Equilibrium Price Dynamics in Perishable Goods Markets: The Case of Secondary Markets for Major League Baseball Tickets

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Preliminary and Incomplete. Comments Welcome.

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Abstract

This paper analyzes the dynamics of prices in two online secondary markets for Major League Baseball tickets. Controlling for ticket quality, prices tend to decline significantly as a game approaches. The paper describes and tests alternative theoretical explanations for why this happens in equilibrium, considering the problems of both buyers and sellers. It shows that sellers cut prices (either fixed prices or reserve prices in auctions) because of declining opportunity costs of holding onto tickets as their future selling opportunities disappear. Even though prices can be expected to fall, the vast majority of observed early purchasing can be rationalized by plausible values of risk aversion and search costs given the vertically di erentiated nature of tickets and uncertainty about the future availability of particular types of tickets.

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prevents a future sale because of a sell-out. As a result, the optimal price increases when a unit is sold and it tends to fall over time as the probability that all of the remaining units are sold before the end of the interval, which determines the opportunity cost of selling, decreases. McAfee and te Velde show that a “robust prediction” of these models is that the second effect causes expected prices to fall over time. In my setting, sellers are small and very rarely have more than one similar set of tickets (e.g., same game and section). Therefore only the declining opportunity effect should be present and the prediction that prices should decline emerges unambiguously.[2] This theoretical literature has recently expanded to look at the role of strategic consumers who can choose when to purchase (Aviv and Pazgal (2008), Liu and van Ryzin (2008), Dasu and Tong (2008), Levin et al. (2008), Zhou et al. (2006)).[3]

There has been almost no empirical work testing these models.[4] The airline industry has received most attention (McAfee and te Velde (2006), Escobari and Gan (2007)), but the declining price prediction has been rejected. The observation that prices tend to increase can be rationalized by the fact that most consumers who discover they want to travel close to the day of departure have about how prices should decline do not match my data.

The paper is also indirectly related to two other literatures. It has been noted in many contexts that prices for similar or identical items tend to decline when they are sold in sequential auctions (Ashenfelter (1989), Ashenfelter and Genesove (1992), McAfee and Vincent (1993), Ginsburgh (1998) and van den Berg et al. (2001)). Most explanations for this "declining price anomaly" have focused on the characteristics of the particular auction mechanism being used or differences in the unobserved qualities of the goods being sold. In contrast, I show that perishability - a shared characteristic of the goods being sold - lead to price declines across several different sales mechanisms, including fixed prices and auctions.

The paper also sheds light on how secondary event ticket markets work. Forrester Research (2008) projects that revenues in these markets should grow from \$2.6 billion in 2007 to \$4.5 billion in 2012 (with 70% of revenues coming from sports tickets). Secondary markets are also becoming increasingly accepted by primary market sellers (for example, from the 2008 season Stubhub.com will be the official resale site for MLB teams). Existing work on these markets (e.g., theoretical work by Courty (2000, 2003a,b), Karp and Perloff (2005) and an empirical analysis by Leslie and Sorensen (2007)) uses one-shot market clearing models to examine how their existence affects consumer surplus and the profits of the primary market seller. These are important questions from a policy perspective as resale markets have traditionally been restricted in many states. The current paper provides a look inside secondary markets to study the price determination process.

The paper is structured as follows. Section 2 describes the data and Section 3 establishes that prices decline controlling for ticket quality. Section 4 outlines three competing theoretical explanations for why sellers cut prices over time, and it presents reduced-form evidence which is inconsistent with the Lazear learning model. Section 5 estimates structural models of the price-setting problem, assuming no learning, which support the declining opportunity cost of selling story over a story where sellers cut prices because of changing price elasticities. Section 6 examines why some buyers choose to purchase early when prices can be expected to decline. Section 7 concludes.

2 Data

2.1 Secondary Market Data

This paper uses new datasets from two large online secondary markets for tickets for MLB regular season games in 2007.

2.1.1 Stubhub.com

The first dataset contains data on list prices from Stubhub.com, collected 1

Stadium) and the price per seat. The identification number allows only imperfect tracking of listings across days as it is clear that many sellers enter a new listing when changing the price.[6] In the analysis which follows I only use listings with non-missing section information (over 99.7% of the sample), six or fewer seats (91%) and tickets with prices less than $1,000 per seat (99.98%). I also exclude three Tampa Bay games which were played in Orlando and make-up games for rainouts as these are often scheduled at short notice. I include games which were rained out as I am looking at price dynamics in the days and weeks leading up to the game rather than on the day itself.

The limitation of the Stubhub data is that it contains data only on posted prices and not on transactions. While I observe tickets which cease to be listed I do not know whether this is because they are sold on Stubhub or sold elsewhere, possibly at a di erent price. On the other hand, the because the market does not o er a Stubhub-like guarantee.

The full dataset contains information on all event ticket listings from January 1 to September 30, 2007, and I use the subset of observations for single regular season (i.e., no season tickets) MLB recorded capacities for many teams. The single game price (face value) for each game and section was collected from team websites. Some teams, such as the Boston Red Sox, charge the same prices irrespective of the opposition, whereas others, like the New York Mets, have several pricing tiers which depend on the opposition and the day of the week. Face value information is missing for some season ticket only sections and for all Colorado Rockies games. No MLB teams practised dynamic pricing in the primary market.

2.3 Summary Statistics

Table 1 shows how the listings are distributed across MLB teams and, based on transactions observed on Market 2, some additional measures of pricing, market concentration and the timing of sales. Listings may be available for multiple days: on Stubhub the average listing lasts 16 days compared with 4.5 days for auction listings on Market 2 and 19 days for non-auction listings. Stubhub has more listings than Market 2 for every team, although the ratio of listings shows some variation across teams. The teams with the most listings and highest secondary market prices on both sites tend to be those in the largest cities with the highest realized attendances, which is consistent with secondary markets existing partly because of excess demand in the primary market. For MLB they also serve for all games since May 2003 as well as the team having a particularly successful 2007 (they won the World Series).[9] In terms of dynamics the table shows that the majority of listings happen in the last

Figure 1 shows some features of how the markets change as the game approaches. The first diagram shows how the average number of tickets available changes over time. Pure auction listings on Market 2 only count as being available on the day the auction ends. The number of listings on Market 2 peaks much closer to the game. A slightly surprising feature of the data from both markets is that the average face value of listed tickets (and transacted tickets on Market 2) increases slightly as a game approaches. The remaining diagrams show how the choice of sale mechanism and the proportion of listings resulting in a sale on Market 2 change as a game approaches. Auction listings, which o er greater flexibility of price in response to stochastic realizations of demand, become more common as a game approaches. Hybrid auctions become particularly common right before the game, when buyers are likely to value being able to secure a ticket with certainty. The proportion of listings resulting in sales also tends to increase as the game approaches for all sale formats, although it falls slightly for pure single unit auctions in the last ten days before the game.

3 Robust Evidence of Price Declines

This section shows that the dominant pattern in the data is that both list and transaction prices tend to fall as the game approaches controlling for ticket quality. This pattern is very robust to considering di erent sales mechanisms, di erent groups of teams and demand conditions and di erent types of seat, and the e ects are always quite large in size. I emphasize how robust the price declines are as they motivate the rest of the paper.

A possible objection to the claim that prices are falling is that it could be that the unobserved ticket quality is falling instead.[10] It is therefore important to believe that my empirical specification can adequately control for seat quality using di erent types of fixed e ects and it is useful to take a moment to understand how these are defined.[11]

[10] Observable ticket quality does not fall as the game approaches. Controlling for game fixed e ects, the face value of listed and transacted tickets is very similar throughout the 90 days before the game and actually peaks in the days immediately before.

[11] When I control for game-section-row e ects using the Stubhub I am controlling for all of the information observed by buyers on Stubhub's listing screen. This is not true for Marketplace 2 where my dataset only contains a portion of the listed text.

A game refers to a particular fixture between two teams scheduled to be played on a particular day (e.g., Seattle Mariners at the New York Yankees on May 6). A game-section fixed e ect is a dummy for those listings for seats in a particular section for a particular game (e.g., Loge Box 512 for the Seattle Mariners at the New York Yankees on May 6). Many stadia have over two hundred sections defined in this way. A game-face value fixed e ect groups together those sections for a particular game which have the same face value in the primary market (in my example, odd numbered Loge Boxes 473 to 545 and even numbered Loge Boxes 474 to 548, with a face value price of $55). When using game-face value fixed e ects I do not include those sections for which no face value can be identified. A game-section-row fixed e listing identification number. I do not report coe cients on ticket characteristics such as the piggy dummy, the row variables (where applicable), dummy variables for the number of tickets available in a listing which are interacted with a dummy variable for whether it is possible to buy less than the full number of seats and the form variables for the away team.

The specification in column (1) includes game-section fixed e ects so that the coe cients are identifi

form variables again have sensible signs, and the unreported row coe cients indicate that transaction prices fall by 0.3% for each row one moves away from the field, with a 13% front row premium. There are, however, two di erences to the Stubhub results. First, reflecting the smaller sample size, the decline in prices in the last 45 days before the game are not perfectly monotonic, although most of the deviations from monotonicity are small and not statistically significant. Second, there is evidence that prices increase by a small amount prior to 50 days before the game. I return to the question of why this may be happening in a moment.

The column (2) speci

than 50 days before a game, auction start prices are declining at the same time, just like fixed prices. This suggests that transaction prices may be increasing because, a long time before the game, people earlier, which is not true of event tickets. Second, discounting might affect behavior in the timeframes I consider. But it would tend to make buyers willing to pay more for later transactions and sellers willing to accept less for earlier transactions, and so would rationalize prices that were increasing not decreasing.

4.1 Seller Explanations 1 and 2: Falling Opportunity Costs and Time-Varying Demand/Revenue Elasticities

The first two explanations can be described in a single framework. Suppose that a risk-neutral seller i has a single ticket to sell and that there are two time periods before the game, t , , where period 1 happens first. The sellers get a payoff of \$$v_i$ if the ticket is unsold after period 2. This payoff could be the utility from going to the game or giving the ticket to a friend, or the expected price from selling the ticket offline. For now I assume that the seller sets a fixed price p_{it} in each period and that the probability that the ticket sells is Q_{it} p_{it} where $\frac{\partial Q_{it}(p_{it})}{\partial p_{it}} <$. This probability of sale, or demand, function will reflect the quality of i's ticket, the extent of competition from other sellers and the prices that they set, the arrival rate of heterogeneous buyers and their ability to substitute between periods and between differentiated tickets. I assume that seller i knows Q_{it} p_{it} for both periods in advance and that Q_{i2} does not depend on p_{i1}.[17] i will therefore set prices p_{i1} and p_{i2} by solving

$$_{p_{i1},p_{i2}} p_{i1}Q_{i1}\ p_{i1} \quad p_{i2}Q_{i2}\ p_{i2} \quad Q_{i1}\ p_{i1} \quad v_i \quad Q_{i2}\ p_{i2} \quad Q_{i1}\ p_{i1} \tag{1}$$

Assuming that the relevant seco

These are the standard price-setting formulae for sellers with marginal costs of selling of v_i in the second period and $p_{i2}Q_{i2}\ p_{i2} \quad v_i \quad Q_{i2}\ p_{i2}$. In what follows I will call these costs the “opportunity cost” of selling the ticket and it increases with future selling opportunities. Equation (2) implies that $p_{i2} > v_i$. If $Q_{i1}\ p_i \quad Q_{i2}\ p_i$ (i.e., the demand function is the same in both periods) then it also follows that $p_{i1} > p_{i2}$ and prices tend to fall over time and, of course, the same logic applies with more periods.[18]

Given estimates of the Q function and observed prices, this equation can be rearranged to estimate opportunity costs

$$\widehat{o_{it}} \quad p_{it} \quad \frac{Q_{it} \backslash p_{it}}{\widehat{\frac{\partial Q_{it}}{\partial p_{it}}}} \tag{7}$$

and, using (6), the separate roles of declining opportunity costs and changing demand elasticities in causing prices to fall over time can be identified. Observable variables which a ect opportunity costs

The next sub-section details the specifications used. The following sub-section describes how I address price endogeneity. I then describe the empirical results, which support the hypothesis that prices falls because of declining opportunity costs rather than changing elasticities, consistent with revenue management models. This qualitative result is robust across various specifications, although some magnitudes are more sensitive.

5.1 Empirical Specifications

5.1.1 Pure Fixed Price Listings

A fixed price listing can either result in a sale at the stated fixed price or no sale. The probability of sale function is modeled as a probit function of observed listing characteristics (X_{it}), the listed fixed price (p_{it}, defined per seat including shipping costs) and the characteristics and prices of competing listings (X_{-it} and p_{-it})

$$Q_{it} \; p_{it} \qquad p_{it}, X_{it}, p_{-it}, X_{-it}, \theta$$

not include game-section fixed e ects. Instead, I include home team, home team*face value (in levels or logs depending on how prices are defined) and home team*expected attendance variables (based on the attendance model described in Section 3) and address endogeneity issues using the instruments described below.

Competition variables are defined based on listings for the same number of tickets, to the same game and with the same face value which were available at the time the listing was posted. I only use listings available at the time of posting as I want to estimate the seller's expected probability of

5.1.2 Pure Auction Listings

Auction listings have the additional feature that a seller's revenues in the event of sale may be above that start price. The probability that the listing results in a sale is modeled using a probit in the same way as fixed price listings. The observed revenue (R_{it}) in the event of a sale is modelled as a left-censored normal regression where realizations of the latent variable R_{it} below the auction start price result in revenues equal to the start price

$$
\begin{aligned}
R_{it} &\quad f \; p_{it}, X_{it}, p_{-it}, X_{-it}, \theta^{R} \quad \varepsilon_{it} \;\; \varepsilon_{it} \quad N \quad , \sigma_R^2 \qquad (8) \\
R_{it} &\quad R_{it} \text{ if } R_{it} \quad p_{it} \\
&\quad p_{it} \text{ if } R_{it} < p_{it}
\end{aligned}
$$

I assume that there is no correlation in the residual terms in the probit and censored regression functions so that - once I have addressed endogeneity - these models can be estimated separately. The auction start price and revenues are both expressed on a per seat basis and are calculated to include per seat shipping costs. The remaining control variables are the same as in the fixed price model.

The estimation sample consists of pure auction listings made in the 90 days before the game with non-missing face value information.[24]

5.1.3 Hybrid Auction Listings

Hybrid auction listings have the additional complicating feature that a listing can be sold at either the fixed price or at a price weakly above the auction start price. I model the outcome of the auction as being determined by a multinomial logit with three possible outcomes: no sale, a fixed price sale and an auction sale. In the third case, expected revenues are determined using the censored regression model as before.

[24] I include the fixed price with personal o er listings in this specification as all of the sales which I see in this format are at the fixed price.

where Z_{it} are the instruments excluded, by assumption, from the Q_{it} function. u_{it} and v_{it} are mean zero bivariate normal, and prices are endogenous if u_{it} and v_{it} are correlated. The two-step procedure exploits the fact that under joint normality and the normalization that Var u

$$u_{it} \quad v_{it}\theta_3 \quad e_{it} \tag{11}$$

where $\theta_3 \quad \frac{\text{Cov}(u,v)}{\text{Var}(v)}$ estimates and e is normal and independent of $\widetilde{X}$, Z and v. In the first step OLS is used to estimate (10) yielding consistent estimates of the vs. These $\widehat{v}$s estimates are included in the second-step probit equation to give estimates of the θ parameters. The probit coefficients have to be scaled because the variance of e is corr u, v ^{2} rather than 1. The significance of the coefficients on $\widehat{v}$ provides a test of whether there is an endogeneity problem. I calculate standard errors using a bootstrap procedure to account for the effects of sampling error in the first step.

A similar approach can be used for the probit and censored regression (Wooldridge (2002), p. 530) models used for pure auction listings, and the censored regression model used for hybrid auction listings. Addressing endogeneity in the context of the multinomial logit model used to determine the probability of each outcome in the hybrid auction model is theoretically more difficult because the residuals in the logit model are not normal. I follow the "practical" approach suggested by Wooldridge instruments have a sensible pattern, although there is also some evidence that there may be selection of different types of seller into different types of mechanism (which is not necessarily a problem as long as the selection characteristics are not valued by buyers). The distance coefficients show that as

Second Step Coefficients Table 8 shows selected coe cients from three specifications of the probit model. The specification in column (1) ignores the endogeneity of prices. In column (2) I use the two-step approach to account for the endogeneity of a seller's own price and in column (3) I allow for both own and competitors' prices to be endogenous. The coe cients in columns (2) and (3) have been rescaled so that are comparable with those in column (1) and with the coe cients that would be produced by FIML estimation if that was feasible. Average demand elasticities (at observed prices) for each of the four time periods are reported at the bottom of the table.

The own price coe cients and the price elasticities clearly show that taking account of the endogeneity of the seller's own price matters. As usual, addressing endogeneity increases the elasticity of demand. In fact, without controlling for endogeneity the average price elasticities could only be ra-

cients fro.27873.4 b41.7(88(s)-1(e)]T0)4.1()4.3(w1 coe cients and the elasticities of demand, and as these are critical in what follows I use the coe cients from column (2) below.

[NOTE: I will change to column (3), although the numbers are very similar].

Implied Option Values and Illustrative Counterfactuals Figure 2 shows the distributions of implied option values for each of the four time periods. There is one implied option value for each observation and the densities are estimated using a normal kernel density estimator (the default in MATLAB) with 171 points of support. To avoid clutter I do not show standard error bands around the density estimates but these are small (for example, around the peak of the "1-10 Day Prior" density the values of the density minus and plus one standard error would be 0.034 and 0.036). A nice feature of the results is that, consistent with free disposal, only 3.8% of the implied option values are less than $0 even in the final (1-10 day) time period, and less than 0.1% of observations have negative option values in the first (more than 41 day) period. Mean option values fall from $48.95 in the first period to $23.00 in the last period, with median values falling from $41.04 to $15.85.

The role that declining option values and changing demand elasticities play in causing fixed prices to fall can be seen using two counterfactual experiments, the results of which are shown in Table 9. The top section of the table shows the mean and standard deviation of prices observed in each time period in the data.

In the first counterfactual I recompute optimal prices using (6), given the estimated option value for each ticket, removing any demand e ect by making both the intercept and the slope of the demand curve the same as they are estimated to be 41 to 44 days before the game. Optimal prices in this 4 day period are the same as those observed in the data and the remaining prices in first time period change only slightly due to small changes in the demand intercept. In the later time periods, counterfactual prices are slightly lower than observed prices because (in the data) demand becomes less elastic as the

In the second counterfactual I recompute optimal prices using estimated demand, changing option values in the later time periods so that the mean of the distribution of option values in the later periods is the same as in the first period (the shape remains di erent). In this case, with the declining option value e ect removed, the e ect of the falling demand elasticity in tending to increase prices is even clearer.

5.3.2 Auction Listings

5.3.3 Initial Results

Table 10 shows selected coe cients for the two parts of the model using the control function approach. Once again, the coe cients on the time interactions with prices set by the seller are small in both the logit and the truncated normal models and the sign of these coe cients tends to indicate that sale probabilities and revenues tend to become less elastic with respect to the auction start price as the game approaches. This implies that the price declines will be explained by changes in option values.

The implied distribution of option values (calculated using the first order condition for the auction start price) in each of three time periods [NOTE: I will change this to four] is shown in Figure 3. As before only a small proportion of option values are estimated to be less to zero, although a much

6 Why Do Some People Purchase Early if Prices Are Expected to Fall?

A potential objection to falling prices being the equilibrium outcome is that consumers might want to delay purchasing.[28] The issue of how strategic buyers may a ect the strategies of people selling perishable goods has been recently considered in the theoretical literature (e.g., Liu and van Ryzin (2008)). This literature has emphasized how buyer risk aversion, uncertainty about future availability and search costs (i.e., the cost of returning to the market at a later date) can lead to early purchasing even when the prices are expected to fall. In this Section, I ask whether, given uncertainties about availability and prices, observed early purchasing can be rationalized given plausible levels of risk aversion and search costs by calibrating a particular model of buyer utility.[29]

6.1 A Simple Model of Buyer Utility with Risk Aversion, Uncertain Availability and Prices, and Search Costs

Suppose that a buyer i's utility from buying a ticket she values at \$$v_i$ at a price of p is given by

$$u \; v_i, p, \alpha_i \qquad \frac{\quad}{\alpha_i} \qquad \alpha_i \; v_i \quad p \;\;, \; \alpha_i >$$

These preferences display constant absolute risk aversion (CARA). Ackerberg et al. (2006) use CARA preferences to analyze risk aversion on EBay and it is convenient because choices over when to buy tickets will not depend on the buyer's unobserved initial endowment of wealth.

Now suppose that there are two periods and that i's choice is between buying this ticket in period 1 at a price of p_1

pay a search cost \$$s_i$. Assuming that a ticket purchased in period 2 will also be valued at \$$v_i$ then she will choose to purchase in period 1 if and only if

$$\overline{\alpha_i} \quad \alpha_i \; v_i \quad p_1 \quad \overline{\alpha_i} \quad \alpha_i s_i \left(\begin{array}{l} q \int_0^{v_i} \quad \alpha_i \; v_i \quad p_2 \quad f_2 \; p_2 \; dp_2 \\ \qquad\qquad q \quad q \int^{\infty} \end{array} \right.$$

point for considering a question which has not reall

These facts alone suggest that if a buyer was only able to visit the market once then she choose to do so between 5 and 10 days before the game, when availability is highest and prices are lowest. For this reason I focus on early purchasers choosing between purchasing early and returning to the market five days before the game. Their decision not to wait should be driven by the expected gains from waiting being su ciently small. The bottom diagram in Figure 4 shows the average $ per seat potential gain from waiting (in terms of a lower price) if tickets are available for people who actually purchased on di erent dates, together with the proportion of these buyers for whom better tickets would have been available. 88% of people buying 30-34 days before a game would have found better tickets available had they waited until fi a higher face value (at least for the face values covered by almost all of the data), a better row and a better seller. Availability is higher for games with higher expected attendance indicating that the supply curve in the secondary market is upward sloping, although, conditional on expected attendance, it is lower on weekends than during the week (which is consistent with season ticket holders having more time to go to games on weekends). Consistent with Figure 4, the average predicted q is 0.88.

6.3.1 Assumptions on v_i and s_i and the Calculation of α_i

While I observe realized prices and availability, I do not observe buyers' valuations (v_i) or their costs of returning to the market at a later date (s_i). I therefore consider ranges of values for these parameters. Valuations are allowed to be either some proportion above the purchase price paid (10%, 50%, 100% or 400%) or some absolute ($) amount above the purchase price ($10, $20, $50, $100).[35] For convenience, I call $v_i \quad p_1$ the buyer's surplus in what follows. Search costs are assumed to be $0, $5, $10 or $20 per seat.

To understand the calculation of the coe cient of absolute risk aversion (α_i) consider an example. Suppose that a pair of Loge Box 512 Row D tickets to the Seattle Mariners at the New York Yankees on May 6 is purchased 30 days before the game for $80 per seat ($p_1$). These characteristics are used to calculate the expected availability of better tickets and the distribution of the price of the cheapest available better ticket using the probit and gamma models. Suppose that I assume that the valuation is 50% more than the price paid (v_i) and that there are no search costs (s_i), then these values and distributions can be plugged into (13) and a simple computation will find the lowest value of α_i (risk aversion) for which the inequality holds and early purchasing is rationalized. $\widehat{\alpha_i}$ is set equal to 0 if the purchase is rationalized by risk neutrality.

6.4 Results

Figure 5 shows the proportion of purchases made more than ten days before the game with non-missing ticket face value information which can be rationalized for di erent levels of α under various assumptions on v_i and s_i. The diagram does not show standard errors, but application of a bootstrap shows that these are small (of the order of 2 percentage points or less which would make them hard to see).

In the first diagram, valuations are assumed to be proportional to prices paid and there are assumed

[35] In the proportional valuation case I assume that valuatio

to be no search costs. Even when buyer surplus is assumed to be only 10% of the purchase price, risk neutrality rationalizes nearly 40% of observed purchases. This set includes purchases at unusually low prices (even though they happen some time before the game) and purchases where better tickets are relatively unlikely to be available. For example, 75% of purchases for 4 or more seats are rationalized under risk neutrality.

To interpret the figure it is necessary to have some idea of what levels of risk aversion are plausible. Suppose that a person is o

Costs of return of $10 or $20 per seat may seem high for a market which is readily accessible

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Figure 1

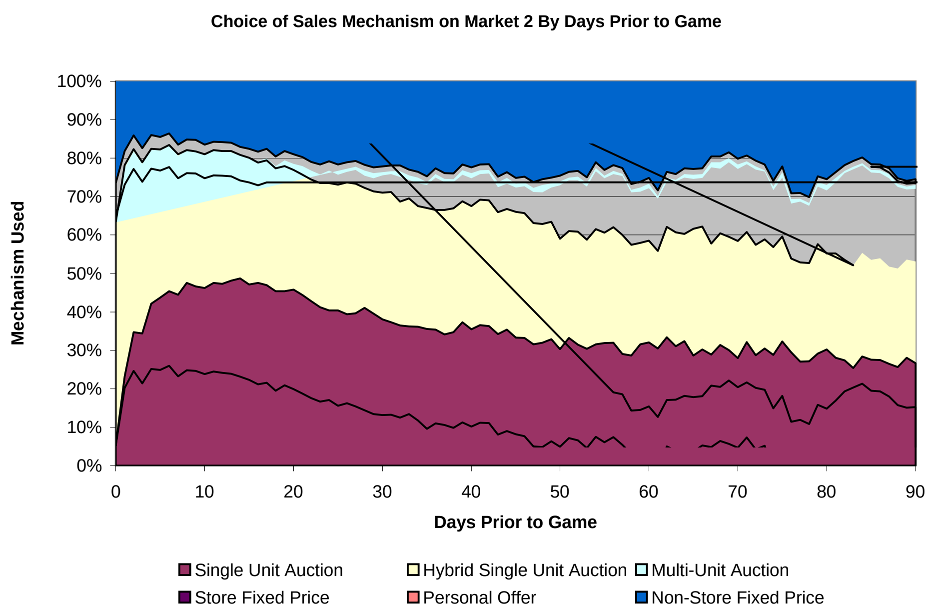

Choice of Sales Mechanism on Market 2 By Days Prior to Game
Mechanism Used
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
0
10
20
30
40
50
60
70
80
90
Days Prior to Game
Single Unit Auction
Hybrid Single Unit Auction
Multi-Unit Auction
Store Fixed Price
Personal Offer
Non-Store Fixed Price

Figure 3: Distribution of Option Values Implied by Control Function Auction Model (Log Specification)

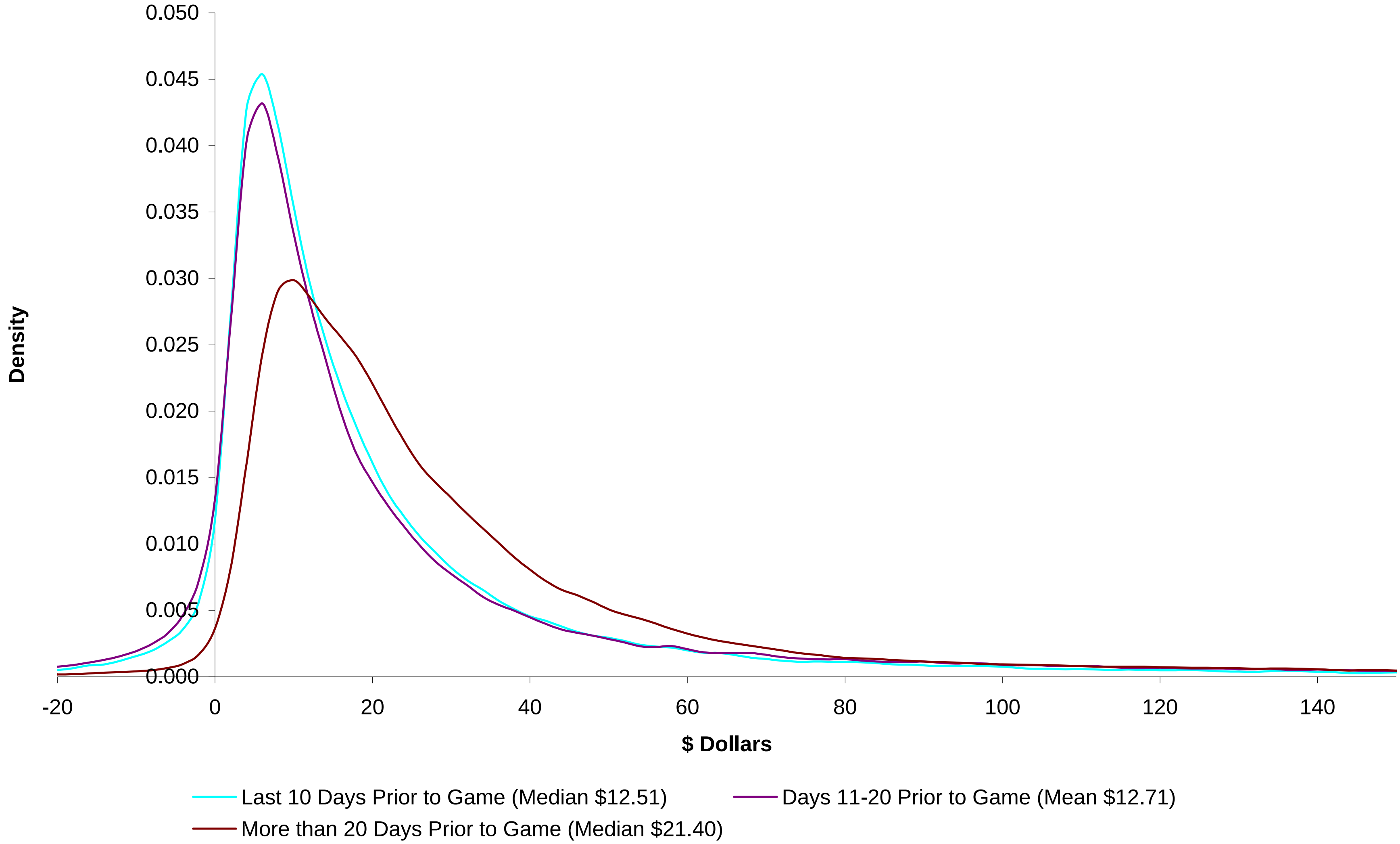


Figure 4: Analysis of Prices and Availability of "Better" Tickets

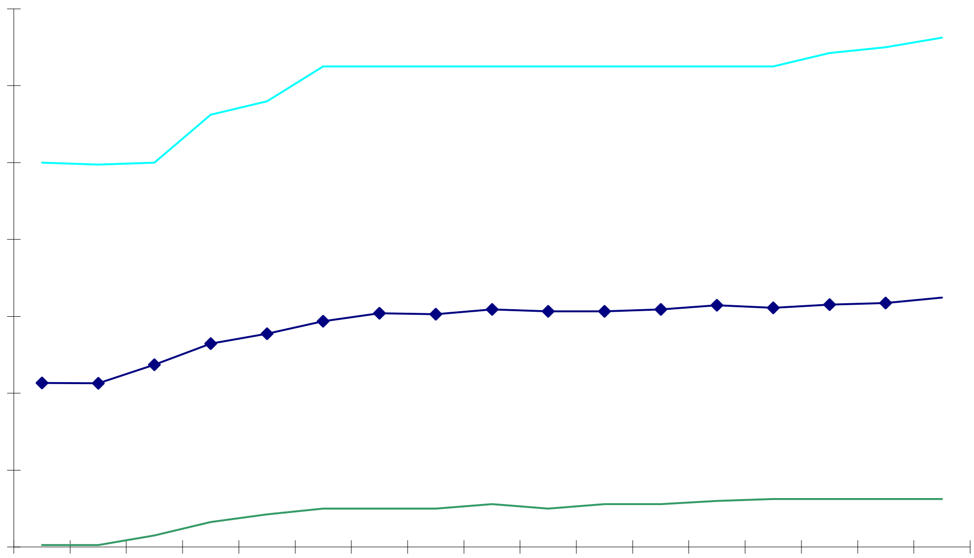
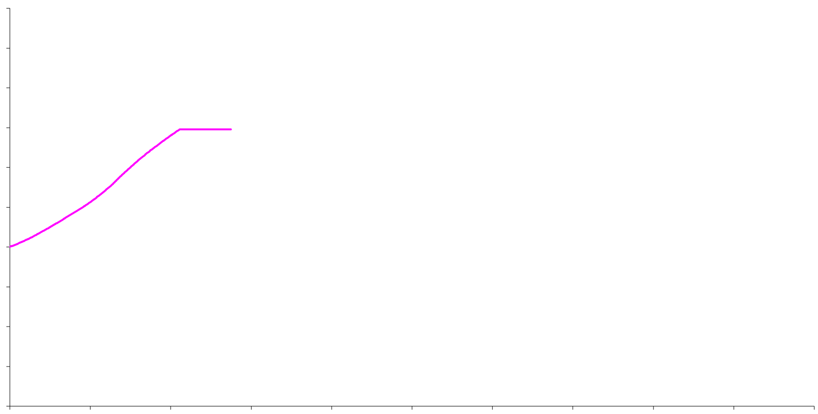


Figure 5
Coefficients of Absolute Risk Aversion Required to Rationalize Observed Early Purchasing
When Alternative is to Return to Market 2 5 Days Before the Game
Sample Includes All Tickets Purchased More than
10 Days Before the Game for More than $10 Per Seat



	Average Attendance As % of Max Attendance	Stubhub # listings	Market 2 # listings	Market 2 # transactions	Market 2 HHI*10,000	Market 2 Mean $ Transaction Price Per Seat	Market 2 Mean $ Face Value of Purchased Tickets			Median Distance of Buyer from Stadium (Miles)
Arizona Diamondbacks	0.57	91,758	4,883	2,246	186	42.01	39.97	15.5	6	20.6

No.of Seats in Listing	Stubhub # listings	Market 2 # listings	Market 2 # transactions

No. of Listings	No. of Transactions

Table 3: Stubhub List Prices

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Sample	All	All	All	All	Face not missing	Face <= $20	Face >=$45	Exp Att > 95%	Exp Att 85-95%	Exp Att 75-85%	Exp Att <75%
Dep. Var	Log(Seller Price)	Log(Seller Price)	Seller Price $	Log(Buyer Price)	Seller/Face	Log(Buyer Price)	Log(Buyer Price)	Log(Buyer Price)	Log(Buyer Price)	Log(Buyer Price)	Log(Buyer Price)
Day to Go Dummies (0-2 excluded)											
3 to 5 days	0.0727***	0.0954***	4.558***	0.0954***	0.114***	0.104***	0.0956***	0.0538***	0.0891***	0.104***	0.120***
	(0.0046)	(0.0042)	(0.3100)	(0.0036)	(0.0092)	(0.0110)	(0.0055)	(0.0088)	(0.0073)	(0.0100)	(0.0074)
6 to 8 days	0.113***	0.146***	7.407***	0.144***	0.186***	0.159***	0.148***	0.0916***	0.144***	0.163***	0.178***
	(0.0052)	(0.0048)	(0.3600)	(0.0041)	(0.0110)	(0.0130)	(0.0062)	(0.0097)	(0.0084)	(0.0120)	(0.0086)
9 to 11 days	0.142***	0.181***	9.317***	0.173***	0.239***	0.196***	0.182***	0.117***	0.179***	0.204***	0.215***
	(0.0053)	(0.0050)	(0.3700)	(0.0042)	(0.0110)	(0.0130)	(0.0064)	(0.0099)	(0.0088)	(0.0130)	(0.0089)
12 to 14 days	0.162***	0.205***	10.69***	0.193***	0.273***	0.221***	0.206***	0.136***	0.203***	0.226***	0.242***
	(0.0054)	(0.0050)	(0.3800)	(0.0043)	(0.0110)	(0.0140)	(0.0065)	(0.0099)	(0.0088)	(0.0130)	(0.0090)
15 to 17 days	0.175***	0.223***	11.54***	0.171***	0.296***	0.240***	0.224***	0.140***	0.218***	0.245***	0.269***
	(0.0054)	(0.0051)	(0.3800)	(0.0044)	(0.0110)	(0.0140)	(0.0065)	(0.0099)	(0.0089)	(0.0130)	(0.0090)
18 to 20 days	0.187***	0.237***	12.33***	0.184***	0.318***	0.256***	0.237***	0.149***	0.231***	0.260***	0.289***
	(0.0054)	(0.0051)	(0.3800)	(0.0044)	(0.0120)	(0.0140)	(0.0065)	(0.0100)	(0.0090)	(0.0130)	(0.0091)
21 to 23 days	0.197***	0.249***	13.10***	0.194***	0.337***	0.265***	0.249***	0.153***	0.244***	0.271***	0.306***
	(0.0055)	(0.0052)	(0.3800)	(0.0044)	(0.0120)	(0.0140)	(0.0065)	(0.0100)	(0.0090)	(0.0130)	(0.0092)
24 to 26 days	0.204***	0.260***	13.70***	0.204***	0.357***	0.278***	0.256***	0.158***	0.256***	0.281***	0.320***
	(0.0055)	(0.0052)	(0.3800)	(0.0044)	(0.0120)	(0.0140)	(0.0065)	(0.0100)	(0.0091)	(0.0130)	(0.0093)
27 to 29 days	0.211***	0.269***	14.20***	0.212***	0.372***	0.292***	0.265***	0.164***	0.263***	0.293***	0.329***
	(0.0055)	(0.0052)	(0.3800)	(0.0044)	(0.0120)	(0.0140)	(0.0066)	(0.0100)	(0.0091)	(0.0130)	(0.0093)
30 to 32 days	0.217***	0.276***	14.66***	0.219***	0.384***	0.301***	0.273***	0.170***	0.270***	0.302***	0.340***
	(0.0055)	(0.0052)	(0.3800)	(0.0045)	(0.0120)	(0.0140)	(0.0066)	(0.0100)	(0.0091)	(0.0130)	(0.0094)
33 to 35 days	0.222***	0.283***	15.15***	0.225***	0.396***	0.309***	0.281***	0.173***	0.278***	0.314***	0.348***
	(0.0055)	(0.0052)	(0.3800)	(0.0045)	(0.0120)	(0.0140)	(0.0066)	(0.0100)	(0.0091)	(0.0130)	(0.0094)
36 to 38 days	0.229***	0.291***	15.65***	0.233***	0.411***	0.316***	0.286***	0.175***	0.287***	0.325***	0.358***
	(0.0055)	(0.0052)	(0.3900)	(0.0045)	(0.0120)	(0.0140)	(0.0066)	(0.0100)	(0.0092)	(0.0130)	(0.0095)
39 to 41 days	0.234***	0.297***	16.07***	0.238***	0.423***	0.323***	0.292***	0.177***	0.291***	0.331***	0.368***
	(0.0056)	(0.0053)	(0.3900)	(0.0045)	(0.0120)	(0.0150)	(0.0067)	(0.0100)	(0.0092)	(0.0130)	(0.0095)
42 to 44 days	0.237***	0.302***	16.39***	0.242***	0.432***	0.328***	0.296***	0.182***	0.296***	0.337***	0.371***
	(0.0056)	(0.0053)	(0.3900)	(0.0045)	(0.0120)	(0.0150)	(0.0067)	(0.0100)	(0.0092)	(0.0140)	(0.0096)
45 to 47 days	0.243***	0.308***	16.79***	0.248***	0.445***	0.337***	0.301***	0.188***	0.302***	0.345***	0.376***
	(0.0056)	(0.0053)	(0.3900)	(0.0046)	(0.0120)	(0.0150)	(0.0067)	(0.0100)	(0.0093)	(0.0140)	(0.0096)
48 to 50 days	0.245***	0.312***	17.05***	0.252***	0.452***	0.343***	0.304***	0.191***	0.307***	0.350***	0.380***
	(0.0056)	(0.0053)	(0.3900)	(0.0046)	(0.0120)	(0.0150)	(0.0068)	(0.0100)	(0.0094)	(0.0140)	(0.0097)
51 to 55 days	0.248***	0.317***	17.35***	0.257***	0.462***	0.351***	0.309***	0.197***	0.312***	0.354***	0.385***
	(0.0057)	(0.0054)	(0.3900)	(0.0046)	(0.0120)	(0.0150)	(0.0068)	(0.0100)	(0.0094)	(0.0140)	(0.0097)
56 to 60 days	0.251***	0.322***	17.73***	0.262***	0.474***	0.358***	0.313***	0.201***	0.318***	0.359***	0.390***
	(0.0057)	(0.0054)	(0.4000)	(0.0046)	(0.0120)	(0.0150)	(0.0068)	(0.0110)	(0.0095)	(0.0140)	(0.0098)
61 to 70 days	0.256***	0.330***	18.30***	0.269***	0.490***	0.365***	0.319***	0.209***	0.323***	0.370***	0.400***
	(0.0058)	(0.0055)	(0.4000)	(0.0047)	(0.0130)	(0.0150)	(0.0069)	(0.0110)	(0.0096)	(0.0140)	(0.0099)
71 to 80 days	0.260***	0.339***	18.95***	0.278***	0.509***	0.378***	0.326***	0.213***	0.333***	0.380***	0.412***
	(0.0059)	(0.0056)	(0.4100)	(0.0048)	(0.0130)	(0.0150)	(0.0070)	(0.0110)	(0.0098)	(0.0140)	(0.0100)
81 plus	0.276***	0.363***	20.70***	0.301***	0.559***	0.413***	0.349***	0.226***	0.355***	0.412***	0.436***
	(0.0061)	(0.0058)	(0.4200)	(0.0050)	(0.0130)	(0.0160)	(0.0073)	(0.0110)	(0.0100)	(0.0150)	(0.0100)
Home Team Form Variables											
Games Ahead	0.00987***	0.00102	0.589***	0.000673	0.00933*	-0.0240***	0.00846***	-0.00454**	-0.00444	-0.0290***	-0.00831
	(0.0021)	(0.0018)	(0.1700)	(0.0016)	(0.0056)	(0.0070)	(0.0021)	(0.0023)	(0.0050)	(0.0064)	(0.0053)
Games Back	-0.0195***	-0.0185***	-0.792***	-0.0161***	-0.0264***	-0.0235***	-0.0138***	-0.0157***	-0.0124***	-0.0215***	-0.0156***
	(0.0009)	(0.0008)	(0.0520)	(0.0007)	(0.0020)	(0.0021)	(0.0009)	(0.0023)	(0.0014)	(0.0018)	(0.0013)
Games Ahead *	-0.0000741***	-0.0000174	-0.00642***	-0.0000157	-0.0000939*	0.000183***	-0.0000889***	0.0000205	-0.0000116	0.000191***	0.0000657
Games to Go	(0.0000)	(0.0000)	(0.0016)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
Games Back *	0.000102***	0.0000970***	0.00259***	0.0000814***	0.000108***	0.000166***	0.0000662***	0.0000653***	0.0000302**	0.000119***	0.0000980***
Games to Go	(0.0000)	(0.0000)	(0.0005)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Fixed Effects	Game-Section	Game-Section -Row	Game-Section -Row	Game-Section -Row	Game-Section -Row	Game-Section -Row	Game-Section -Row	Game-Section -Row	Game-Section -Row	Game-Section -Row	Game-Section -Row
Average Seller Price $	74.48	74.48	74.48	74.48	73.5	31.35	119.32	95.93	73.71	61.83	64.44
Within R^2	0.12	0.10	0.05	0.08	0.04	0.09	0.14	0.06	0.11	0.12	0.15
Observations	3,361,062	3,361,062	3,361,062	3,361,062	3,299,714	845,651	1,107,116	828,083	1,012,336	657,482	863,161

Notes: all regressions include dummies for the number of seats in the listing (1-6), the feedback score of the seller (4 dummies), whether the seller is a store owner, dummies for ticket characteristics (piggy back, aisle seats and whether parking included) and a dummy for if seller feedback or shipping cost information is missing (1,352 observations). Regressions with game-section fixed effects also include variables to control for row quality (row number, first row and second row dummies and dummies for if row information is not available or not applicable). Standard errors in parentheses. ***,** and * denote significance at the 1, 5 and 10% levels. Within R^2 does not include fixed effects. Full R^2s are around 0.8.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Sample	All	All	All	All	Fixed Price Sales	Face <= $20	Face >=$45	Exp Att > 95%	Exp Att 85-95%	Exp Att 75-85%	Exp Att <75%
Dep. Var	Log(Buyer Price)	Log(Buyer Price)	Log(Seller Price)	Log(Buyer Price)	Log(Buyer Price)	Log(Buyer Price)	Log(Buyer Price)	Log(Buyer Price)	Log(Buyer Price)	Log(Buyer Price)	Log(Buyer Price)
Day to Go Dummies (0-2 excluded)											
3 to 5 days	0.0526***	0.0469***	-0.0147***	0.0746***	0.118***	0.0297***	0.0345***	0.0551***	0.0311***	0.0490***	0.0858***
	(0.0042)	(0.0065)	(0.0057)	(0.0041)	(0.0074)	(0.0079)	(0.0097)	(0.0070)	(0.0080)	(0.0120)	(0.0086)
6 to 8 days	0.0484***	0.0618***	-0.00814	0.0768***	0.161***	0.0151*	0.0559***	0.0699***	0.0216**	0.0162	0.0788***
	(0.0046)	(0.0070)	(0.0062)	(0.0045)	(0.0086)	(0.0086)	(0.0110)	(0.0077)	(0.0089)	(0.0120)	(0.0091)
9 to 11 days	0.117***	0.122***	0.0904***	0.133***	0.192***	0.110***	0.119***	0.153***	0.103***	0.0656***	0.117***
	(0.0051)	(0.0077)	(0.0070)	(0.0050)	(0.0091)	(0.0096)	(0.0120)	(0.0084)	(0.0100)	(0.0140)	(0.0100)

Table 5: Market 2 Listings

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample	Fixed Prices	Auctions	Fixed Prices	Auctions	Fixed Prices	Auctions	Fixed Prices	Auctions
Teams	All	All	All	All	Most Listed	Most Listed	Less Listed	Less Listed
Dep. Var	Log(Fixed Price)	Log(Auction Start)	Log(Fixed Price)	Log(Auction Start)	Log(Fixed Price)	Log(Auction Start)	Log(Fixed Price)	Log(Auction Start)
DTG Counted	Listing Start Date	Listing Start Date	Listing End Date	Listing End Date	Listing Start Date	Listing Start Date	Listing Start Date	Listing Start Date
Day to Go Dummies (0-2 excluded)								
3 to 5 days	0.134***	0.0228	0.114***	-0.0409***	0.142***	0.0382*	0.103***	-0.0494
	(0.007)	(0.018)	(0.005)	(0.014)	(0.007)	(0.020)	(0.013)	(0.037)
6 to 8 days	0.200***	-0.0356*	0.165***	-0.0663***	0.206***	-0.00264	0.173***	-0.178***
	(0.007)	(0.019)	(0.005)	(0.017)	(0.008)	(0.022)	(0.013)	(0.040)
9 to 11 days	0.264***	0.00351	0.205***	0.0900***	0.271***	0.0443*	0.237***	-0.172***
	(0.007)	(0.020)	(0.006)	(0.019)	(0.008)	(0.023)	(0.014)	(0.043)
12 to 14 days	0.302***	-0.0153	0.233***	0.204***	0.306***	0.0122	0.281***	-0.144***
	(0.007)	(0.021)	(0.006)	(0.020)	(0.008)	(0.024)	(0.014)	(0.043)
15 to 17 days	0.327***	0.107***	0.256***	0.319***	0.331***	0.167***	0.308***	-0.121**
	(0.007)	(0.023)	(0.006)	(0.022)	(0.009)	(0.026)	(0.014)	(0.048)
18 to 20 days	0.365***	0.242***	0.267***	0.326***	0.364***	0.264***	0.357***	0.125**
	(0.007)	(0.024)	(0.007)	(0.025)	(0.009)	(0.028)	(0.014)	(0.050)
21 to 23 days	0.382***	0.344***	0.288***	0.346***	0.385***	0.385***	0.365***	0.164***
	(0.008)	(0.025)	(0.007)	(0.028)	(0.009)	(0.028)	(0.015)	(0.055)
24 to 26 days	0.386***	0.371***	0.287***	0.351***	0.384***	0.412***	0.383***	0.188***
	(0.008)	(0.028)	(0.007)	(0.028)	(0.009)	(0.032)	(0.017)	(0.060)
27 to 29 days	0.405***	0.366***	0.297***	0.380***	0.410***	0.394***	0.385***	0.233***
	(0.008)	(0.030)	(0.008)	(0.030)	(0.010)	(0.034)	(0.016)	(0.059)
30 to 32 days	0.413***	0.388***	0.302***	0.518***	0.417***	0.388***	0.394***	0.357***
	(0.009)	(0.031)	(0.008)	(0.030)	(0.010)	(0.036)	(0.017)	(0.062)
33 to 35 days	0.416***	0.411***	0.323***	0.537***	0.418***	0.430***	0.405***	0.308***
	(0.009)	(0.033)	(0.008)	(0.031)	(0.010)	(0.038)	(0.018)	(0.062)
36 to 38 days	0.422***	0.462***	0.318***	0.567***	0.425***	0.494***	0.406***	0.309***
	(0.009)	(0.033)	(0.008)	(0.034)	(0.010)	(0.038)	(0.020)	(0.065)
39 to 41 days	0.440***	0.552***	0.303***	0.642***	0.440***	0.584***	0.431***	0.403***
	(0.010)	(0.034)	(0.008)	(0.036)	(0.011)	(0.039)	(0.021)	(0.070)
42 to 44 days	0.440***	0.601***	0.313***	0.551***	0.437***	0.665***	0.449***	0.321***
	(0.010)	(0.035)	(0.009)	(0.037)	(0.012)	(0.040)	(0.019)	(0.070)
45 to 47 days	0.440***	0.587***	0.307***	0.621***	0.436***	0.610***	0.451***	0.493***
	(0.009)	(0.038)	(0.010)	(0.038)	(0.011)	(0.043)	(0.019)	(0.077)
48 to 50 days	0.434***	0.659***	0.320***	0.611***	0.433***	0.716***	0.432***	0.412***
	(0.010)	(0.040)	(0.009)	(0.039)	(0.011)	(0.045)	(0.023)	(0.077)
51 to 55 days	0.430***	0.625***	0.305***	0.706***	0.431***	0.652***	0.418***	0.511***
	(0.009)	(0.034)	(0.008)	(0.033)	(0.010)	(0.038)	(0.020)	(0.069)
56 to 60 days	0.447***	0.710***	0.321***	0.694***	0.446***	0.718***	0.445***	0.664***
	(0.009)	(0.035)	(0.008)	(0.035)	(0.010)	(0.040)	(0.019)	(0.065)
61 to 70 days	0.464***	0.741***	0.341***	0.752***	0.462***	0.751***	0.460***	0.698***
	(0.008)	(0.030)	(0.007)	(0.030)	(0.009)	(0.035)	(0.018)	(0.059)
71 to 80 days	0.479***	0.806***	0.357***	0.761***	0.482***	0.814***	0.458***	0.780***
	(0.009)	(0.033)	(0.008)	(0.032)	(0.009)	(0.037)	(0.020)	(0.064)
81 plus	0.521***	0.907***	0.385***	0.892***	0.528***	0.897***	0.483***	0.952***
	(0.008)	(0.029)	(0.008)	(0.028)	(0.009)	(0.032)	(0.017)	(0.060)
Home Team Form Variables								
Games Ahead	0.0109***	-0.0374***	0.00814***	-0.0374***	0.00961***	-0.0431***	0.00162	-0.0509
	(0.003)	(0.013)	(0.003)	(0.013)	(0.003)	(0.013)	(0.011)	(0.032)
Games Back	-0.0208***	-0.0222***	-0.0199***	-0.0221***	-0.0288***	-0.0354***	-0.00874***	-0.000856
	(0.001)	(0.004)	(0.001)	(0.004)	(0.002)	(0.005)	(0.002)	(0.008)
Games Ahead * Games to Go	-0.000036	0.000393***	-0.0000221	0.000393***	-0.0000209	0.000422***	0.0000501	0.000552*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Games Back * Games to Go	0.0000734***	0.000285***	0.0000658***	0.000290***	0.000129***	0.000375***	0.0000221	0.000137
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fixed Effects	Game-Section	Game-Section	Game-Section	Game-Section	Game-Section	Game-Section	Game-Section	Game-Section
Sale Format Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Average Dep Var $	69.88	34.94	69.88	34.94	73.22	36.19	60.61	31.29
Within R^2	0.12	0.16	0.10	0.16	0.12	0.16	0.12	0.17
Observations	390,834	450,425	390,834	450,425	287,067	335,020	103,767	115,405

Notes: all regressions include dummies for the number of seats in the listing (1-6), the feedback score of the seller (4 dummies), whether the seller is a store owner, dummies for ticket characteristics (piggy back, aisle seats and whether parking included) and a dummy for if seller feedback is missing. Regressions with game-section fixed effects also include variables to control for row quality (row number, first row and second row dummies and dummies for if row information is not available or not applicable). Standard errors in parentheses. ***,** and * denote significance at the 1, 5 and 10% levels.

Fixed price sample includes pure fixed price, personal offer and hybrid auction listings. Auction sample includes pure single unit auctions, hybrid auctions and multiple unit auctions.

Cluster

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)		
Sample	Market 2 Fixed Prices	Market 2 Fixed Prices	Market 2 Auctions	Market 2 Auctions	Stubhub Likely First Listing	Stubhub Likely First Listing	Market 2 Fixed Prices Experienced	Market 2 Fixed Prices Experienced	Market 2 Fixed Prices Inexperienced	Market 2 Fixed Prices Inexperienced		
Dep. Var	Log(Fixed Price)	Log(Fixed Price)	Log(Auction Start)	Log(Auction Start)	Log(Fixed Price)	Log(Fixed Price)	Log(Fixed Price)	Log(Auction Start)	Log(Fixed Price)	Log(Auction Start)		
Day to Go Dummies (0-2 excluded)												
3 to 5 days	0.197***	0.194***	0.165***	0.142***	0.0990***	0.0979***	0.235***	-0.310***	0.0912***	0.0632		
	(0.004)	(0.004)	(0.013)	(0.013)	(0.003)	(0.003)	(0.019)	(0.063)	(0.014)	(0.041)		
6 to 8 days	0.323***	0.316***	0.296***	0.251***	0.138***	0.136***	0.370***	-0.191***	0.158***	0.0720*		
	(0.005)	(0.005)	(0.014)	(0.014)	(0.003)	(0.003)	(0.019)	(0.065)	(0.016)	(0.043)		
9 to 11 days	0.408***	0.398***	0.470***	0.401***	0.168***	0.166***	0.468***	0.167**	0.230***	0.0824*		
	(0.005)	(0.005)	(0.015)	(0.015)	(0.003)	(0.003)	(0.019)	(0.071)	(0.017)	(0.046)		
12 to 14 days	0.468***	0.455***	0.614***	0.524***	0.193***	0.189***	0.516***	0.207***	0.268***	0.0714		
	(0.005)	(0.005)	(0.015)	(0.016)	(0.003)	(0.003)	(0.019)	(0.066)	(0.018)	(0.048)		
15 to 17 days	0.521***	0.505***	0.706***	0.596***	0.214***	0.209***	0.568***	0.363***	0.299***	0.130**		
	(0.005)	(0.005)	(0.016)	(0.017)	(0.003)	(0.003)	(0.020)	(0.068)	(0.019)	(0.054)		
18 to 20 days	0.564***	0.545***	0.832***	0.703***	0.232***	0.225***	0.618***	0.580***	0.313***	0.222***		
	(0.005)	(0.006)	(0.017)	(0.018)	(0.003)	(0.003)	(0.020)	(0.068)	(0.019)	(0.056)		
21 to 23 days	0.586***	0.565***	0.923***	0.777***	0.247***	0.239***	0.620***	0.541***	0.344***	0.324***		
	(0.006)	(0.006)	(0.017)	(0.019)	(0.003)	(0.003)	(0.020)	(0.068)	(0.021)	(0.059)		
24 to 26 days	0.605***	0.581***	0.976***	0.814***	0.263***	0.253***	0.625***	0.590***	0.359***	0.338***		
	(0.006)	(0.006)	(0.018)	(0.020)	(0.003)	(0.003)	(0.019)	(0.081)	(0.027)	(0.066)		
27 to 29 days	0.620***	0.594***	1.027***	0.848***	0.273***	0.262***	0.647***	0.517***	0.342***	0.369***		
	(0.006)	(0.006)	(0.019)	(0.021)	(0.003)	(0.003)	(0.020)	(0.076)	(0.026)	(0.069)		
30 to 32 days	0.641***	0.612***	1.053***	0.857***	0.282***	0.270***	0.663***	0.579***	0.354***	0.299***		
	(0.006)	(0.006)	(0.020)	(0.022)	(0.003)	(0.003)	(0.021)	(0.077)	(0.024)	(0.072)		
33 to 35 days	0.655***	0.624***	1.116***	0.906***	0.290***	0.276***	0.666***	0.627***	0.381***	0.475***		
	(0.006)	(0.007)	(0.020)	(0.022)	(0.003)	(0.003)	(0.021)	(0.083)	(0.026)	(0.078)		
36 to 38 days	0.669***	0.636***	1.135***	0.912***	0.298***	0.282***	0.671***	0.585***	0.387***	0.424***		
	(0.007)	(0.007)	(0.022)	(0.024)	(0.003)	(0.003)	(0.021)	(0.076)	(0.027)	(0.083)		
39 to 41 days	0.676***	0.641***	1.219***	0.982***	0.305***	0.287***	0.675***	0.673***	0.384***	0.433***		
	(0.007)	(0.007)	(0.022)	(0.025)	(0.003)	(0.003)	(0.022)	(0.082)	(0.028)	(0.084)		
42 to 44 days	0.679***	0.642***	1.223***	0.972***	0.310***	0.291***	0.692***	0.729***	0.406***	0.515***		
	(0.007)	(0.007)	(0.023)	(0.025)	(0.003)	(0.003)	(0.022)	(0.082)	(0.030)	(0.091)		
45 to 47 days	0.699***	0.662***	1.230***	0.962***	0.315***	0.294***	0.712***	0.810***	0.437***	0.495***		
	(0.007)	(0.007)	(0.024)	(0.027)	(0.003)	(0.003)	(0.021)	(0.097)	(0.033)	(0.100)		
48 to 50 days	0.700***	0.661***	1.275***	0.995***	0.320***	0.297***	0.689***	0.739***	0.404***	0.443***		
	(0.007)	(0.008)	(0.024)	(0.027)	(0.003)	(0.003)	(0.022)	(0.095)	(0.034)	(0.110)		
51 to 55 days	0.707***	0.666***	1.303***	0.999***	0.325***	0.300***	0.710***	0.793***	0.388***	0.458***		
	(0.006)	(0.007)	(0.022)	(0.026)	(0.003)	(0.003)	(0.022)	(0.080)	(0.031)	(0.097)	0.793***	(5533.7()-550.034((5533.7

Listings Price (relative to face value)	Pure Fixed Price Fixed Price	Pure Auction Auction Start	Auction Start	Fixed Price
Seller Distance from Stadium Less than 40km	-0.0218	0.000816	-0.0329***	-0.0375***
	(0.014)	(0.011)	(0.011)	(0.014)
* 1-10 Days Prior to Game	0.0482***	0.0362***	0.0291**	0.0298*
	(0.018)	(0.013)	(0.012)	(0.017)
* 11-20 Days Prior to Game	0.0223	-0.00146	0.0357***	0.0349*
	(0.021)	(0.013)	(0.013)	(0.018)
* 21-40 Days Prior to Game	-0.0224	0.00597	0.00393	0.0384**
	(0.020)	(0.014)	(0.014)	(0.019)
Seller Distance from Stadium More than 200km	0.163***	-0.0525***	-0.0366***	-0.0294**
	(0.012)	(0.009)	(0.010)	(0.013)
* 1-10 Days Prior to Game	-0.229***	-0.0410***	-0.00819	-0.0304*
	(0.018)	(0.011)	(0.012)	(0.016)
* 11-20 Days Prior to Game	-0.133***	-0.0248**	-0.015	0.0102
	(0.019)	(0.012)	(0.013)	(0.017)
* 21-40 Days Prior to Game	-0.0566***	0.0199	-0.0368***	-0.0283
	(0.018)	(0.013)	(0.013)	(0.018)
Proportion of Seller's Unsold Listings	-0.118***	-0.0240*	0.137***	0.0700***

Table 8: Fixed Price Listings Probability of Sale/Demand Model

	(1) PROBIT MODEL	(2) PROBIT MODEL WITH CONTROL FUNCTION FOR OWN PRICES (SCALED COEFFICIENTS)	(3) PROBIT MODEL WITH CONTROL FUNCTION FOR OWN AND COMPETITOR PRICES (SCALED COEFFICIENTS)
OWN PRICE COEFFICIENTS			
Ln(Fixed Price)	-0.269	-1.754	-1.783
	(0.014)	(0.088)	(0.079)
1-10 Days Prior to Game*Ln(Fixed Price)	0.087	0.203	0.475
	(0.016)	(0.135)	(0.142)
11-20 Days Prior to Game*Ln(Fixed Price)	0.065	0.369	0.570
	(0.018)	(0.106)	(0.100)
21-40 Days Prior to Game*Ln(Fixed Price)	0.012	0.309	0.418
	(0.018)	(0.104)	(0.113)
SELECTED OWN CHARACTERISTICS			
Feedback 10-100	0.779	0.464	0.422
	(0.038)	(0.035)	(0.034)
Feedback 100-1000	0.876	0.561	0.528
	(0.037)	(0.032)	(0.029)
Feedback Greater Than 1000	0.795	0.599	0.539
	(0.038)	(0.029)	(0.033)
First Row	0.094	0.200	0.197
	(0.017)	(0.016)	(0.015)
Second Row	-0.033	0.013	0.017
	(0.018)	(0.016)	(0.014)
Row Number	-0.007	-0.004	-0.003
	(0.001)	(0.001)	(0.001)
No Row Listed	-0.168	-0.152	-0.152
	(0.022)	(0.022)	(0.023)
COMPETITOR LISTING PRICE COEFFICIENTS (Variables defined based on tickets available on day of listing; fixed prices in hybrid auction listings included in the calculation of fixed price competition; all competition variables based on tickets to the same game with same face value)			
Mean Log(Price) for Fixed Price Listings	0.172	0.633	1.400
	(0.017)	(0.015)	(0.177)
Mean Log(Start Price) for Auction Listings	-0.010	0.001	-0.029
	(0.005)	(0.006)	(0.024)
Min Log(Price) for Fixed Price Listings	0.003	-0.027	-0.956
	(0.013)	(0.008)	(0.145)
Min Log(Start Price) for Auction Listings	-0.008	-0.011	-0.043
	(0.003)	(0.003)	(0.017)
COMPETITOR LISTING CHARACTERISTICS			
Dummy Variable for No Competing Fixed Price Listings	0.756	2.404	1.698
	(0.045)	(0.054)	(0.500)
Dummy Variable for No Competing Auction Listings	-0.140	-0.181	-0.197
	(0.020)	(0.014)	(0.044)
Number of Competing Fixed Price Listings	-0.007	-0.016	-0.037
	(0.001)	(0.002)	(0.004)
Proportion of Competing Fixed Price Listings with Seller Feedback Scores Above 100	-0.082	-0.022	-0.407
	(0.030)	(0.024)	(0.069)
Number of Competing Auction Listings	0.001	0.007	0.003
	(0.001)	(0.001)	(0.002)
Proportion of Competing Auction Listings with Seller Feedback Scores Above 100	-0.035	-0.106	-0.028
	(0.019)	(0.014)	(0.026)
Other Controls	Home Team, Home Team*Log(Face Value), Home Team*Log(Face Value)^2, Home Team*Expected Attendance, Listing Chracteristics (e.g., Highlighted Listing), Ticket Characteristics (e.g., parking), Sale Format Dummies, Game Day of Week Dummies, Small Seller Dummy (Less than 10 MLB Listings), Day to Go Dummies		
MEAN ELASTICITES AT OBSERVED PRICES			
1-10 Days Prior to Game	-0.172	-2.034	-1.850
	(0.011)	(0.110)	(0.179)
11-20 Days Prior to Game	-0.238	-2.248	-2.125
	(0.018)	(0.160)	(0.151)
21-40 Days Prior to Game	-0.363	-2.854	-2.910
	(0.022)	(0.298)	(0.285)
More than 41 Days Prior to Game	-0.484	-4.407	-4.824
	(0.028)	(0.294)	(0.281)
Log-Likelihood	-54327.6	-54019.2	-53988.9
Number of observations	108,325	108,325	108,325

Note: standard errors in parentheses calculated using a bootstrap with 100 repetitions

	1-10	11-20	21-40	More than 41
Actual				
Mean Price	52.21	58.29	63.21	66.20
Std Dev Price	(49.93)	(50.68)	(50.36)	(51.13)
Counterfactual 1: demand 41-44 days prior to game applies throughout				
Mean Price	49.29	51.66	57.60	66.91
	(1.87)	(1.88)	(1.58)	(0.49)
Std Dev Price	41.96	38.76	42.65	51.68
	(2.98)	(2.58)	(2.32)	(0.98)
Counterfactual 2:				

Table 10: Auction Model (Preliminary Results)

Multinomial Logit Model Using Control Function - Coefficients on Own Prices

	Auction Sale at Auction Start Price	*Auction Sale above Auction Start Price*	*Sale at Fixed Price*
Hybrid Auction Dummy	-6.5204	-7.7333	-7.6743
	(0.3057)	(0.2843)	(0.3653)
Ln(Auction Start Price)	-1.232	-2.9111	-0.3726
	(0.0371)	(0.0322)	(0.0421)
Last 10 Days Prior to Game*Ln(Auction Start Price)	0.3096	0.5347	-0.0825
	(0.0419)	(0.0356)	(0.0485)
Days 11-20 Prior to Game*Ln(Auction Start Price)	0.249	0.5375	-0.1676
	(0.0434)	(0.0370)	(0.0535)
Ln(Fixed Price)	1.6945	2.0249	-2.8286
	(0.0789)	(0.0734)	(0.0717)
Last 10 Days Prior to Game*Ln(Fixed Price)	0.043	0.0375	-0.0654
	(0.0138)	(0.0118)	(0.0421)
Days 11-20 Prior to Game*Ln(Fixed Price)	0.053	-0.0175	0.0511
	(0.0143)	(0.0121)	(0.0460)

Truncated Normal Regression Model Using Control Function to Predict Price Above Auction Start Price
Log Specification

Hybrid Auction Dummy	0.5116
	(0.0002)
Ln(Auction Start Price)	-0.1476
	(0.0006)
Last 10 Days Prior to Game*Ln(Auction Start Price)	0.0255
	(0.0006)
Days 11-20 Prior to Game*Ln(Auction Start Price)	0.0126
	(0.0005)
Ln(Fixed Price)	-0.147
	(0.0003)
Last 10 Days Prior to Game*Ln(Fixed Price)	-0.0352
	(0.0009)
Days 11-20 Prior to Game*Ln(Fixed Price)	-0.0151
	(0.0009)
σ (Std. Deviation of Normal Distribution)	0.5244
	(0.0023)

Probit Model for Ticket Availability	Shape Parameters	Scale Parameters		Probit Model for Ticket Availability	Shape Parameters	Scale Parameters

Table 12: Complementary Investments
Distance of Buyers from the Home Team's Stadium

Dep. Var	Log(Buyer Distance)
Day to Go Dummies (0-2 excluded)	
3 to 5 days	0.0808***
	(0.013)
6 to 8 days	0.248***
	(0.014)
9 to 11 days	0.374***
	(0.016)
12 to 14 days	0.439***
	(0.017)
15 to 17 days	0.533***
	(0.019)
18 to 20 days	0.612***
	(0.020)
21 to 23 days	0.607***
	(0.022)
24 to 26 days	0.636***
	(0.023)
27 to 29 days	0.695***
	(0.025)
30 to 32 days	0.734***
	(0.026)
33 to 35 days	0.709***
	(0.028)
36 to 38 days	0.763***
	(0.030)
39 to 41 days	0.842***
	(0.031)
42 to 44 days	0.760***
	(0.033)
45 to 47 days	0.802***
	(0.034)
48 to 50 days	0.744***
	(0.036)
51 to 55 days	0.755***
	(0.030)
56 to 60 days	0.743***
	(0.033)
61 to 70 days	0.815***
	(0.027)
71 to 80 days	0.815***
	(0.028)
81 plus	0.849***
	(0.022)
Fixed Effects	Game-Section
Average Buyer Distance (km)	295
Within R^2	0.03
Observations	296,558