ijt}) \equiv \log(V_{ijt}) - \tilde{X}'_{jt}\hat{\mu}_1$, which then yield consistent estimates of the remaining parameters, μ_0 and σ_t. Even though this method might not be as efficient as the one-shot PMLE, it is considerably faster and still makes use of the equilibrium relation (3) which provides identification of the distributions of valuations.

6.2 Arrival processes

Following the insight of Hammond (2013), the arrival processes can be recovered from the probability of sales. In particular, letting $I_{j,t,t'}$ be a dummy variable that takes the value 1 if listing j, with mechanism k, price p, created on day t, and purchase opportunity at day $t' \leq t$, is sold, then:

$$\Pr^k(I_{j,t,t'} = 1) = \sum_{n=0}^{\infty} \Pr^k(N_{j,t,t'} = n) \left[1 - F_{V,t'}(p)^n\right]. \tag{4}$$

Thus, the arrival probabilities can be recovered from expression (4) above under a parametric assumption for the distribution of N_{jt}. I assume that the daily arrival process is given by independent random draws from a Poisson distribution. Though restrictive, this assumption simplifies the estimation process dramatically, as it will be made clear below.

More specifically, letting $W_{jt} = \left(Z'_{jt}, M'_{jt}\right)'$, then $N^k_{jt} \sim \text{Poisson}\left(\lambda^k_{jt}\right)$ where $\lambda^k_{jt} \equiv \exp\{W'_{jt}\lambda^k\}$. In addition, due to properties of the Poisson distribution and the assumption of independence it follows that for an auction of length ℓ that starts at day t, the total number of arriving potential buyers is given by $N^{A_\ell}_{jt} \sim \text{Poisson}\left(\lambda^{A_\ell}_{jt}\right)$, where $\lambda^{A_\ell}_{jt} \equiv \sum_{d=0}^{\ell-1} \exp\{W'_{j,t-d}\lambda^A\}$. Finally, letting $\lambda^k_{j,t,t'}$ denote the parameter of the Poisson distribution associated with listing j which was created with mechanism k and price p on day t with a purchase opportunity at time t', it follows that expression (4) can be simplified and rewritten as:

$$\Pr^k(I_{j,t,t'} = 1) = 1 - \exp\left\{- \left[1 - F_{V,t'}(p)\right] \lambda^k_{j,t,t'}\right\} \equiv 1 - \zeta^k_{j,t,t'}(p). \tag{5}$$

Estimation will be conducted based on (5) via nonlinear least squares (NLLS). I choose NLLS rather than MLE for computational reasons: in the data there are cases in which $F_{V,t}(p)$ is very close to 1, leading the probability in the left-hand side in (5) to be close to 0, which, in turn, leads the log-likelihood function not to be well defined. I include in the vector Z_{jt} an intercept, weekly daily trends, an indicator of whether the seller rating is above 99%, dummies for the quintiles of the seller score distribution, and an indicator of whether the seller is specialized in sports or tickets.[19] The vector M_{jt} contains the demand-to-supply ratio presented in Figure 3 and the percentage of posted prices among all existing listings. It depends on the subscript j because it is computed based on the game associated with j's tickets. These variables are included to approximate in a stylized way how consumers search is affected by current market conditions as well as sellers' characteristics, which can all influence their search outcomes as discussed, for instance, by Dinerstein et al. (2017). Finally, in practice the distributions $F_{V,t}(\cdot)$ are estimated, which means that inference needs to account for the first-stage estimation error. This is done analytically via the influence function representation of the first and second-stage estimators.

It is important to note that Hammond (2013) adopted a different approach, estimating λ^k, μ, and σ_t jointly from (4). Such method indeed has several advantages: it allows the econometrician to estimate different distributions of valuations for the auction and posted price markets, makes use of all auctions in the data instead of only those which received at least two bids, does not require corrections to conduct inference, and does not rely on equilibrium bidding, only assuming that sellers are individually rational. Nevertheless, I choose to adopt the aforementioned two-stage procedure because Hammond (2013)'s approach not only is computationally more intensive, but it does not make use of bidding data, which are also informative of buyers' valuations.

6.3 Risk aversion and outside option parameters

Having estimated the distributions of valuations and the parameters of the arrival processes, the remaining parameters to be estimated are the outside option and risk aversion parameters. I assume that seller j's utility functions is $u_j(c) = c^{1-\rho_j}$, where $\rho_j \in [0, 1)$. In other words, sellers are (weakly) risk averse, with constant relative risk aversion given by ρ_j. For the outside options, I specify $\tilde{\pi}_{jt} = \psi_{1j}\mathbb{1}\{t < 8\} + \psi_{2j}\mathbb{1}\{7 < t < 15\} + \psi_{3j}\mathbb{1}\{14 < t < 22\} + \psi_{4j}\mathbb{1}\{t > 21\}$ to account for the fact that proximity to the deadline can affect

[19]This indicator is constructed based on the seller's title: it take te value one if such title contains the words "sports", "football", or "tickets" as well as related terms.

sellers aggregately.

Given this utility function, the sellers' problem is solved by backward induction, which is straightforward because they face a finite-horizon problem. The term $\tilde{\pi}^P_{jt}$ is obtained by evaluating it with the proposed utility function. In particular, remember that

$$\tilde{\pi}^P_{jt}(p) = \max_p \left\{ p^{1-\rho_j}[1-\zeta^P_{jt}(p)]) + \zeta^P_{jt}(p)\Pi_{j,t-1} \right\},$$

and it can be shown that for the relevant parameter values this expression is concave in p.[20] Thus, the *unique* p given by the optimization problem above solves the first-order condition:

$$(1-\rho_j)p^{-\rho_j}\left[1-\zeta^P_{jt}(p)\right] - \frac{\partial \zeta^P_{jt}(p)}{\partial p}\left(p^{1-\rho_j} - \Pi_{j,t-1}\right) = 0. \tag{6}$$

In practice I solve numerically for the price p which solves this first-order condition using a bisection procedure.

Computing the term $\tilde{\pi}^{A_\ell}_{jt}$, however, is more involved. This is because it requires computing the expectation of $\left(\max\{V^{(N-1:N)}, r\}\right)^{1-\rho}$ over both V and N. While this integral is well-defined, computing it requires numerical integration techniques, whose details are presented in Appendix F. To obtain the optimal reserve price sellers choose, I invoke Proposition 5 in Hu et al. (2010), which shows that the *unique* optimal reserve price r is given by the solution of the following expression:

$$\frac{(\Pi_{j,t-\ell}r^{\rho_j} - r)}{1-\rho_j} + \frac{1-F_{V,t-\ell+1}(r)}{f_{V,t-\ell+1}(r)} = 0, \tag{7}$$

which I also solve numerically as described above. Note that when $\rho_j = 0$ the seller is risk-neutral, and expression (7) simplifies to the usual one which defines optimal reserve prices when distributions of valuations are regular. Optimal reserve prices do not depend on the number of bidders or on the parameters that determine their arrival because this is a symmetric IPV model. It is important to emphasize that even though closed-form expressions for the optimal posted and reserve prices do not exist, these quantities are well defined and unique. As a consequence, given a guess of the vector of parameters $\theta_j \equiv \left(\rho_j, \psi_{1j}, \psi_{2j}, \psi_{3j}, \psi_{4j}\right)'$ the predicted sequence of mechanism choices by seller j is also unique, which allows me to construct the likelihood of such sequence.

[20] In the notation of equation (5), $t = t'$, so I omit the second time subscript to ease notation.

The backward induction procedure works as follows. If seller j reaches day 0 (game day) she has two options: either she chooses to exit and obtains π_{j0}^O or she chooses π_{j0}^P (since auctions need to last for at least one day it follows that $\pi_{j0}^A = 0$). For the purposes of estimation I will assume that the elements of the vector of shocks ϵ_{jt} are drawn from a Type-1 Extreme Value (T1EV) distribution with location parameter $-\Gamma$ and scale parameter equal to 1, where Γ is the Euler-Mascheroni constant, independently distributed across time, alternatives, and sellers. This implies that the day 0 conditional choice probabilities (CCP's) are given by a simple logit binary choice expression:

$$\Pr(k_{j0} = k) = \frac{\exp\{\tilde{\pi}_{j0}^k\}}{\exp\{\tilde{\pi}_{j0}^P\} + \exp\{\tilde{\pi}_{j0}^O\}}.$$

Now consider a seller that reaches day 1. She now has three options: run a one-day auction, create a posted price listing, or leave the market. In addition, her continuation value is given by:

$$\Pi_{j0} = \mathbb{E}_{\epsilon_{j0}}[\max\{\tilde{\pi}_{j0}^P + \epsilon_{j0}^P, \tilde{\pi}_{j0}^O + \epsilon_{j0}^O\}] = \log\left(\exp\left\{\tilde{\pi}_{j0}^P\right\} + \exp\left\{\tilde{\pi}_{j0}^O\right\}\right),$$

where the second equality is due to properties of the T1EV distribution. Consequently, the day 1 CCP's are:

$$\Pr(k_{j1} = k) = \frac{\exp\{\tilde{\pi}_{j1}^k\}}{\exp\{\tilde{\pi}_{j1}^{A_1}\} + \exp\{\tilde{\pi}_{j1}^P\} + \exp\{\tilde{\pi}_{j1}^O\}}.$$

On day 2 the choice set of seller j is the same as in 1 which leads to directly analogous CCP's as in the previous equation, with the main difference being that the continuation value now takes into account the possibility of running a one-day auction on day 1 so that:

$$\Pi_{j1} = \log\left(\exp\left\{\tilde{\pi}_{j1}^{A_1}\right\} + \exp\left\{\tilde{\pi}_{j1}^P\right\} + \exp\left\{\tilde{\pi}_{j1}^O\right\}\right).$$

The remaining CCP's and continuation values (CV's) follow the same pattern, incorporating the additional auction length options as they become available. These quantities as well as the choice sets are displayed for all periods in Table 8. The CCP's for the period in which sellers enter the market are analogous, with the only difference being the exclusion of the term associated with $\tilde{\pi}_{jt}^O$. Finally, note that the likelihood for sellers who enter on day 0 is simply 1 because they have only one alternative, posted prices.

The estimation procedure works as follows. For any value of θ_j, the trajectory of choices made by a seller is unique, including the prices chosen by said seller. Let T_j be the set which contains all the days in which seller j is observed making active choices.[21]. Given θ_j, j's individual likelihood is then given by:

$$l_j(\theta_j) = \prod_{t \in T_j} \left[\prod_{k \in \mathbb{L}_t} \left(\frac{\exp(\tilde{\pi}^k_{jt})}{\sum_{k' \in \mathbb{L}_t} \exp(\tilde{\pi}^{k'}_{jt})} \right)^{\mathbb{1}\{k_{jt}=k\}} \right]. \tag{8}$$

However, remember that the vector θ_j is unknown and seller-specific. Thus, I assume that $\theta_j \overset{iid}{\sim} H(\theta)$, so that the individual likelihood becomes:

$$l_j(\theta) = \int_{\Theta} \prod_{t \in T_j} \left[\prod_{k \in \mathbb{L}_t} \left(\frac{\exp(\tilde{\pi}^k_{jt})}{\sum_{k' \in \mathbb{L}_t} \exp(\tilde{\pi}^{k'}_{jt})} \right)^{\mathbb{1}\{k_{jt}=k\}} \right] dH(\theta_j|\theta), \tag{9}$$

and the log-likelihood function of the data is given by $\mathcal{L}(\theta) = \sum_{j=1}^{J} \log[l_j(\theta)]$.[22]

To compute and maximize this likelihood the distribution $H(\theta)$ needs to be specified. In practice, I assume that:

$$\begin{pmatrix} \log \frac{1-\rho_j}{\rho_j} \\ \psi_{1j} \\ \psi_{2j} \\ \psi_{3j} \\ \psi_{4j} \end{pmatrix} \overset{iid}{\sim} N\left(\bar{\theta}, \Omega\right),$$

where Ω is a diagonal matrix. Rather than numerically solving the integral in (9), I employ the importance sampling simulation procedure proposed in Ackerberg (2009). For each observation j I draw R simulation draws from the importance sampling density $\iota(\cdot)$.

[21]For example, if seller j enters ten days before the game, chooses a three-day auction that is not successful, followed by a posted-price listing in the next two days, and then exits the market without selling the tickets, then $T_j = \{5, 6, 7, 10\}$

[22]This approach is not as efficient as possible because predicted prices are not matched to the observed ones. The reason why I follow this route is threefold: first, the estimates are consistent regardless of whether these additional quantities are matched. Second, the observed prices are employed in the estimation of the arrival processes parameters, so the information is not completely disregarded in the estimation procedure. Finally, matching the observed price moments to data is not straightforward. A possibility would be to follow the discrete-continuous choice literature and include a structural shock to the continuous choice, that is, the price choice. However, the natural way for this to be done would be to make the ρ_j's coefficients random, possibly as $\rho_{jt} = \rho + \eta_{jt}$. However, since this is a dynamic decision problem the shocks η_{jt} would have a persistent effect, which is unwieldy to account for.

Denoting each of these draws by s_{jr} and letting $\phi(\cdot)$ denote the probability density function of the normal distribution, the individual simulated likelihood is:

$$\hat{l}_j(\theta) = \frac{1}{R}\sum_{r=1}^{R}\left\{\prod_{t\in T_j}\left[\prod_{k\in\mathbb{L}_t}\left(\frac{\exp(\tilde{\pi}^k_{jt,r})}{\sum_{k'\in\mathbb{L}_t}\exp(\tilde{\pi}^{k'}_{jt,r})}\right)^{\mathbb{1}\{k_{jt,r}=k\}}\right]\right\}\frac{\phi(s_{jr}|\bar{\theta},\Omega)}{\iota(s_{jr})}, \tag{10}$$

where the subscript r also indicates that the model is solved and conditional choice probabilities are computed for each simulation draw. To estimate the parameters $(\bar{\theta},\Omega)$ I maximize the simulated log-likelihood function $\hat{\mathcal{L}}(\theta) = \sum_{j=1}^{J}\log[\hat{l}_j(\theta)]$. I choose $\iota(\cdot)$ to be the density of the t-distribution with $\nu = 3$ degrees of freedom and centered at 0. To guarantee that the resulting estimator is consistent and asymptotically normal I set $R = \lfloor J^{0.6}\rfloor = 372$.

6.4 Identification

The formal argument for the identification of the distributions of valuations was given in subsection 6.1. Given the specific parametric assumption made, the scale of the distributions are obtained from the levels of the two highest bids, while the shape is explained by the dispersion of the difference between these bids. The arrival parameters are estimated to rationalize the sales outcomes observed in the data given knowledge of the distributions of valuations. Differences in sellers' risk aversion are identified from cases in which auctions gave higher expected revenue but the sellers picked posted prices instead, while outside options are obtained from exit decisions. Finally, the assumption that agents behave according to how the model describes is required for all these identification results to hold.

7 Results

This section presents the estimation results from the procedure described above. First, results regarding the distributions of valuations are presented. Then, I display results for the arrival processes parameters. Finally, I show results for the seller-specific parameters.

7.1 Distributions of valuations

This subsection presents estimates of the distributions of valuations, following the procedure described in the previous section. Table 9 displays the estimates for the key parameters. Because estimation is conducted in two steps, to account for the first-step estimates standard errors are computed using the influence function representation of the first-order conditions.

Since the estimates are based on the logistic distribution, interpretation is not direct. Instead, these estimates indicate the statistical significance of the results. The linear trends are not significant three and four weeks before the game, becoming economically and statistically relevent two weeks before and especially on the week of the game. Roughly, exponentiating the coefficients indicates that, all else constant, the average valuation per ticket of consumers at the market increases 4.61% as the sale date is anticipated by one day during the week of the game and 1.92% on the week before.

For illustrative purposes, Figure 14 displays the distributions on four different days, week on each week, for lower level, sideline tickets for the game between the New England Patriots and the Buffalo Bills, which took place on 9/8/13. As somewhat expected given the descriptive evidence presented before, these distributions display a pattern of first-order stochastic dominance, with distributions from weeks further from game day dominating the remaining ones. However, it is interesting to note that the increase in the discrepancy of the distributions over time becomes more intense as the deadline approaches. Finally, Table 10 shows estimates of the means and standard deviations of the average ticket in the data separately for each week until the game. As expected from the descriptive analysis, the average valuation decreases as the deadline approaches: in the week of the game the mean valuation for an average ticket is just below 78 dollars, while four weeks before the game it is almost 98. Furthermore, it is interesting to note that the standard deviations follow a comparable monotone pattern: the standard deviation on the week of the game is 15.47 dollars, while four weeks before it exceeds 21 dollars. One possible explanation is reduced uncertainty about the games' quality, which could reduce the dispersion of valuations.

7.2 Arrival processes parameters

This subsection presents estimates of the arrival processes parameters based on NLLS applied to equation (5). Parameter estimates are displayed in Table 11 and standard errors are also obtained with the influence function representation of first-order conditions.

Due to the nonlinear specification of the Poisson parameters these coefficients cannot be interpreted directly, but the results indicate the statistical significance of the chosen variables as well as the overall correlations. The patterns are as expected: as the deadline approaches, the expected number of arriving buyers increases, except during the week of the game, when there is no significant temporal effect. In addition, increases on the demand-to-supply ratio and sellers' quality measures have a positive impact on this quantity, even though the quintiles of the sellers' score do not seem to be relevant, and an increase in the share of posted prices over total supply affects the number of arriving buyers negatively. These results hold both for posted prices and auctions.

To further interpret these estimates, Tables 12 and 13 show the average marginal effect of the aforementioned variables for auctions and posted prices, respectively, on four different days, each on a different week. The last rows display the average Poisson parameters so that the marginal effects can be compared to the baseline. On the first row of Table 12 the average marginal effects on moving one day away from game day decrease the expected number of arriving buyers by around 5% across all weeks except for the week of the game, when doing so slightly decreases the expected number of arriving buyers. The first row of Table 13 shows a more intense effect for posted prices, even though the same holds qualitatively.

The second row of Table 12 indicates that an increase of one unit in the demand-to-supply ratio has a substantial positive effect on the expected number of buyers for auctions. On the other hand, the effect on posted prices is not as strong, despite being significant and displaying the same qualitative pattern. In addition, the effects of an increase of one percentage point in the fraction of posted prices over total supply has a more pronounced impact for auctions when compared to posted prices.

The last rows of comparing Tables 12 and 13 indicate that for the average ticket posted prices attract less potential buyers. This can in part explain why both listed and transaction prices are higher in this side of the market, as a lower arrival rate implies that for this format to be advantageous in terms of expected revenue a seller would need to receive a high payment in case a sale was made. Finally, note that the ratio between the expected arrivals to auctions and the expected arrivals to posted prices increases as the deadline approaches: it equals 1.33 on the week of the game, 1.21 two weeks before the game, 1.19 three weeks before, and 1.07 four weeks before.

7.3 Distribution of risk aversion and outside option parameters

Based on the estimates from the previous two subsections, I estimate the distribution of seller-specific parameters following the method discussed in Subsection 6.3. Results are displayed in Table 14.

To compute the standard errors the influence function representation is no longer attractive. This is because the CCP's depend on the previous estimators in a highly non-linear fashion, which makes the computation of derivatives with respect to such quantities unwieldy. Instead, I calculate standard errors by random subsampling without replacement at the chain level, as in Politis and Romano (1994). To ensure that the required conditions for its validity are satisfied and to obtain integer numbers, I choose the number of observations per subsample to be $B = \lfloor J^{0.5866} \rfloor$, which equals 325 in this sample and yields $Q = 59$ subsamples.[23]

The subsampling procedure deserves some attention. For each subsample I keep the parameters of the distributions of valuations fixed, which implies that inference for the parameters of the distribution of sellers' characteristics is conditional on the game and ticket features as in Abadie et al. (2014). The reason is twofold. First, with only 325 observations in each subsample, it is not possible to estimate all the game and ticket type fixed effects (which constitute 253 dummies in total). The second and more important reason is conceptual: the counterfactual exercises I aim to perform in this paper consist of simulating what would have happened in the marketplace if the menu of available mechanisms was different. This leads me to consider different realizations of sellers arriving to the marketplace with the same set of tickets, for the same game, and at the same point in time. Thus, game and ticket characteristics are indeed fixed, with variation coming from differences across sellers, which justifies this procedure.

Results are displayed in Table 14. As expected, the subsampling procedure yields

[23] An alternative valid resampling procedure for this estimator is the bootstrap, but I chose subsampling instead because computing the CCP's for each value of the parameters is computationally intensive.

somewhat large standard errors. The distribution of relative risk aversion is displayed on Figure 15. The estimates yield considerably dispersion, with the median exceeding the mean by more than 14%.

8 Counterfactuals

Based on the estimates of the model's primitives I now conduct counterfactual exercises in which the menu of available mechanisms is altered. In particular, I investigate how removing all auctions and posted prices from the sellers' choice set impacts their decisions, as well as transaction outcomes. For the purposes of these counterfactuals, I focus on four specific games from my sample. The games were chosen based on the game fixed effects estimates from the distributions of valuations. In particular, I select the games associated to the 20th, 40th, 60th, and 80th quantiles among such fixed effects. These games are:

1. *20th quantile – Indianapolis Colts (2-1) at Jacksonville Jaguars (0-3), 09/29/13*
2. *40th quantile – Tennessee Titans (4-6) at Oakland Raiders (4-6), 11/24/13*
3. *60th quantile – Arizona Cardinals (3-2) at San Francisco 49ers (3-2), 10/13/13*
4. *80th quantile – Tampa Bay Buccaneers (0-7) at Seattle Seahawks (7-1), 11/03/13*

To conduct these counterfactual exercises, I simulate 1,000 realizations of each game. I keep fixed the moment in time when sellers entered the platform and their characteristics, but redraw their risk aversion and outside option parameters and the structural shocks they receive. The underlying assumption is that the change in the availability of auctions would not affect the entry decision and timing of sellers. Since eBay corresponded to a small part of the secondary market for football tickets, I believe that this assumption is not strong because changes in this platform would probably have no consequential impact on sellers' and outside options and buyers' willingness-to-pay. In addition, I assume that the evolution of demand-to-supply ratio would have been the same as it is observed in the data. Since sellers' exit decisions are endogenous, this assumption states that demand readjusts accordingly depending on whether supply is higher or lower.

8.1 No auctions

The first counterfactual I perform is to remove all auctions from the platform. This exercise was motivated by the fact that the use of online auctions has substantially decreased. As addressed by Cullen and Farronato (2016) and Einav et al. (2016), TaskRabbit began as an auction-only platform but since then has abandoned auctions altogether. The same phenomenon was studied by Huang (2016) and Wei and Lin (2017) in the context of Prosper.com. Finally, within eBay Einav et al. (2017) have shown that sellers are moving away from auctions towards other mechanisms. These changes bring into question whether auctions can be helpful to sellers, as theory predicts. Results are given at Table 15.

Eliminating auctions reduces the probability of a sale between 3.23% and 18.75%, averaging a decrease of a little over 12%. On the other hand, expected transaction prices always increase, with increments ranging from 23.68% to more than 30%, with an average of almost 27%. Combining these two results always yields higher unconditional expected revenues: gains range from 1.56% to almost 20%, averaging 11.45%.

Hence, sellers would benefit from a platform with only posted prices and, to the extent that such platform charges a fee over transaction amounts, so would the platform. Notice, however, that consumers would unambiguously be harmed, as the probability of purchase would decrease while the expected prices paid would increase. Nevertheless, it is important to bare in mind that these counterfactuals do not account for the decisions to enter the platform by both buyers and sellers. Since auctions for NFL tickets can be found almost exclusively on eBay, it is not unreasonable to conjecture that buyers and sellers are attracted to this market precisely because of the existence of auctions. Therefore, eliminating auctions could substantially alter the market entirely.

8.2 No posted prices

The natural comparison to the previous counterfactual is with an auction-only platform, as originally were eBay, TaskRabbit, and Prosper.com. Results from this exercise are displayed on Table 16.

The overall patterns are qualitatively similar to the previous ones: the probability of sale always decreases but expected transaction prices increase. Consequently, consumers would once again be unambiguously harmed by a specialized platform. However, in the case of moving to an auction-only platform the decrease in the probability of selling is far stronger, ranging between 29% and almost 42% and averaging 35.56%, while expected sale prices increase from 4.55% to 34.09%. The resulting effect on unconditional expected revenues is now negative, between 7.81% and 35.82%, with an average of 25.95%.

Thus, transiting to an auction-only platform would be detrimental not only to consumers but also to sellers. As a result, the platform itself would be harmed at least concerning revenues accrued from transaction fees from these transactions. However, these results are greatly influenced by the nature of this market, namely by the perishability of tickets. The market becomes more active close to the deadline, when consumers are less willing to take part in auctions. As a result, an auction-only platform would fail to provide the consumers' preferred mean of trade precisely when most consumers would participate, yielding the sharp decrease in the probability of sales.

9 Conclusion

This study has analyzed how the availability of different selling mechanisms impact a perishable good market. Using data on NFL tickets offered at eBay, it first documented that both buyers and sellers respond to proximity of games. In particular, sellers are relatively more likely to choose posted prices if sufficiently far and especially close to the deadline, mostly because auctions need to last for at least one day in this platform. In turn, buyers seem to become relatively more interested in posted prices as the deadline approaches, possibly because they become less willing to wait until the end of an auction to find out if they will have tickets for a game. Further evidence of forward-looking behavior is the pattern that prices set by sellers decrease with proximity to game day even though the number of potential buyers relative to the supply of tickets dramatically increase when the deadline approaches.

Motivated by these patterns, I propose a dynamic structural model in which forward-looking sellers, who have perfect foresight over market conditions, optimally choose between the available mechanisms. To recover the demand side parameters, namely the time-varying distributions of valuations and the mechanism-specific arrival rate of buyers, it is necessary to deal with the difficulty of unobserved arrival of buyers. I accomplish this by leveraging tools from the empirical analysis of auctions with an unknown number of bidders and by using sales results to infer how many buyers would be expected to arrive given their willingness-to-pay to match the observed outcomes. On the supply side, I allow for two sets of parameters, risk aversion and outside options. This is necessary so that the two sets of seller decisions, mechanism choice and exit, are rationalized. To account for heterogeneity in sellers' choices, I allow these parameters to be seller-specific, and recover the parameters of the distribution from which these parameters are drawn by solving the sellers' problem by backward induction, which is possible because it has a finite horizon, and utilizing an importance sampling simulated maximum likelihood estimator.

Having estimates of this model I then conduct counterfactual exercises in which the menu of mechanisms available to sellers changes. In particular, I focus on four games chosen according to the fixed effects estimated for the distributions of valuations and simulate their outcomes without auctions and without posted prices. Results suggest that expected revenues would on average increase by 11.45% if auctions were removed, while an auction-only platform would yield on average 25.95% lower revenues. Thus, sellers would benefit from a platform specialized in posted prices and, to the extent that fees are charged over transaction prices, so would the platform itself. However, consumers would always be harmed if one of the mechanisms was to be removed, because it is always the case that the probability of purchasing tickets would decrease while expected prices would increase.

These results can be valuable not only to better understand the drivers of mechanism choice but also to platform design. However, care should be taken when extrapolating these findings to other environments. This is because the perishability of tickets play a significant role in the functioning of this market. In particular, it becomes more active when the deadline is close, which is also when buyers are less willing to take part in auctions. As a result, this environment is not favorable for auctions to be conducted.

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Tables

Table 1: Comparison between sports leagues in 2015-2016

League (Season)	Mean ticket price	Mean attendance/game	Mean capacity/game
NFL (2016)	92.98	68,400	97.9%
MLB (2015)	31	30,517	71.2%
NBA (2015-16)	55.88	17,864	94.0%
NHL (2014-15)	62.18	17,481	95.5%

Sources: Ticket prices come from Statista (2016) and attendance numbers from Sports Business Daily (2015, 2016a,b,c).

Table 2: Key quantities

Variable	Quantity	% sold
Listings	43,221	32.69
Sets of tickets	27,047	51.94
Sellers	10,799	–
Games	245	–

Notes: Table displays quantities of the final sample described in Subsections 4.2 and 4.3. Multi-bundle listings were considered to have been sold if at least one of the offered bundles was sold.

Table 3: Distribution of listings across mechanisms

Type	Quantity	% of total	% sold
Auctions	27,040	62.56	35.11
Posted prices	16,181	37.44	28.66
Total	43,221		32.69

Notes: Table displays quantities of the final sample described in Subsections 4.2 and 4.3. Hybrid auctions are included within auctions with the exception of those who were sold via the buy-it-now option, and bargaining-enabled posted prices are included as usual posted price listings.

Table 4: Types of chains of tickets

Type	Quantity	% sold	% of all chains	% of all listings
Single-listing	17,754	57.87	65.64	41.08
Multi-listing, always auctions	4,545	40.51	16.8	27.08
Multi-listing, always posted prices	2,747	36.11	10.16	14.61
Multi-listing, mechanism changes	2,001	46.98	7.4	17.23
Total	27,047	51.94		

Notes: Table displays quantities of the final sample described in Subsections 4.2 and 4.3. Hybrid auctions are included within auctions with the exception of those who were sold via the buy-it-now option, and bargaining-enabled posted prices are included as usual posted price listings. A mechanism change is defined as going from any auction to any posted price or vice-versa.

Table 5: Single-listing chains and mechanisms

Type	Quantity	% of total	% sold
Auctions	11,289	63.59	64.99
Posted prices	6,465	36.41	45.43
Total	17,754		57.87

Notes: Table displays quantities of the final sample described in Subsections 4.2 and 4.3. Hybrid auctions are included within auctions with the exception of those who were sold via the buy-it-now option, and bargaining-enabled posted prices are included as usual posted price listings.

Table 6: Transitions across mechanisms

	Auctions	Posted prices
Auctions	0.8512	0.1488
Posted prices	0.1817	0.8183
Total	0.618	0.382

Notes: Table displays quantities of the final sample described in Subsections 4.2 and 4.3. Hybrid auctions are included within auctions with the exception of those who were sold via the buy-it-now option, and bargaining-enabled posted prices are included as usual posted price listings. Probabilities refer to going from the row mechanism to the column mechanism.

Table 7: Sellers' supply and listing decisions

	Quantity	% of sellers	% of chains	% of listings
Offer only one set of tickets	6,431	59.55	21.67	21.06
Offer tickets of only one team	10,502	97.25	75.69	81.25
Offer tickets for only one game	6,878	63.69	25.26	24.65
Never relist	6,741	62.42	40.35	26.7
Relist, auctions only	1,744	16.15	15.51	21.98
Relist, posted prices only	689	6.38	7.37	10.09
Relist, change mechanism	1,625	15.05	23.49	41.24

Notes: Table displays quantities of the final sample described in Subsections 4.2 and 4.3. Hybrid auctions are included within auctions with the exception of those who were sold via the buy-it-now option, and bargaining-enabled posted prices are included as usual posted price listings. A mechanism change is defined as going from any auction to any posted price or vice-versa. Sellers are classified according to their observed behavior on the entire final sample.

Table 8: Choice sets, conditional choice probabilities, and continuation values

Days until game day (t)	Choice set ($\mathbb{L}_t$)	CCP's ($Pr(k_{jt}=k)$)	CV's ($\Pi_{j,t-\ell+1}$)
$t=0$	$\{P,O\}$	$\frac{\exp\{\tilde{\pi}_{jt}^{k}\}}{\exp\{\tilde{\pi}_{jt}^{P}\}+\exp\{\tilde{\pi}_{jt}^{O}\}}$	0
$t=1$	$\{A_1,P,O\}$	$\frac{\exp\{\tilde{\pi}_{jt}^{k}\}}{\exp\{\tilde{\pi}_{jt}^{A_1}\}+\exp\{\tilde{\pi}_{jt}^{P}\}+\exp\{\tilde{\pi}_{jt}^{O}\}}$	$\log\left(\exp\left\{\tilde{\pi}_{j,t-1}^{P}\right\}+\exp\left\{\tilde{\pi}_{j,t-1}^{O}\right\}\right)$
$t=2$	$\{A_1,P,O\}$	$\frac{\exp\{\tilde{\pi}_{jt}^{k}\}}{\exp\{\tilde{\pi}_{jt}^{A_1}\}+\exp\{\tilde{\pi}_{jt}^{P}\}+\exp\{\tilde{\pi}_{jt}^{O}\}}$	$\log\left(\exp\left\{\tilde{\pi}_{j,t-1}^{A_1}\right\}+\exp\left\{\tilde{\pi}_{j,t-1}^{P}\right\}+\exp\left\{\tilde{\pi}_{j,t-1}^{O}\right\}\right)$
$t=3$	$\{(A_\ell)_{\ell\in\{1,3\}},P,O\}$	$\frac{\exp\{\tilde{\pi}_{jt}^{k}\}}{\sum_{\ell\in\{1,3\}}\exp\{\tilde{\pi}_{jt}^{A_\ell}\}+\exp\{\tilde{\pi}_{jt}^{P}\}+\exp\{\tilde{\pi}_{jt}^{O}\}}$	$\log\left(\exp\left\{\tilde{\pi}_{j,t-1}^{A_1}\right\}+\exp\left\{\tilde{\pi}_{j,t-1}^{P}\right\}+\exp\left\{\tilde{\pi}_{j,t-1}^{O}\right\}\right)$
$t=4$	$\{(A_\ell)_{\ell\in\{1,3\}},P,O\}$	$\frac{\exp\{\tilde{\pi}_{jt}^{k}\}}{\sum_{\ell\in\{1,3\}}\exp\{\tilde{\pi}_{jt}^{A_\ell}\}+\exp\{\tilde{\pi}_{jt}^{P}\}+\exp\{\tilde{\pi}_{jt}^{O}\}}$	$\log\left(\sum_{\ell\in\{1,3\}}\exp\left\{\tilde{\pi}_{j,t-1}^{A_\ell}\right\}+\exp\left\{\tilde{\pi}_{j,t-1}^{P}\right\}+\exp\left\{\tilde{\pi}_{j,t-1}^{O}\right\}\right)$
$t=5$	$\{(A_\ell)_{\ell\in\{1,3,5\}},P,O\}$	$\frac{\exp\{\tilde{\pi}_{jt}^{k}\}}{\sum_{\ell\in\{1,3,5\}}\exp\{\tilde{\pi}_{jt}^{A_\ell}\}+\exp\{\tilde{\pi}_{jt}^{P}\}+\exp\{\tilde{\pi}_{jt}^{O}\}}$	$\log\left(\sum_{\ell\in\{1,3\}}\exp\left\{\tilde{\pi}_{j,t-1}^{A_\ell}\right\}+\exp\left\{\tilde{\pi}_{j,t-1}^{P}\right\}+\exp\left\{\tilde{\pi}_{j,t-1}^{O}\right\}\right)$
$t=6$	$\{(A_\ell)_{\ell\in\{1,3,5\}},P,O\}$	$\frac{\exp\{\tilde{\pi}_{jt}^{k}\}}{\sum_{\ell\in\{1,3,5\}}\exp\{\tilde{\pi}_{jt}^{A_\ell}\}+\exp\{\tilde{\pi}_{jt}^{P}\}+\exp\{\tilde{\pi}_{jt}^{O}\}}$	$\log\left(\sum_{\ell\in\{1,3,5\}}\exp\left\{\tilde{\pi}_{j,t-1}^{A_\ell}\right\}+\exp\left\{\tilde{\pi}_{j,t-1}^{P}\right\}+\exp\left\{\tilde{\pi}_{j,t-1}^{O}\right\}\right)$
$t=7$	$\{(A_\ell)_{\ell\in\{1,3,5,7\}},P,O\}$	$\frac{\exp\{\tilde{\pi}_{jt}^{k}\}}{\sum_{\ell\in\{1,3,5,7\}}\exp\{\tilde{\pi}_{jt}^{A_\ell}\}+\exp\{\tilde{\pi}_{jt}^{P}\}+\exp\{\tilde{\pi}_{jt}^{O}\}}$	$\log\left(\sum_{\ell\in\{1,3,5\}}\exp\left\{\tilde{\pi}_{j,t-1}^{A_\ell}\right\}+\exp\left\{\tilde{\pi}_{j,t-1}^{P}\right\}+\exp\left\{\tilde{\pi}_{j,t-1}^{O}\right\}\right)$
$t=8,9$	$\{(A_\ell)_{\ell\in\{1,3,5,7\}},P,O\}$	$\frac{\exp\{\tilde{\pi}_{jt}^{k}\}}{\sum_{\ell\in\{1,3,5,7\}}\exp\{\tilde{\pi}_{jt}^{A_\ell}\}+\exp\{\tilde{\pi}_{jt}^{P}\}+\exp\{\tilde{\pi}_{jt}^{O}\}}$	$\log\left(\sum_{\ell\in\{1,3,5,7\}}\exp\left\{\tilde{\pi}_{j,t-1}^{A_\ell}\right\}+\exp\left\{\tilde{\pi}_{j,t-1}^{P}\right\}+\exp\left\{\tilde{\pi}_{j,t-1}^{O}\right\}\right)$
$t=10$	$\{(A_\ell)_{\ell\in\{1,3,5,7,10\}},P,O\}$	$\frac{\exp\{\tilde{\pi}_{jt}^{k}\}}{\sum_{\ell\in\{1,3,5,7,10\}}\exp\{\tilde{\pi}_{jt}^{A_\ell}\}+\exp\{\tilde{\pi}_{jt}^{P}\}+\exp\{\tilde{\pi}_{jt}^{O}\}}$	$\log\left(\sum_{\ell\in\{1,3,5,7\}}\exp\left\{\tilde{\pi}_{j,t-1}^{A_\ell}\right\}+\exp\left\{\tilde{\pi}_{j,t-1}^{P}\right\}+\exp\left\{\tilde{\pi}_{j,t-1}^{O}\right\}\right)$
$t>10$	$\{(A_\ell)_{\ell\in\{1,3,5,7,10\}},P,O\}$	$\frac{\exp\{\tilde{\pi}_{jt}^{k}\}}{\sum_{\ell\in\{1,3,5,7,10\}}\exp\{\tilde{\pi}_{jt}^{A_\ell}\}+\exp\{\tilde{\pi}_{jt}^{P}\}+\exp\{\tilde{\pi}_{jt}^{O}\}}$	$\log\left(\sum_{\ell\in\{1,3,5,7,10\}}\exp\left\{\tilde{\pi}_{j,t-1}^{A_\ell}\right\}+\exp\left\{\tilde{\pi}_{j,t-1}^{P}\right\}+\exp\left\{\tilde{\pi}_{j,t-1}^{O}\right\}\right)$

Table 9: Main parameters of distributions of valuations

Parameter	Week	Estimate	t-statistic
Shape	1	2.1504	112.5748
	2	2.1427	64.3137
	3	2.2164	39.4283
	4	2.2322	46.8
Intercept	1	4.993	390.2147
	2	4.8547	61.8923
	3	4.7664	25.9127
	4	4.7016	12.2908
Trend	1	0.0461	9.8715
	2	0.0192	2.6926
	3	0.0088	0.8615
	4	0.0045	0.3022
Number of auctions		8,719	

Notes: Game and ticket type dummies are omitted for ease of exposition. Standard errors used to construct the t-statistics were obtained via the influence function representation of the first-order conditions.

Table 10: Means and standard deviations of distributions of valuations

Parameter	Weeks before game			
	1	2	3	4
Mean	77.6388	93.2975	96.8682	98.7723
Standard deviation	15.4653	18.8947	21.2007	21.4414

Notes: Shape and scale parameters were obtained by averaging over observations separately for each week. Means and standard deviations were then obtained using properties of the log-logistic distribution.

Table 11: Estimates of Poisson arrival processes parameters

Parameter	Auctions	Posted prices
Constant	-0.0122 (-0.0798)	-0.0014 (-0.0085)
Daily trend (week 1)	0.0307 (1.2531)	0.0056 (0.2486)
Daily trend (week 2)	-0.0496 (-5.0646)	-0.0421 (-4.8727)
Daily trend (week 3)	-0.0217 (-2.5976)	-0.0426 (-7.8837)
Daily trend (week 4)	-0.0403 (-5.7524)	-0.0237 (-5.0385)
Demand-to-supply ratio	0.1396 (6.1078)	0.0496 (1.9089)
% of posted prices relative to supply	-0.0117 (-5.8038)	-0.0055 (-2.8742)
Specialized seller	0.0014 (0.0021)	-0.0015 (-0.0104)
Seller's rating >0.99	0.3241 (4.1601)	0.0033 (0.0339)
Seller's score (2nd quintile)	0.0591 (0.6308)	0.0045 (0.0369)
Seller's score (3rd quintile)	0.1807 (1.9394)	0.004 (0.0343)
Seller's score (4th quintile)	0.1068 (1.0237)	0.0039 (0.0291)
Seller's score (5th quintile)	0.0211 (0.1994)	-0.0084 (-0.0651)

Notes: Table shows estimates of equation (5), ran separately for auctions and posted prices, with t-statistics displayed between parentheses. Standard errors used to construct the t-statistics were obtained via the influence function representation of the first-order conditions.

Table 12: Average marginal effects of arrival processes for auctions

Variable	Days before the game			
	3	9	15	23
Daily trend	0.0378	-0.0505	-0.0206	-0.0333
Demand-to-supply ratio	0.1719	0.1422	0.1328	0.1153
% of posted prices relative to supply	-0.0144	-0.0119	-0.0112	-0.0097
Average arrival	1.2311	1.0182	0.9508	0.826

Notes: Table shows estimates of the average marginal effects and expected arrivals from equation (5) for auctions across each week before the game and over all observations.

Table 13: Average marginal effects of arrival processes for posted prices

Variable	Days before the game			
	3	9	15	23
Daily trend	0.0051	-0.0354	-0.0341	-0.0183
Demand-to-supply ratio	0.0459	0.0418	0.0398	0.0383
% of posted prices relative to supply	-0.005	-0.0046	-0.0044	-0.0042
Average arrival	0.9244	0.8422	0.8008	0.7715

Notes: Table shows estimates of the average marginal effects and expected arrivals from equation (5) for posted prices across each week before the game and over all observations.

Table 14: Estimates of sellers' risk aversion and outside option parameters

Mean	Coefficient	S.E.
Risk aversion $\left(\log \frac{1-\rho}{\rho}\right)$	-2.93	0.79
Outside option: 1 week (ψ_1)	1.22	0.81
Outside option: 2 weeks (ψ_2)	1.55	0.79
Outside option: 3 weeks (ψ_3)	0.61	0.88
Outside option: 4 weeks (ψ_4)	0.4	0.68
Variance	**Coefficient**	**t-statistic**
Risk aversion (ω_ρ^2)	6.62	3.39
Outside option: 1 week (ω_1^2)	9.95	4.17
Outside option: 2 weeks (ω_2^2)	13.21	4.75
Outside option: 3 weeks (ω_3^2)	15.33	5.09
Outside option: 4 weeks (ω_4^2)	13.99	5.1

Notes: Table shows estimates of the simulated log-likelihood function based on equation (10). Standard errors were obtained via subsampling based on 59 subsamples with 325 observations each.

Table 15: Counterfactual – no auctions

Game	Quantity	Predicted	Counterfactual	Change (%)
Colts at Jaguars	Pr(sale)	0.3	0.26	-13.33
	$\mathbb{E}$ [price|sale]	0.32	0.41	28.13
Titans at Raiders	Pr(sale)	0.32	0.26	-18.75
	$\mathbb{E}$ [price|sale]	0.44	0.55	25
Cardinals at 49ers	Pr(sale)	0.31	0.27	-12.9
	$\mathbb{E}$ [price|sale]	0.66	0.86	30.3
Buccaneers at Seahawks	Pr(sale)	0.31	0.3	-3.23
	$\mathbb{E}$ [price|sale]	0.76	0.94	23.68

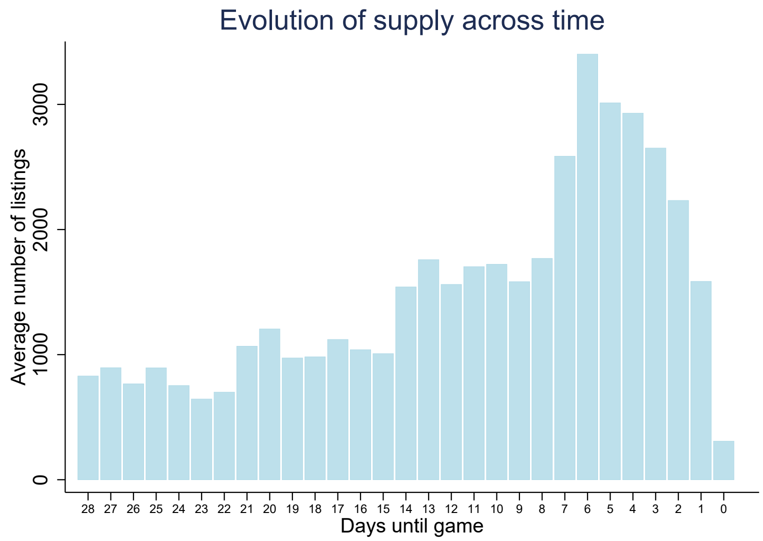
Notes: Predicted and counterfactual results are averages across 1,000 simulations. Average sale prices are calculated with respect to the face values of the tickets.

Table 16: Counterfactual – no posted prices

Game	Quantity	Predicted	Counterfactual	Change (%)
Colts at Jaguars	Pr(sale)	0.3	0.18	-40
	$\mathbb{E}$ [price|sale]	0.32	0.35	9.38
Titans at Raiders	Pr(sale)	0.32	0.22	-31.25
	$\mathbb{E}$ [price|sale]	0.44	0.59	34.09
Cardinals at 49ers	Pr(sale)	0.31	0.22	-29.03
	$\mathbb{E}$ [price|sale]	0.66	0.69	4.55
Buccaneers at Seahawks	Pr(sale)	0.31	0.18	-41.94
	$\mathbb{E}$ [price|sale]	0.76	0.83	10.53

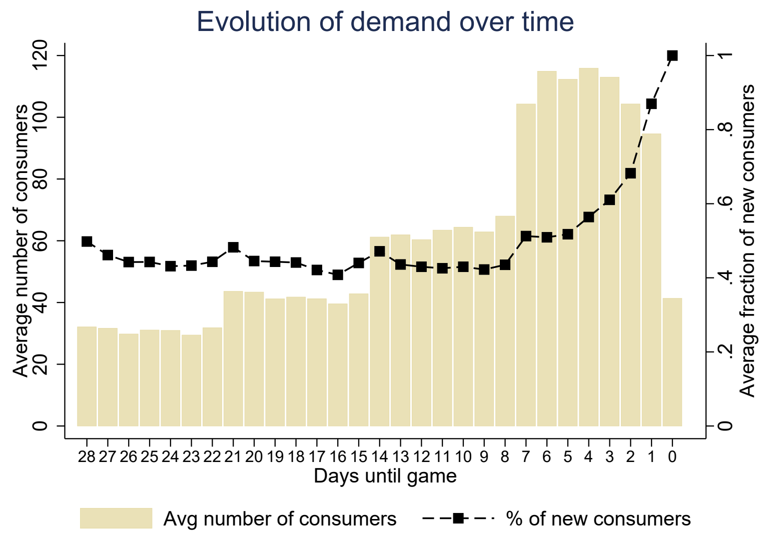
Notes: Predicted and counterfactual results are averages across 1,000 simulations. Average sale prices are calculated with respect to the face values of the tickets.

Figures



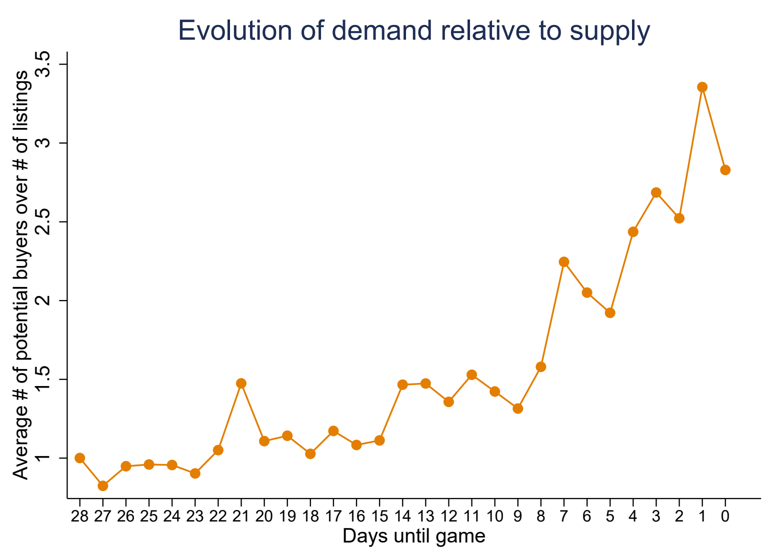
Notes: Figure displays the number of existing listings on each day including game day (0) in the sample discussed in Subsections 4.2 and 4.3.

Figure 1



Notes: Figure displays the average number of consumer in the market on each day including game day (0) in the sample discussed in Subsections 4.2 and 4.3.

Figure 2

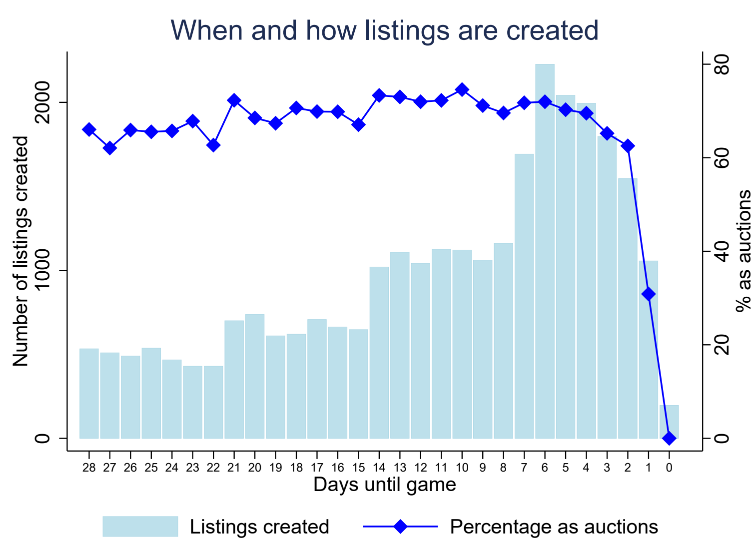


Notes: Figure displays the ratio between the number of different potential buyers (IPs) and the number of existing listings on each day including game day (0), averaged across the 245 games in the sample discussed in Subsections 4.2 and 4.3.

Figure 3

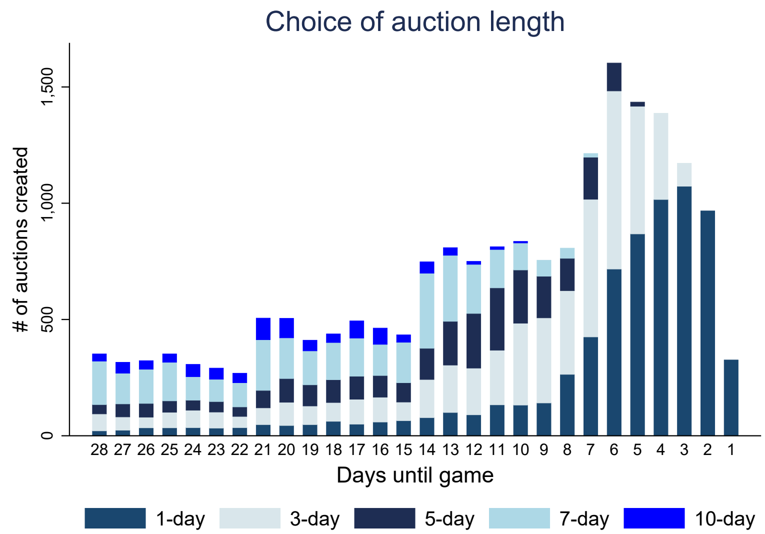
Notes: Figure displays the average auction start price and posted price, with respect to prices in the primary market, on each day including game day (0) in the sample discussed in Subsections 4.2 and 4.3.

Figure 4



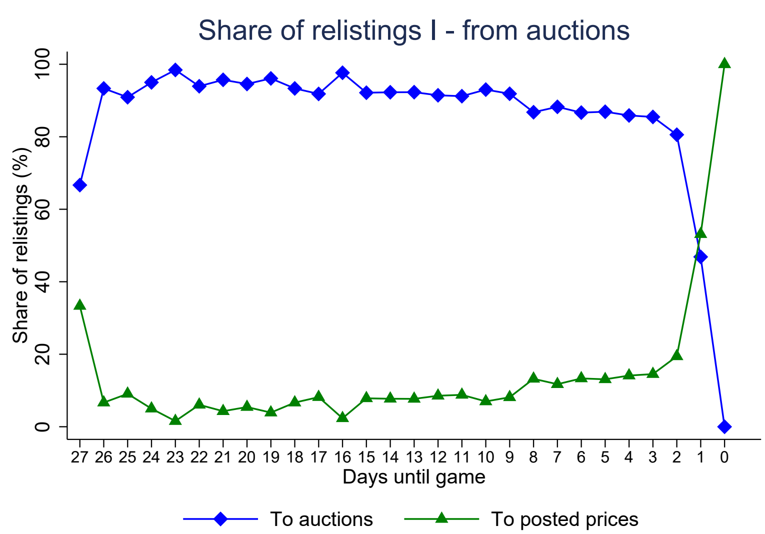
Notes: Histogram displays the number of listings on each day including game day (0), with quantities shown in the left Y-axis, and scatter shows the fraction of these listings that were created as auctions, with percentages on the right Y-axis, in the sample discussed in Subsection 4.4.

Figure 5



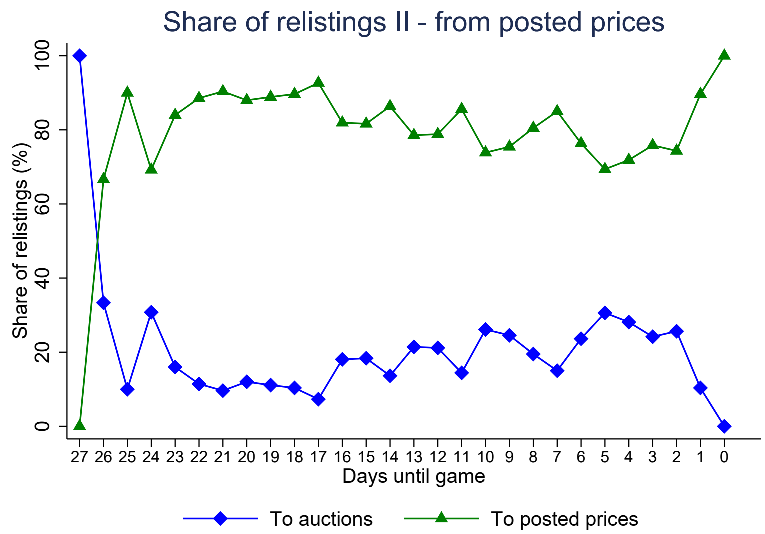
Notes: Histogram breaks down the choice of length for all auctions created on each day including game day (0) in the sample discussed in Subsection 4.4.

Figure 6



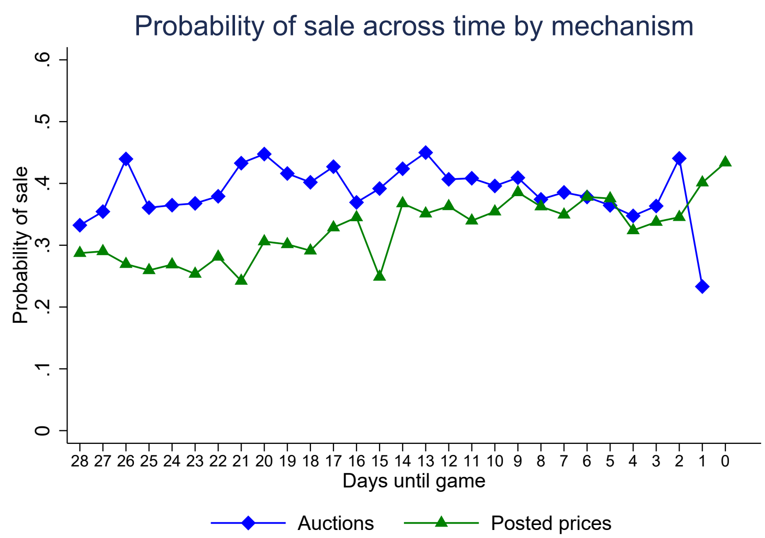
Notes: Graph shows the probability of switching from an auction to another auction or a posted price on each day including game day (0) in the sample discussed in Subsection 4.4.

Figure 7



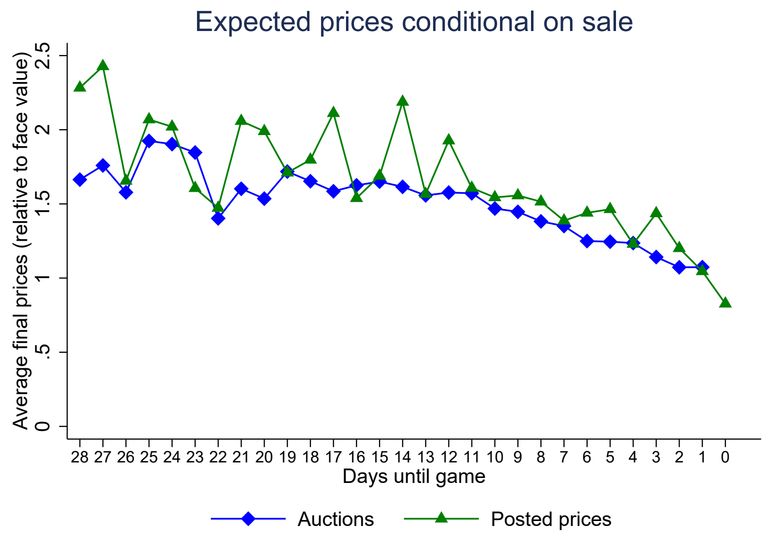
Notes: Graph shows the probability of switching from a posted price to an auction or another posted price on each day including game day (0) in the sample discussed in Subsection 4.4.

Figure 8



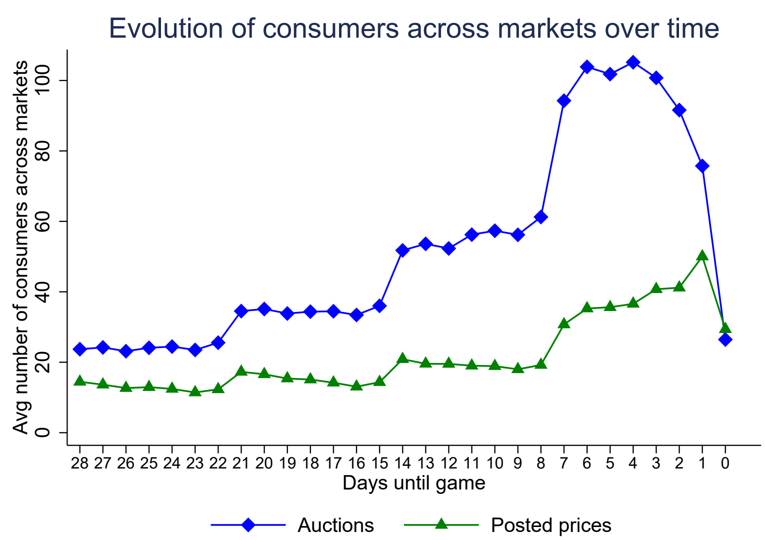
Notes: Graph shows the probability of sales of auctions posted prices by the day the listing was created on each day including game day (0) in the sample discussed in Subsection 4.4.

Figure 9



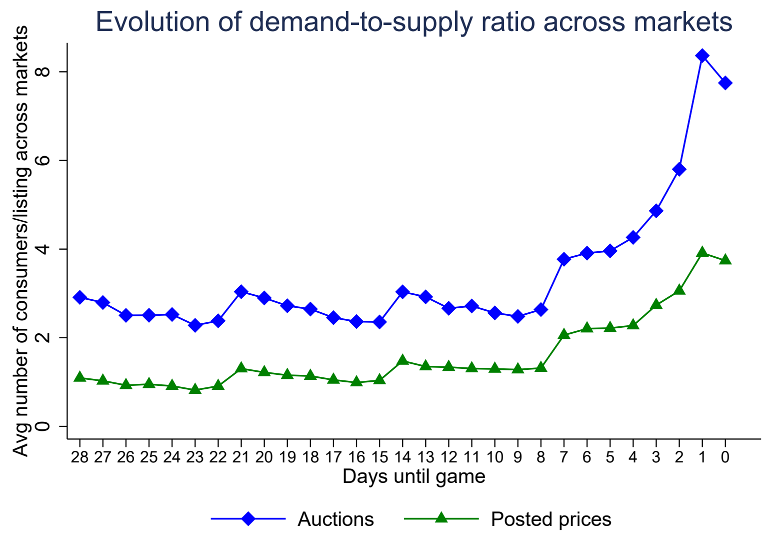
Notes: Graph shows the average final prices relative to prices in the primary of auctions posted prices conditional on a sale by the day the listing was created on each day including game day (0) in the sample discussed in Subsection 4.4.

Figure 10



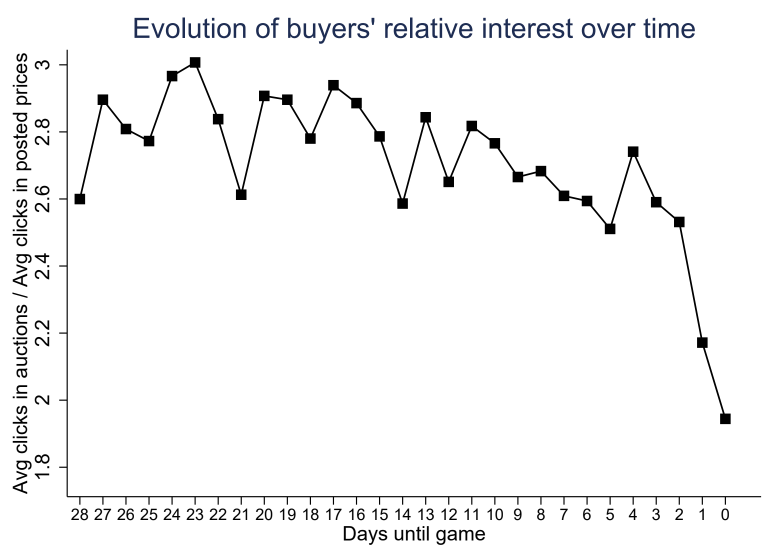
Notes: Graph shows the average number of consumers who viewed at least one listing across auctions and posted prices on each day including game day (0) in the sample discussed in Subsections 4.2 and 4.3.

Figure 11



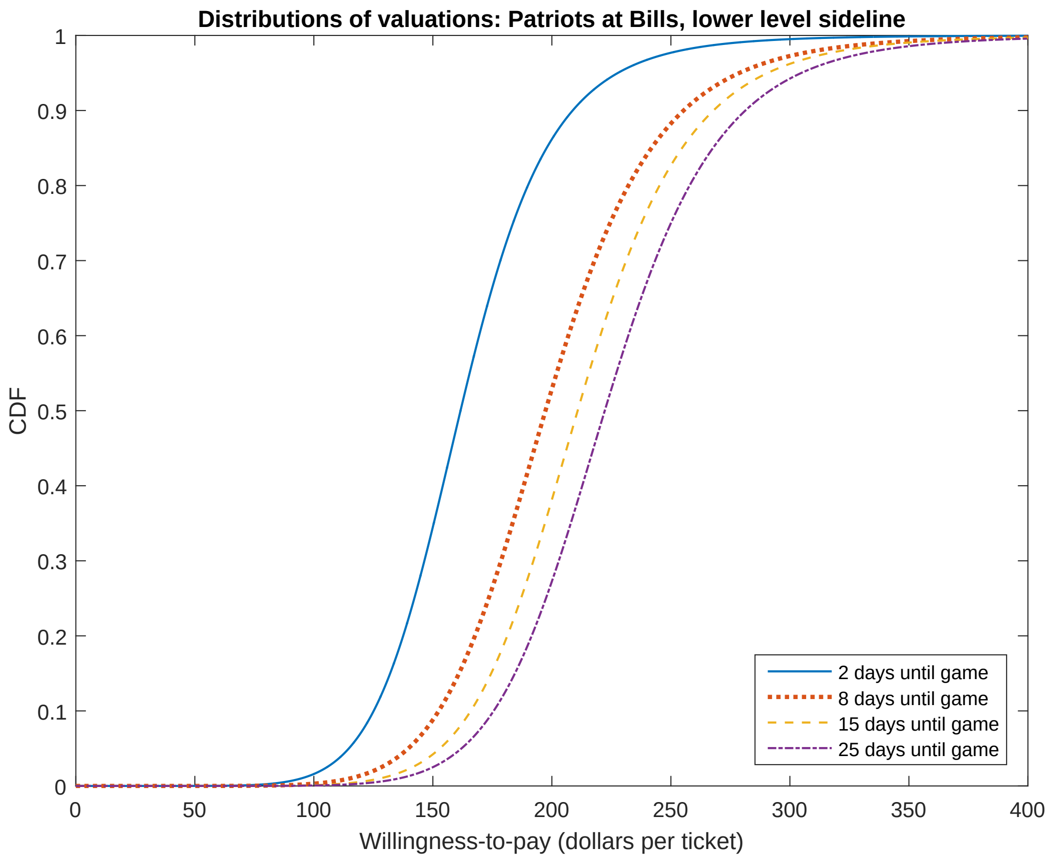
Notes: Figure displays the ratio between the number of different potential buyers (IPs) and the number of existing listings across mechanisms on each day including game day (0), averaged across the 245 games in the sample discussed in Subsections 4.2 and 4.3.

Figure 12



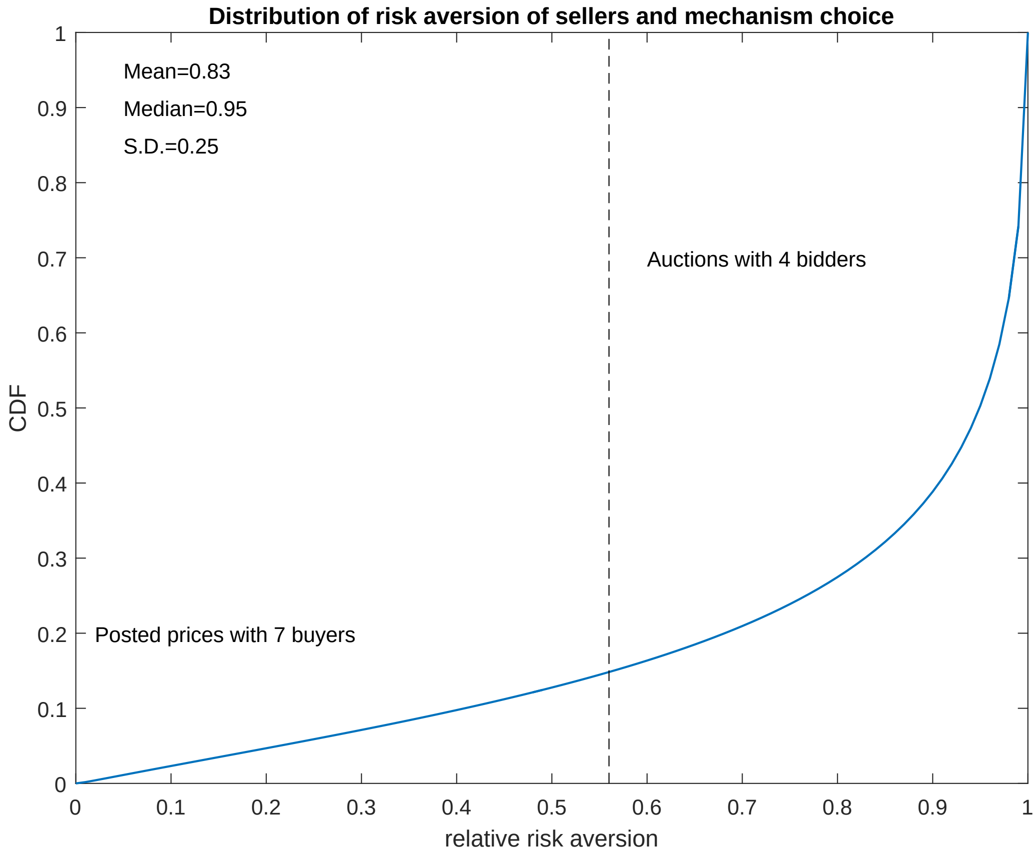
Notes: Graph shows the ratio between the average number of different potential buyers (IPs) who viewed auction pages and the same quantity for posted prices on each day including game day (0) in the sample discussed in Subsections 4.2 and 4.3.

Figure 13



Notes: Graph shows the distributions of valuations for lower level sideline tickets for the game hosted by the Buffalo Bills against the New England Patriots on four different days. Estimates are based on based the sample on all auctions which received at least two bids from Subsections 4.2 and 4.3.

Figure 14



Notes: Graph shows the distributions of sellers' coefficient of relative risk aversion.

Figure 15

Appendix

A Sample construction

I describe here in detail the procedure I used to create the chains of listings described in Section 4. The key information used to create the chains consists of the number of tickets being offered, and the section and row in which the tickets were located. This information is key for two reasons. First, the linking process to track the same set of tickets over time is based on them.[24] Second, these variables allow me to identify the price of these tickets on the primary market, which, in turn, yields a measure of their quality.

Information on the game corresponding to a given listing is often available in a standardized fashion. When this is not the case, I attempt to obtain this information from the title or subtitle of the listings. When these are not informative, the dates in which listings were created by the sellers are ordered to potentially fill in this missing information. I also make use of this procedure to correct listings for games that were created after these games had taken place, which were usually instances in which the seller corrected the information shortly after. When this was not the case sellers just removed the listing within a few days indicating that they were erroneous and possibly the result of automatic re-listing.

Around 97% of the remaining listings have information on number of tickets, section, and row. To fill in the missing information I use the listing's title or subtitle. I also verify whether sellers had offered multiple listings for the same team at the same location and whether the listings with missing information were created and terminated in between listings with complete information. This procedure was also useful to correct instances in which the information was erroneous, either because the section and row numbers were exchanged or because the information did not conform with what was reported on the title or subtitle.

With this information in hand I define as potential chains of listings combinations of different seller-game-section-row quadruples. I then identify instances in which listings within the same chain are created before the previous one was over. These cases are inspected and classified into five scenarios. First, multiple chains at the same location of-

[24] Ideally the process would be based on the seat numbers being offered as this would make the linking trivial. Unfortunately this information was rarely available, a difficulty also faced by Leslie and Sorensen (2014). A possible explanation is that potential buyers make their decision based on location of the seats at the section and row level, but not the exact seat. One fact that corroborates this explanation is that the ticket pricing in the primary market is almost always a function of the section and row only.

fered by the same seller. This is done based on information on the titles, complete sales, and other chains by the same seller. Cases in which the seller creates two identical listings across all dimensions at virtually the same time are assumed to be for the different tickets. The second scenario is reorganization of quantities, or rebundling. For example, turning a single listing for four tickets into two listings of two tickets each. Third, listings which were removed within a day and recreated shortly after are assumed to be mistakes and deleted. The final two scenarios concern listing the same set of tickets more than once concurrently, which I call doublelisting.

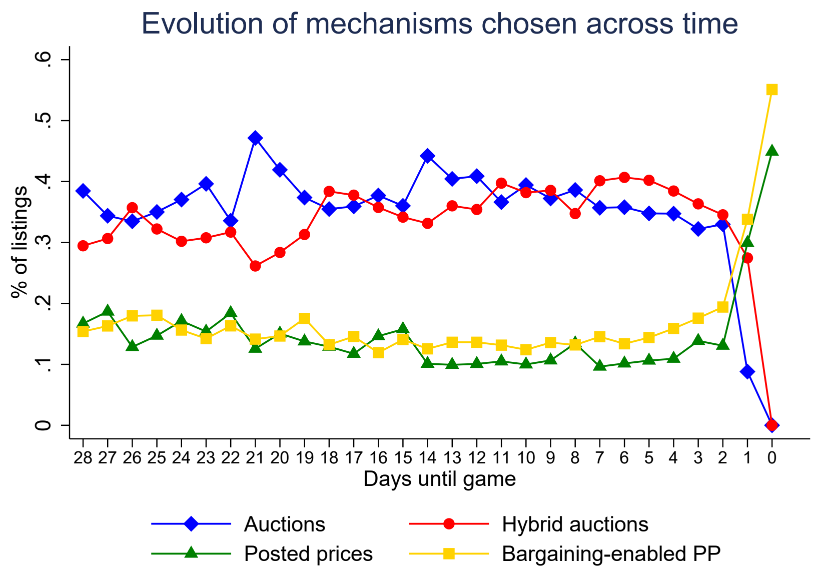
I classify doublelisting scenarios into two cases. The first is separation across quantities: for example, having a listing for four tickets and, at the same time, two separate listings for two tickets each. This is again cross-checked with the seller's story of listings and their outcomes. Returning to the example, if both a two-ticket and four-ticket listings are sold then they were for different sets of tickets, while if the four-ticket one is sold and the other two two-ticket listings are then removed from the website it suggests that the same tickets were listed twice. Finally, the second case consists of listing the same set of tickets through different mechanisms. I verified these cases according to the same procedure that I employed in the previous case.

At the end of this procedure I obtain a sample of 38,520 sets of tickets, which were offered across 78,865 listings. However, the analysis will be restricted to activity within four weeks of a game. This restriction is not extreme: in this period, almost 61% of tickets were introduced to the market, more than 70% of tickets are offered, and more than 73% of the transactions observed in the data took place. Therefore, the final sample contains 27,047 sets of tickets across 43,221 listings. Of these, 290 listings across 223 chains do not have information on the number of tickets, section, or row, and therefore are not used for estimation, but are used to create measures of market conditions.

The remaining chains are used to estimate parameters of the demand side of the market. To study seller behavior, I further restrict the sample to tickets that were introduced to the market during the period of interest, were always offered as a pair, and were not rebundled or doublelisted. This is a considerably smaller sample, containing 19,175 pairs of tickets over 28,266 listings. Nevertheless, pairs are the most common bundle offered (more than 74% of listings). Furthermore, even though rebundling and doublelisting are ruled out, just a little more than 5% of chains display these features.

B Mechanism choice: hybrid auctions and bargaining

This subsection documents patterns relative to mechanisms which were not explicitly considered: auctions with an immediate purchase option and bargaining-enabled posted prices. To do so it employs the main subsample, which was also used in Subsection 4.4. First, Figure B.1 shows which among the four options sellers choose across time.



Notes: Graph shows the fraction of each mechanism among all listings created on each day including game day (0) in the sample discussed in Subsection 4.4.

Figure B.1

The aggregate pattern across all auctions and all posted prices can be seen within each specific mechanism, showing that they are not driven by one specific type. However, it becomes more clear that sellers are more likely to choose more flexible options as the deadline approaches. This can be seen in at least two ways. First, while hybrid auctions display the same sharp decrease as auctions due to the aforementioned reasons, this decrease starts earlier and is more intense for usual auctions than for hybrid auctions. Second, sellers become more prone to allow for bargaining when closer to the game. It is noticeable how the probability of choosing each posted price is virtually the same across time, until it decouples with bargaining-enabled listings becoming substantially more likely to be chosen in the last two days.

Table B.1 displays the overall choices by sellers to give a sense of the magnitudes as well as the outcomes per mechanism.

Table B.1: Distribution of listings across mechanisms II

Type	Quantity	Sold	Sold via buy price	Sold via bargaining
Auctions	10,051	4,581	–	–
Hybrid auctions	10,059	3,692	588	–
Posted prices	3,692	1,029	–	–
Posted prices with bargaining	4,464	1,155	–	694

Notes: Table displays quantities of the sample described in Subsection 4.4.

While hybrid auctions are slightly more numerous than usual auctions, buyers rarely make use of this option. In part this is due to the fact that whenever a bid equal to at least half the buy-it-now price is submitted the option of immediate purchase goes away. Therefore, abstracting from hybrid auctions is arguably inconsequential for the results. On the other hand, most posted price listings are bargaining-enabled, in part because this is the default option on eBay. Furthermore, most purchases of bargaining-enabled listings are through bargaining, and the average discount buyers obtain conditional on a purchase is roughly 21%. These figures are not negligible, but I choose to disregard this option for a few reasons.

The first reason is simplicity: negotiations between buyers and sellers probably displays two-sided incomplete information. In addition, eBay caps the number of offers within a single negotiation at six. Embedding bargaining interactions between buyers and sellers with these features would almost surely require a so-called "reduced form" approach, in which case it is not clear whether ignoring negotiations is a higher order concern. Second, it mitigates one potential concern about the empirical model. In practice, sellers rarely change prices every day, and it is not possible to determine the reason why. Since valuations decrease daily, according to the model the probability of a sale, conditional on a price level, would decrease. The actual probability of a sale with a discount possibly mitigates this issue, and is as least in part captured through the daily price decision.

C Buyers' behavior: hybrid auctions and bargaining

This subsection presents further evidence that buyers also change their behavior as game day approaches. To do so it shows how buyers make choices regarding whether to accept the buy-it-now option in hybrid auctions and how they initiate negotiations in bargaining-enabled posted price listings.

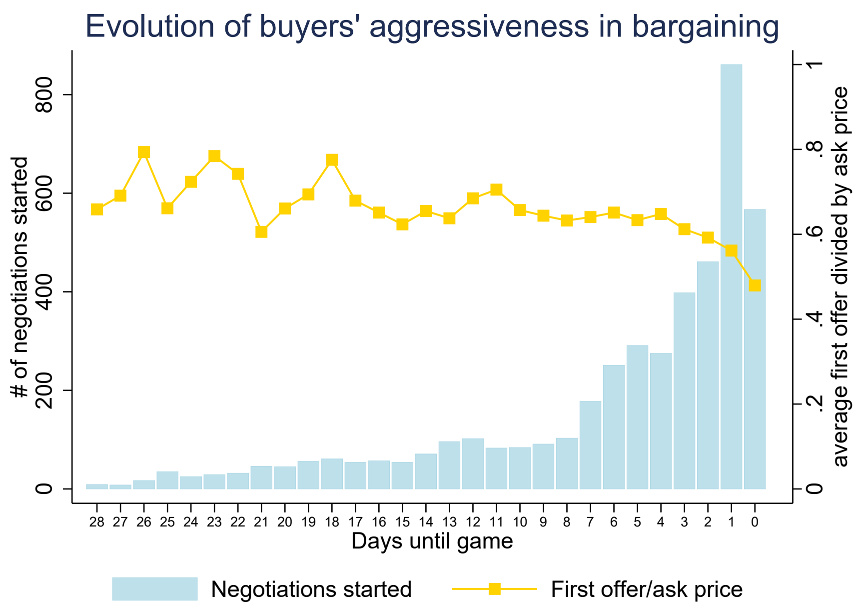
Figure C.1 below shows how many hybrid auctions are created on each day, and the share of such auctions that are sold via buy price purchase.

Notes: Histogram displays the number of listings on each day including game day (0), with quantities shown in the left Y-axis, and scatter shows the fraction of these listings that were created as hybrid auctions, with percentages on the right Y-axis, in the sample discussed in Subsection 4.4.

Figure C.1

Buyers are noticeably more likely to use the buy-it-now option on the day before the game. A possible explanation is that if a buyer wishes to make sure that she will attend the game she will choose pay the buy price rather than submit a bid not to wait until the auctions is over to find out if she won, despite expecting to make a higher payment.

Another example of a change in buyers' behavior is displayed in Figure C.2.



Notes: Histogram displays the number of negotiation that on each day including game day (0), with quantities shown in the left Y-axis, and the scatter shows the ratio between the amount of the first offer and the ask price, with numbers on the right Y-axis, in the sample discussed in Subsection 4.4.

Figure C.2

The histogram shows how many negotiations started on each day. A bargaining interaction begins when a potential buyers send an offer to the seller. The plot displays the average ration between this first offer and the original posted price chosen by the seller, which I simply call "buyers' aggressiveness", showing that this ratio is weakly decreases as the deadline approaches. This suggests that buyers become more relatively more aggressive in bargaining if game day is close, possibly because they take into account that sellers' option value of waiting is smaller, which implies that they are more likely to accept offers with lower prices.

D Seller heterogeneity and choices

This subsection expands the aforementioned analysis of seller heterogeneity and its relation to sellers' choices and the estimation of sellers' parameters described above. First, I categorize sellers into five groups:

- *Casual:* sellers that offer at most two chains of tickets for only one home team.
- *Recurring:* sellers who offer more than two chains for only one team or chains for multiple home teams, all in the same state.
- *Medium:* sellers who offer chains for multiple home teams from different states, but all located in the same region of the country or belonging to the same division.
- *Big:* sellers who offer chains for multiple home teams who are neither "recurring" nor "medium".
- *Specialized:* sellers specialized in football or sports as defined by their titles on the website.

Table D.1 below shows the distribution of sellers across types as well as their listing behavior.

Table D.1: Seller types, supply, and listing decisions

Type	Quantity	% relist	% switch mechanism
Casual	8,076	28.98	11.1
Recurring	2,481	62.07	40.95
Medium	66	65.15	46.97
Big	176	76.7	52.27
Specialized	20	55	25

Notes: Table displays quantities of the final sample described in Subsections 4.2 and 4.3. Hybrid auctions are included within auctions with the exception of those who were sold via the buy-it-now option, and bargaining-enabled posted prices are included as usual posted price listings. A mechanism change is defined as going from any auction to any posted price or vice-versa.

As could be predicted, more active and larger sellers are also more likely to relist and to switch between mechanisms. However, it is also important to note that the absolute number of casual sellers that relist and that switch between mechanisms is comparable to the sum over all remaining types of sellers, indicating that all comparably contribute to the source of variation utilized in estimation.

To investigate seller entry, exit, and mechanism choice decisions I run a series of regressions, which are displayed on Table D.2 below.

Table D.2: Regressions of relative prices and mechanism chosen on time and controls

Variable	Days at entry	$\mathbb{1}\{\text{unsold}\}$	$\mathbb{1}\{\text{auction}\}$
Recurring seller	0.89 (0.17)	0.16 (0.01)	0.03 (0.01)
Medium seller	1.84 (0.69)	0.06 (0.05)	-0.02 (0.07)
Big seller	1.88 (0.81)	0.11 (0.03)	-0.07 (0.06)
Specialized seller	3.66 (1.14)	-0.12 (0.03)	-0.35 (0.06)
Constant	13.36 (1.24)	0.73 (0.08)	0.04 (0.09)
Mean dependent variable	12.03	0.61	0.63
Number of observations	27,047	27,047	43,221
Number of clusters	10,799	10,799	10,799
R–squared	0.05	0.09	0.1

Notes: Table shows coefficients of seller types on regressions whose dependent variables are how many days there were until the game when the tickets first entered the market, whether the tickets went unsold, and whether the listing was an auction. Standard errors, clustered at the seller level, are shown between parentheses. All regressions include game fixed effects and ticket type fixed effects. The first two columns are at the chain level, while the third is at the listing level. The second and third columns also include dummies for how many days there were until the game when the tickets entered the market and the listing was created, respectively.

The first column displays estimates from a regression whose dependent variable is how many days there were until the game when the tickets first entered the market. Results indicate that more active and bigger sellers tend to enter the market earlier as all coefficients are positive, and economically and statistically significant. The relationship between these results and the assumptions made in the model is twofold. First, it indicates that the assumption that sellers randomly enter the market is questionable. On the other hand, to the extent that these types of sellers are more experienced and acquainted with this market, the assumption of perfect foresight becomes less stringent, because this hypothesis is arguably stronger when sellers enter the market early.

The dependent variable on the second column is an indicator for whether the ticket went unsold, that is, if they were neither sold on the website nor removed before game day. Even though it is not a perfect indicator, results from this regression are meaningful and suggest that different types of seller were differentially likely to sell on the platform, despite controlling for the time when tickets first enter the market. In the context of the model, this suggests that the outside options sellers have might depend on their type.

Finally, the third column uses as dependent variable an indicator for whether the seller chose to list the tickets as auctions. Once again, results are significant and indicate that different types of seller prefer different kinds of mechanism, which, in the model, is captured via the arrival rates they induce of buyers to their listings.

E Empirical patterns with observed heterogeneity

The empirical patterns displayed in Section 4 ignored observed heterogeneity for ease of interpretation. This subsection incorporates observed variables to show that the main empirical patterns persist even after taking them into account. The patterns of interest addressed here are decreasing prices and auctions being relatively less likely to be chosen in the very long or short term.

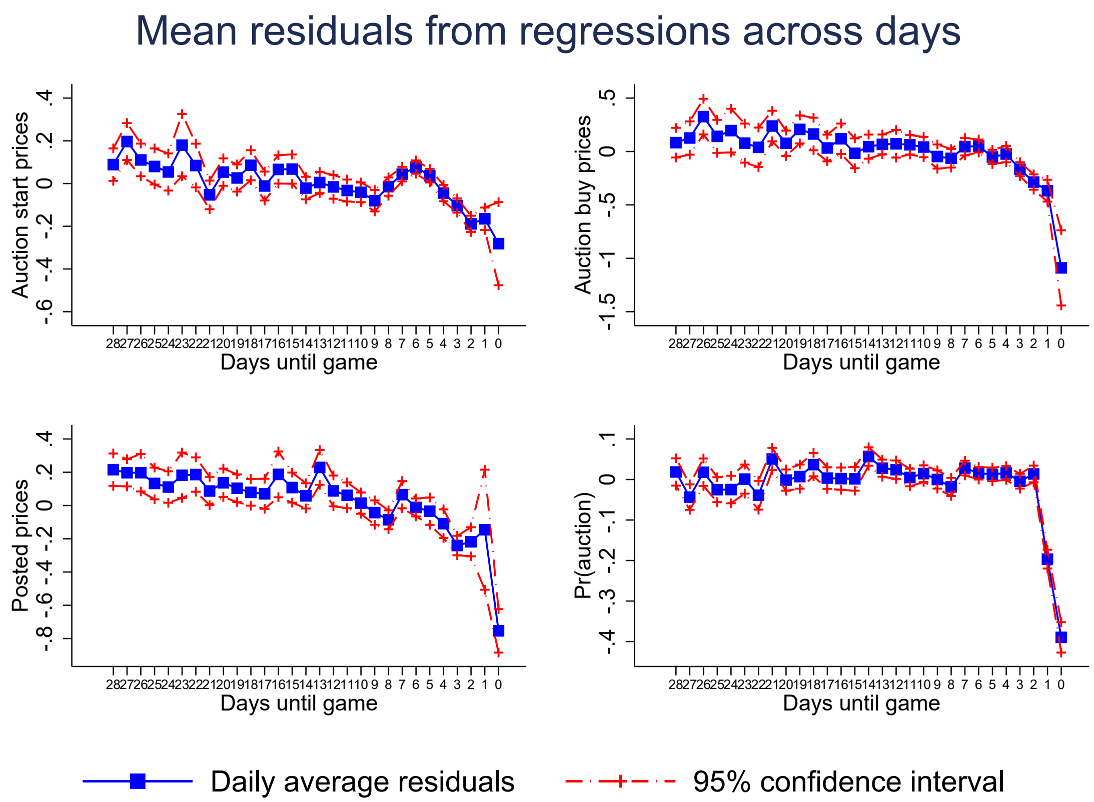
Table E.1 shows the results from a series of regressions. The regressors are the same across all specifications, namely game fixed effects, ticket type fixed effects, a dummy indicating whether the seller was specialized in sports or tickets based on the user's name, and at the time the listing was created: seller's feedback score, percentage of positive reviews, number of tickets sold via auctions and posted prices in the last year, the market demand-to-supply ratio, and the number of competing posted prices and auctions. The dependent variables are auction start prices, posted prices, and auction buy prices, all relative to the face value of the ticket, and an indicator of whether an auction was chosen rather than a posted price, and the coefficient of a daily time trend for the date of creation is displayed.

Table E.1: Regressions of relative prices and mechanism chosen on time and controls

Variable	Auction start prices	Posted prices	Auction buy prices	$\mathbb{1}\{\text{auction}\}$
Days until deadline	0.0174	0.0356	0.0365	0.0033
	(0.0015)	(0.0029)	(0.003)	(0.0007)
Number of observations	28,223	14,640	13,904	43,221
Number of clusters	245	244	245	245
R–squared	0.28	0.24	0.40	0.10

Notes: Table shows the coefficient of a daily time trend for the date of creation on regressions whose dependent variable is the ticket price relative to face values as well as an indicator of whether a seller created an auction instead of a posted price. Standard errors, clustered at the game level, are shown between parentheses. All regressions include game fixed effects, ticket type fixed effects, a dummy indicating whether the seller was specialized in sports or tickets based on the user's name, and at the time the listing was created: seller's feedback score, percentage of positive reviews, number of tickets sold via auctions and posted prices in the last year, the market demand-to-supply ratio, and the number of competing posted prices and auctions.

These results indicate that sellers make different choices across time even when controlling for seller, ticket, market, and game heterogeneity. All coefficients are are significant at the 1% level and have the expected sign higher prices are set farther from the game. The coefficient is positive when the dependent variable is the auction indicator possibly because auctions are effectively not an option on game day. To take into account non-linear time effects in a more flexible way, I run the same regressions without the time trend, and then plot the average of the residuals with a 95% pointwise confidence interval for each day. Results are shown in Figure E.1.



Notes: Graph shows the average residuals on each day from regressions that include game fixed effects, ticket type fixed effects, a dummy indicating whether the seller was specialized in sports or tickets based on the user's name, and at the time the listing was created: seller's feedback score, percentage of positive reviews, number of tickets sold via auctions and posted prices in the last year, the market demand-to-supply ratio, and the number of competing posted prices and auctions. Dependent variables are auction start and buy prices as well as posted prices and an indicator of whether an auction was chosen.

Figure E.1

These results are aligned with those shown in Table E.1: all prices and the probability of a seller choosing an auction fall as game day approaches. Overall I these results as simply indicating that while observed variables are potentially relevant factors in sellers' choices, the main empirical patterns across time shown in Section 4 are not driven by these covariates.

F Computing CSVF for auctions

In this subsection I describe how the CSVF's for auctions ($\pi_{jt}^{A_\ell}$) were computed. To ease notation I will drop the subscripts for seller (j), date when the auction started (t), and auction length (ℓ), as well as the superscript indicating that an auction was chosen ($k = A$).

To calculate $\mathbb{E}\left[\max\{V^{(N-1:N)}, r\}^{1-\rho}\right]$, I first re-write the seller's payoff using analogous equivalences from static auction theory. First, for any number of bidders n, any reserve price r, and any seller continuation value, π_0, it follows that revenue can be expressed as $\left(\max\{V^{(n-1:n)}, r\}\right)^{1-\rho} + \left(\pi_0 - r^{1-\rho}\right) \mathbb{1}\{V^{(n:n)} < r\}$. Hence, the expected payoff from an auction is given by:

$$\pi^A = \mathbb{E}_N\left[\max\{V^{(n-1:n)}, r\}^{1-\rho} \middle| N = n\right] + \left(\pi_0 - r^{1-\rho}\right) Pr_N\left(V^{(n:n)} < r \middle| N = n\right) \quad \text{(F.1)}$$

Computing the second term in the right-hand side of (F.1) is straightforward since it follows the same pattern as in expression (4) in subsection 6.2. In particular, it follows that:

$$\left(\pi_0 - r^{1-\rho}\right) Pr_N\left(V^{(n:n)} < r \middle| N = n\right) = \left(\pi_0 - r^{1-\rho}\right) e^{-[1-F_V(r)]\lambda}. \quad \text{(F.2)}$$

To compute the first term in the right-hand side of (F.1) first note that if $N \leq 1$, then $r \geq V^{N-1:N}$ with probability one. For these two values the expression simply is:

$$\sum_{n=0}^{1} \frac{\lambda^n e^{-\lambda}}{n!} r^{1-\rho} = e^{-\lambda} r^{1-\rho} (1 + \lambda). \quad \text{(F.3)}$$

Finally, consider now the case when $N > 1$. In particular, for any n and r it follows that:

$$\begin{aligned}\mathbb{E}\left[\max\left\{V^{n-1:n}, r\right\}^{1-\rho}\middle|N=n\right] &= \int_0^\infty \max\{u,r\}^{1-\rho} f_{n-1:n}(u)du \\ &= \int_0^r r^{1-\rho} f_{n-1:n}(u)du + \frac{1}{1-\rho}\int_r^\infty u^{1-\rho} f_{n-1:n}(u)du.\end{aligned} \tag{F.4}$$

The two terms in (F.4) are now evaluated separately, beginning with the first in the right-hand side. Remember that due to properties of order statistics it follows that $F_{n-1:n}(r) = nF(r)^{n-1} - (n-1)F(r)^n$. Thus,

$$\begin{aligned}\mathbb{E}_N\left[r^{1-\rho}F_{n-1:n}(r)\middle|N=n\right] &= r^{1-\rho}\sum_{n=2}^{\infty}\frac{\lambda^n e^{-\lambda}}{n!}\left[nF_V(r)^{n-1} - (n-1)F_V(r)^n\right] \\ &= r^{1-\rho}\left\{\lambda\left[1-F_V(r)\right]\sum_{n=2}^{\infty}\frac{\left[\lambda F_V(r)\right]^{n-1}e^{-\lambda}}{(n-1)!} + \sum_{n=2}^{\infty}\frac{\left[\lambda F_V(r)\right]^{n}e^{-\lambda}}{n!}\right\} \\ &= r^{1-\rho}e^{-\lambda[1-F_V(r)]}\left\{\lambda\left[1-F_V(r)\right]\left(1-e^{-\lambda F_V(r)}\right)\right. \\ &\qquad \left. +1-\left[1+\lambda F_V(r)\right]e^{-\lambda F_V(r)}\right\} \\ &= r^{1-\rho}e^{-\lambda[1-F_V(r)]}\left\{1+\lambda\left[1-F_V(r)\right]\right\} - r^{1-\rho}e^{-\lambda}\left(1+\lambda\right).\end{aligned} \tag{F.5}$$

Now I compute the expectation over N of the second term in the RHS of (F.4):

$$\sum_{n=2}^{\infty}\frac{\lambda^n e^{-\lambda}}{n!}\int_r^{\infty} y^{1-\rho} f_{n:1:n}(y)dy = \int_r^{\infty} y^{1-\rho}\left[\sum_{n=2}^{\infty}\frac{\lambda^n e^{-\lambda}}{n!} f_{n-1:n}(y)\right]dy$$
$$= \int_r^{\infty} y^{1-\rho}\left[\sum_{n=2}^{\infty}\frac{\lambda^n e^{-\lambda}}{n!}\left[n f_{n-1:n-1}(y) - (n-1) f_{n:n}(y)\right]\right]dy$$
$$= \int_r^{\infty} y^{1-\rho}\left[\sum_{n=2}^{\infty}\frac{\lambda^n e^{-\lambda}}{n!}\left[n(n-1)F(y)^{n-2}f(y) - n(n-1)F(y)^{n-1}f(y)\right]\right]dy$$
$$= \lambda^2\int_r^{\infty} y^{1-\rho}e^{-\lambda[1-F(y)]}[1-F(y)]f(y)\left[\sum_{n=2}^{\infty}\frac{[\lambda F(y)]^{n-2}e^{-\lambda[1-F(y)]}}{(n-2)!}\right]dy$$
$$= \lambda^2\int_r^{\infty} y^{1-\rho}e^{-\lambda[1-F(y)]}[1-F(y)]f(y)dy$$
$$= \int_r^{\infty} e^{-\frac{\lambda\alpha^\beta}{\alpha^\beta+y^\beta}}\frac{\beta(\lambda\alpha^\beta)^2 y^{\beta-\rho}}{(\alpha^\beta+y^\beta)^3}dy$$
$$= \alpha^{1-\rho}\int_0^{\frac{\lambda\alpha^\beta}{\alpha^\beta+r^\beta}} xe^{-x}\left(\frac{\lambda-x}{x}\right)^{\frac{1-\rho}{\beta}}dx \equiv \eta, \tag{F.6}$$

where the first equality follows from Fubini's theorem, the second from properties of order statistics, the penultimate from the log-logistic distribution which was assumed, and the last from a change of variables in which $x = \frac{\lambda\alpha^\beta}{\alpha^\beta+y^\beta}$. The last integral, defined as η, is solved via Gauss-Chebyshev quadrature using ten nodes.

Plugging (F.5) and (F.6) in (F.4) yields:

$$\mathbb{E}_N\left[\max\left\{V^{N-1:N}, r\right\}^{1-\rho}\right] = r^{1-\rho}e^{-\lambda[1-F_V(r)]}\left\{1+\lambda\left[1-F_V(r)\right]\right\} - r^{1-\rho}e^{-\lambda}\left(1+\lambda\right) + \eta, \tag{F.7}$$

and plugging (F.2), (F.3), and (F.7) in (F.1) finally yields:

$$\pi^A = r^{1-\rho}\lambda[1-F_V(r)]e^{-\lambda[1-F_V(r)]} + \eta + e^{-\lambda[1-F_V(r)]}\pi_0. \tag{F.8}$$