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

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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 majority of observed early purchases can be rationalized by plausible ticket valuations and return to market costs given product differentiation and uncertainties about ticket availability.

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1 Introduction

This paper analyzes the dynamics of prices in two online resale markets for Major League Baseball (MLB) tickets. I show that various types of list and transaction prices all tend to decline as a game approaches by economically significant amounts (e.g., 25% or more in the last month before the game). I also explore *why* declining prices are the equilibrium outcome by examining the behavior of both buyers and sellers. I show that, consistent with the theoretical literature on the dynamic pricing of perishable goods, of which event tickets are a classic example, sellers cut prices over time because, as a game approaches, they become increasingly desperate to sell as their future selling opportunities disappear. Alternative explanations for why sellers cut prices, such as changing demand and seller learning, are rejected. I also show that the majority of observed early purchases can be rationalized despite falling expected prices by uncertain future availability and plausible valuations and costs of returning to the market at a later date.

The paper makes four contributions. First, it describes a pattern (systematically declining prices) which many economists, perhaps conditioned by their experience when buying airline tickets, find surprising. The pattern is very robust to considering different cuts of the data and it is found in two different marketplaces and across different types of selling mechanism (fixed price listings and auctions).[1]

Second, the paper provides strong empirical support for theoretical models of dynamic pricing of perishable goods which have appeared in the economics and operations research literatures, motivated by the pricing problems facing airlines, hotels, sports teams, radio and television stations selling commercial time to advertisers and sellers of goods with strong seasonal demand. The models which are most relevant to the current paper are those where the seller freely adjusts prices over time rather than committing to a price schedule at the beginning (McAfee and te Velde (2006), Gallego and van

[1] The pattern that prices for similar or identical items tend to decline when they are sold in sequential auctions has been noted by 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 - leads to price declines across several different sales mechanisms, including fixed prices and auctions.

Ryzin (1994) and Bitran and Mondschein (1993)).[2]

A stylized version of these models has a seller with a given inventory which can be sold during a fixed time interval. Customers arrive according to an exogenous stochastic process and their valuations for one unit of the good are drawn from a distribution which is time invariant. Arriving customers either buy at once or exit the market. The seller's optimal price at any point in time is determined by the opportunity cost of a sale which reflects the probability that a current sale prevents a future sale because of a stock-out. The optimal price decreases with the number of unsold units and it falls as the end of the interval approaches as there are fewer future opportunities to sell the remaining units. McAfee and te Velde show that a "robust prediction" of these models is that this second effect causes the expected price to fall over time.

There has been very little empirical work testing whether these models describe how sellers price perishable goods.[3] McAfee and te Velde examine data from the airline industry but reject the declining price prediction as prices tend to increase as the day of departure approaches (a pattern also found by Escobari and Gan (2007) and Puller et al. (2008) using different airline datasets). Plausible explanations for this rejection are that, contrary to the assumptions made in the theory, consumers arriving close to the departure date tend to have higher valuations (e.g., business travellers) or that airlines seek to commit to increasing prices in order to affect when potentially strategic customers purchase.

In my data commitment incentives are unlikely to be important because each seller is small relative to the market and they are also relatively anonymous. Each seller is also typically only trying to sell one set of similar tickets (e.g., same game and section) so that the prediction of declining prices emerges directly (i.e., there are no inventory effects for most sellers). I show that not only do prices

[2] These models are the most relevant to my paper because they assume that sellers adjust prices in response to realizations of demand. Prescott (1975) and Dana (1999) show that equilibrium price dispersion can be generated in models where sellers commit to prices or price distributions before demand is realized. In the airline industry, this type of assumption would be consistent with airlines preallocating groups of seats to different pricing buckets. Gale and Holmes (1992, 1993) and Dana (1998) study the role of another airline industry practice, advance purchase discounting, at efficiently spreading demand across flights.

[3] There has been some empirical work on the dynamics of prices in settings without perishability (e.g., Aguirregabiria (1999)).

decline as a game approaches but also that prices fall because of declining opportunity costs just as the theoretical models predict.

The third contribution relates to my analysis of early purchasing. Declining prices can only be the equilibrium outcome if some people are willing to purchase early when expected prices are relatively high.[4] The theoretical literature has recently started to examine how the ability of consumers to strategically time their purchases should affect pricing policies (Aviv and Pazgal (2008), Liu and van Ryzin (2008), Dasu and Tong (2008), Levin et al. (2008), Zhou et al. (2006)) and it has shown that early purchases can be rationalized even when expected prices are falling by uncertainty about future availability and prices, search costs or risk aversion.[5] I provide the first empirical analysis of these ideas by using calibrated models of buyer utility to analyze observed early purchase decisions. I show that uncertainties about the future availability and prices of particular types of ticket combined with plausible valuations and return to market (search) costs can rationalize the majority of observed early purchases. There are also patterns in the data, concerning who tends to purchase early and which types of ticket tend to purchased early, that are consistent with uncertainty and return to market costs being important.

The paper's final contribution is to shed some new light on how secondary event ticket markets work. Revenues in these markets are projected to grow from $2.6 billion in 2007 to $4.5 billion in 2012 with 70% of revenues coming from sports tickets (Forrester Research (2008)) and they are also becoming increasingly accepted by primary market sellers. For example, Stubhub.com became the official resale site for MLB in 2008. The existing theoretical (Courty (2000, 2003a,b), Karp and Perloff (2005)) and empirical (Leslie and Sorensen (2007)) literatures analyze these markets using one-shot market clearing models. My analysis provides insights into how the price formation and allocation

[4] An alternative objection is that declining prices would provide sellers with short-selling opportunities: a seller would sell a pledge to provide a ticket a long time before the game before buying the ticket closer to the game at a lower price. This type of strategy is inhibited by the importance of product differentiation: it is difficult for a seller to know which sections and rows will be available in advance but buyers value knowing the particular section and row of the tickets they are purchasing. In my Market 2 data the transaction price is, on average, around 17% lower if row information is missing than would be expected for a third row listing for the same game and section.

[5] Strategic consumer behavior has, of course, played an important role in the durable goods literature (e.g., Coase (1972), Stokey (1979)).

process actually works.

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 as a game approaches, and it presents reduced-form evidence which is inconsistent with one of them, the Lazear learning model. Section 5 estimates structural models of the price-setting problem. The results support the theory that sellers cut prices because of declining opportunity costs of sale. Section 6 examines why some buyers choose to purchase early when prices are 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 regular season MLB games in 2007.

2.1.1 Stubhub.com

The first dataset contains data on *list prices* from Stubhub.com, collected using an automated script.[6] Stubhub operates as a market for all types of event tickets. From the perspective of a buyer, sellers are anonymous but Stubhub guarantees to supply tickets at least as good as those purchased if the seller fails to do so. Tickets to a particular game are listed on a single page and since 2006 Stubhub has provided a clickable map of each stadium which shows the availability and prices of tickets in each seating section. I only use listings in Stubhub's fixed price format which accounted for 99.5% of all listings in 2007, with auctions accounting for the remainder. Seller can change prices at any time, and a small number of listings (0.4%) use a format where prices decline linearly as the game approaches. I also exclude these listings from the analysis of the Stubhub data, although the fact that Stubhub

[6] Stubhub was purchased by EBay in January 2007 and from 2008 it is acting as MLB's official "Fan to Fan Marketplace".

chooses to make such an option available is instructive about how sellers may want to price.

Sellers list tickets on Stubhub for free, but pay a 15% commission in the event of a sale. Buyers pay a 10% commission in the event of sale plus Stubhub-set shipping costs ($11.95 per listing if the transaction is more than 14 days before the game and $16.95 per listing if the transaction is between 4 and 14 days before the game). Tickets can only be sold within 3 days of the game if hard copies are supplied to Stubhub which can pass them to buyers, who pay a $15 handling charge, at offices close to each stadium.

Data was collected from Stubhub.com's "buy" page for each game on a daily basis from January 6, 2007 to September 30, 2007. For each listing I observe a listing identification number, the game (e.g., Seattle Mariners at the New York Yankees on May 6), the number of seats available and whether less than the full number can be bought, the section and row (e.g., Loge Box 512 row D at Yankee Stadium) and the listed 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.[7] 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 different price. On the other hand, the dataset contains a huge number of observations and allows me to confirm the pricing patterns I find in my second dataset.

[7] To be specific, for roughly two-thirds of the occassions where I see a ticketid exit the data I see a new listing for seats in the same section and row appearing the next day.

2.1.2 "Market 2"

The second dataset comes from a major online market where all types of products, not just event tickets, are traded. The data license prevents me from disclosing the identity of the market so the following description is in relatively general terms and I shall refer to it as Market 2. A seller can list tickets in several different sale formats, including auctions of different durations, a pure fixed price format, a fixed price format where buyers can also make offers to the seller and a hybrid auction format where a customer can buy a ticket at a fixed price if no bids have yet been placed in the auction. When selling in an auction the buyer sets a start price for the auction and may also choose to set a secret reserve price.

Sellers pay a small listing fee and a small commission (between 1% and 7%) which varies with the transaction price and the sale format. Buyers pay no commission but pay shipping costs set by the seller. Buyers are able to see a seller's username and current feedback score, and are likely to care about reputations because the market does not offer 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 games excluding the Orlando games and make-ups.[8] For each listing I observe the game, the identity number of the seller, the number of seats available, the section and row, the sale format and the relevant prices (e.g., fixed price, auction start price or both and whether there is a secret reserve), the start date and duration of the listing, the seller's revenues from the listing and some of the additional text from the listing provided by the seller. I also know if the listing was highlighted on a search page or contained additional information such as pictures. For every auction bid, offer or fixed price purchase the data records the identity number of the bidder and the level of the bid together with an indicator for if the bid was successful. For each transaction, the data records the feedback scores of the seller and the buyer, the shipping cost and (a relatively novel aspect of the data) the zipcodes

[8] Market 2 was unable to supply me with attribute (section, row, number of seats) data for listings which ended on May 18, 2007, so these listings are excluded in what follows. The full (all event ticket) dataset is useful in filling in information, such as zipcodes and feedback scores, on sellers who only have a few MLB listings.

of the buyer and seller. Section and row information is reported in a less uniform pattern than on Stubhub, so considerable effort was spent linking tickets to specific sections within each stadium.[9] The section could not be identified for 0.5% of listings which were dropped. Dummies are included for listings with missing row data in all of the analysis which follows. I exclude listings with more than six seats, prices above $1,000 or shipping costs above $40 (0.7% of the sample).

2.2 Primary Market Data

The secondary market data is complemented by several types of data from the primary market and on team performance. Game results and attendances for 2000 to 2007 are taken from Retrosheet.org and are used to model expected attendance as well as to control for the current record (form) of each team. Stadium capacities are measured using the maximum observed attendance each year as these exceed 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 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. Most listings are available for more than one day: on Stubhub the average listing lasts 16 days; on Market 2 auction listings last for an average of 4.5 days and non-auction listings for 19 days. 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

[9] On Stubhub sellers also have strong incentives to provide the section and row information in a standard format as otherwise their listing will not appear on the clickable map.

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. Secondary markets for baseball tickets also allow season ticket holders, who may have the right to go to 81 home games, to sell their seats for games they do not want. This leads to there being many very small sellers: 63% of sellers on Market 2 have only one or two listings across all games and 90% of sellers have fewer than 15 listings and list tickets for only one team. 139 sellers, who are likely to be professional resellers, have more than 500 listings each and these account for around 30% of all listings. However, even these largest sellers are small relative to the total market.

For all but two teams the average secondary market is above the average primary market price, even though the reported average primary market price is biased downwards because I cannot identify face values for some premium season-ticket only sections. The Boston Red Sox appear to have underpriced their tickets the most, consistent with Fenway Park having been sold out for all games since May 2003 as well as the team having a particularly successful 2007 (they won the World Series).[10] Most purchases happen in the last three weeks before the game, although the average number of days before the game is significantly higher. There is a positive correlation between the median distance buyers live from the ground (based on the shipping zipcode) and the average number of days before the game when purchases take place. This correlation will play a role in rationalizing buyer behavior.

Table 2 provides some more detailed statistics on listings. Stubhub has many more 4 seat listings than Market 2, but 93% of these listings allow a pair of seats to be purchased. Single unit (e.g., a listing for a pair of seats) pure auctions are the most popular sales mechanism on Market 2, followed by single unit hybrid auctions and fixed price listings. Multi-unit auctions, where different buyers can buy different quantities of similar seats, are relatively rare. More single-unit pure auctions result in sales than other formats.

The lower part of Table 2 provides further summary statistics on prices. The average face value of tickets listed on the two sites is similar. The large difference between buyer and seller prices

[10] Of course, whether teams like the Red Sox are mispricing depends on the dynamics of demand (e.g., fan loyalty, the value of future TV rights) and the objective function that teams are trying to maximize.

on Stubhub reflects the large commissions and shipping costs. Of course, buyers may be willing to pay a premium for buying on Stubhub if it offers more secure transactions and easier purchasing. Comparing secondary market prices across the sites is not straightforward because I only observe listed fixed prices on Stubhub while I observe many different types of price, such as auction start prices, on Market 2. The most direct comparison is between listed seller prices on Stubhub and listed pure fixed prices on Market 2 from which seller commissions have been deducted (the bottom line in the table). These prices are very similar as a proportion of ticket face value.

The paper is focused on how prices change as the game approaches. Figure 1 summarizes how several features of the market evolve. Figure 1(a) shows that the number of listings evolves differently on the two sites (I include pure auction listings only on the day the auction ends) with the number of listings on Market 2 peaking five days before the game. The mix of sales mechanisms on Market 2 also changes over time with different types of auction mechanism becoming more prevalent. Regressions show that this shift takes place within sellers as well as across sellers, and it is likely to be explained by sellers placing greater value on the price flexibility provided by auctions when they are very keen to sell. All types of listing are more likely to result in sales as the game approaches, except for single unit pure auctions where the probability of sale declines in the last few days. This may be explained by buyers valuing the certainty offered by fixed price listings when there are fewer buying opportunities left. Figure 4(d) shows what happens to the observable quality of listed tickets as a game approaches (higher face values and lower row numbers are better). Changes in quality are relatively small, with row quality increasingly slightly and face values declining slightly until the last few days. A similar analysis of transacted tickets (rather than listings) shows slight increases in both average row quality and face values as the game approaches.

3 Robust Evidence of Price Declines

This section shows that both list and transaction prices tend to fall, controlling for ticket quality, as a game approaches. This finding is very robust and the declines are large in size.

To examine pricing patterns for vertically differentiated products it is necessary to control for ticket quality. I control for quality using different types of fixed effect and it is useful to take a moment to understand how these are defined. A game refers to a particular fixture between two teams scheduled for a particular day (e.g., Seattle Mariners at the New York Yankees on May 6). A game-section fixed effect 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 of these sections and there may be many sections with the same face value (in my example, odd numbered Loge Boxes 473 to 545 and even numbered Loge Boxes 474 to 548 have a face value price of $55). A game-section-row fixed effect is even more detailed (e.g., Loge Box 512 Row D for the Seattle Mariners at the New York Yankees on May 6). When I do not include game-section-row fixed effects I include five variables (the "row variables") to control for row quality: dummies for the first and second rows, a linear count variable for the row number and dummies for the identity of the row not being available and the row not being relevant (e.g., open seating bleachers). I also include variables for other listing characteristics such as the seats not being in the same row (e.g., "piggy back" seats), on an aisle and whether the listing includes parking.[11]

3.1 Stubhub

Table 3 shows the coefficients from linear fixed effects regression models estimated using list prices from Stubhub. Prices are defined per seat. The independent variables are a set of dummies measuring the days to go until the game, measures of form for both teams (only the home team coefficients are reported), the fixed effects, dummies for the number of seats (interacted with a dummy for whether fewer seats can be purchased), listing characteristics such as the piggy back variable and, where relevant, the row variables. The reported coefficients come from regressions using daily observations from a random 5% sample of sections for each game (e.g., all day-listings observations for Loge Box 512 for the New York Yankees vs. Seattle Mariners on May 6) because there are too many daily

[11] Tickets can only be listed on Stubhub if they are directly next to each other (same row or piggy back). I drop listings from Market 2 if there is any indication that the tickets are not together.

listings to use all observations. The coefficients are almost identical using other sub-samples. To allow for correlations across listings available on multiple days, standard errors are correlated on the listing identification number.

The specification in column (1) includes game-section fixed effects so that the coefficients are identified from seats in the same section which are listed at different prices. The dependent variable is the log of the revenues received by the seller excluding commissions and shipping costs (the seller price). The Days to Go coefficients which are precisely estimated indicate that list prices tend decline before a game. For example, prices are 22% higher 30-32 days before the game than 0-2 days before.[12] The estimated decline is quite smooth and it accelerates as the game approaches. The form variables have plausible signs: prices tend to fall when a team slips back from the top of its division. The row coefficients show that prices fall by 1% for each row ones moves back within a section, with a 10% front row premium.

Column (2) includes game-section-row fixed effects to control in a more comprehensive way for row quality. The estimated percentage price declines are slightly larger than in column (1) and I include game-section-row fixed effects in the remaining Stubhub regressions. The dollar value of the seller price is the dependent variable in column (3), with an estimated price decline in the last month of $14.66 per seat. Column (4) uses the log of the buyer price, which includes the shipping cost and the buyer's commission. The shipping cost, which increases two weeks prior to the game, creates a small non-monotonicity in the price decline but otherwise the price declines are similar. Column (5) uses the seller price divided by the face value of the ticket as the dependent variable, with those observations for which no face value can be identified being dropped. On average, prices fall from being 94% above face value 30 days before a game to being 56% above face value 0-2 days before. One can also examine what happens to the prices of individual listings over time by including listing id fixed effects (Table 6, column (6)) and, once again, the percentage price declines are similar. In

[12] I focus on declines in the last 80 or so days prior to the game as I only have three months of pre-game data for games at the beginning of the season. The number of observations covered by the 81 plus dummy therefore varies across the season. All of the estimates are similar using only observations from the last three months prior to a game for all games.

addition, 89% of observed price changes for individual listings are price reductions.

The remaining columns of Table 3 show that this pattern is robust for different sub-samples of the data. Columns (6) and (7) show that price declines are quite similar for cheap (face value less than $20) and expensive (face value more than $45 or season ticket only) sections. The remaining columns divide the sample based on the game's expected attendance 90 days before the game is played. This is predicted using a censored normal regression model estimated using data on all games played from 2000 to 2007. The dependent variable is the proportion of capacity which is filled and the explanatory variables are the form variables (90 days before the game), home team x year, home team x day of week, home team x month and away team dummies, plus dummies for the type of game (interleague, cross-division and within-division).[13] The percentage price declines are larger for games with lower demands.

The regressions show that average prices decline, but this does not rule out the possibility that the upper percentiles of the price distribution simultaneously increase. This would be important as it would provide a simple explanation for why risk-averse buyers might want to purchase early. To examine what happens to the price distribution I regress log prices on the same variables as before excluding the Days to Go dummies. Figure 2(a) shows how the distribution of the residuals from the regression using the seller price changes in the two months before the game. The bottom 85% of the price distribution falls as the game approaches without the higher percentiles increasing.

3.2 Market 2

Table 4 reports the results using transaction data from Market 2. There may be more than one observation per listing for multi-unit listings. The specifications are similar to those for Stubhub, except that I also include observable seller characteristics (including four dummies for the seller's feedback score, less than 10, 11 to 100, 101 to 1000 and greater than 1000) and listing characteristics, such as whether the listing is highlighted. Additional dummies are included for observations where

[13] As I define capacity as the maximum realized attendance and the realized attendance at each game can vary even when all tickets are sold, I topcode the data at 98% of capacity and use this as the censoring point.

shipping costs or feedback scores are missing (1,352 observations).

The column (1) specification uses the log of the buyer price, which includes shipping costs, as the dependent variable and includes game-section fixed effects. Prices tend to fall as the game approaches, declining by 25% on average in the last month before the game. There are two differences 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. However, 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 why this price increase may be happening in a moment.

The column (2) specification includes game-section-row fixed effects. The pattern of declining prices is similar to column (1) but, in the Market 2 data, only 125,848 transactions come from game-section-rows with more than one observation. For this reason, I use the game-section fixed effects and row control variables in the remaining regressions. Column (3) uses the log of the seller price, which takes out the seller's commission and does not include the shipping cost, as the dependent variable. The decline in prices is similar to column (1) except that prices appear to increase immediately before the game. This reflects a surprising fact about how average shipping costs change. The average shipping cost falls from $4.30 per seat 4 days before a game to only $1.49 per seat on the day of the game itself, as many sellers offer to personally deliver tickets to a local buyer or to meet them at the stadium.

Columns (1)-(3) pool tickets sold through different sales mechanisms. The specification in column (4) includes dummy variables to control for the type of mechanism used (e.g., a pure single unit auction sale, a hybrid auction auction sale, a hybrid auction fixed price sale, etc.) to test whether changes in the mechanism mix explain the price declines. The estimated price declines are essentially unchanged. However, further analysis reveals that the increase in average transaction prices between 80 and 50 days before the game are generated only from auction sales. In column (5) auction sales are excluded (fixed price sales in hybrid auctions are included) and there is no evidence of price increases (the difference between the 81 plus coefficient and the 30-32 day coefficient is not significant at the 1% level). On the other hand, when the regression is repeated using only auction sales the 30-32, 39-41, 61-70 and 81 plus day coefficients are 0.251 (0.012), 0.276 (0.014), 0.208 (0.012) and 0.132 (0.010) respectively, and the initial price increase is statistically significant.

The remaining transaction price regressions repeat the column (1) specification for several sub-samples of the data. The number of observations is smaller in these regressions so that the price declines in the last 40 days are less monotonic, although once again the deviations from monotonicity are typically not statistically significant. The price declines are smaller in percentage terms for more expensive tickets. However unlike for Stubhub, there is no clear relationship between the expected attendance of a game and the size of the price decline.

Figure 2(b) shows how the distribution of the residuals from regressing the log of the buyer transaction price on the control variable excluding the Days to Go dummies changes as the game approaches. Once again, the price distribution falls over time below 85^{th} percentile, especially in the last 40 days before the game, without increasing at higher percentiles.

Table 5 presents regressions using two types of list prices: fixed prices (whether as part of pure fixed price listings, fixed price listings with offers, or hybrid auctions) and starting prices in auctions (of all types). There is one observation per listing even if multiple units are available. 4.6% of auctions also have a separate secret reserve price and I include a dummy for these auctions in the regressions, as well as dummies for the type of mechanism used.

In columns (1) and (2) the Days to Go dummy variables are calculated based on the start date of the listing. On average, fixed prices decline as the game approaches by more than transaction prices do. Auction start prices decline by very large amounts until about two weeks before the game and then remain fairly constant. The size of the price declines, particularly for fixed price listings, are sensitive to how the number of days to go is counted. Columns (3)-(4) report results using the number of days from the *end* of the listing to the game. As listings which are more expensive (conditional on quality) tend to remain unsold, prices fall by less using this definition.[14] For auctions, the price declines continue until about a week before the game, although they increase in the last few days. A notable feature of the auction results is that even though auction transaction prices are increasing more than 50 days before a game, auction start prices are always declining. This suggests that transaction prices may be increasing because, a long time before the game, people submit low bids because they know that if they do not win they will have plenty of opportunities to try to buy tickets later on.[15]

Columns (5)-(8) report the list price results dividing the data into the ten MLB teams with the most listings and the rest. The fixed price declines are very similar for the two groups. The declines are also similar for auction start prices except that prices increase in the last five days before the game for the teams with the least listings.

4 Theoretical Explanations for Why Sellers Cut Prices

The rest of the paper examines why declining prices are the equilibrium outcome. I split the problem into two parts: why do sellers tend to cut prices (or accept lower revenues) over time given buyer demand? and second, why are some buyers willing to purchase early when prices are expected to fall? This split is appropriate because individual buyers and sellers are small relative to the total size of the market, so should take the behavior of the other side of the market as given when choosing their pricing or purchasing strategy. For example, an individual seller is unlikely to believe that she can shift demand earlier by trying to commit to increasing prices. Sections 4 and 5 analyze the behavior of sellers while Section 6 examines the early purchase decisions of buyers.

In this section I describe three plausible explanations for why sellers cut prices over time. Some alternative explanations can be disposed of immediately. First, in some markets the existence of

[14] For fixed prices I have also performed the regression using available listings so the same listing may appear more than once, as in the Stubhub regressions. In this case the estimated fall in prices in the 30-32 days prior to the game is 23.9%, which is very similar to the estimate in Table 3 column (1) using the Stubhub data.

[15] There is also slightly less participation in earlier auctions, so that a greater proportion of auctions result in sales at close to the start price. In the last 40 days before a game 25% of auctions result in sales within \$2.50 of the start price, whereas 30% do more than 40 days before.

a set of impatient consumers may explain why some people purchase early when prices are high. Impatience is not a viable explanation here as no-one can use their tickets until the day of the game. Second, while discounting may be important over a time period of several months, it should tend to lead to increasing prices as buyers would have to be compensated for paying for their tickets ahead of when they get to consume the product. Third, any uncertainty about the value of the game (for example, whether it will be important in a playoff race) combined with buyer risk aversion should also tend to lead to increasing equilibrium prices because more information about the quality of the game is revealed over time.

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 unit to sell and that there are two time periods before the game, $t = 1, 2$. The seller gets a payoff of $\$v_i$, which could reflect the value of attending the game herself, giving the ticket to a friend or selling it outside the stadium, if the unit is unsold after period 2. 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 $\frac{\partial Q_{it}(p_{it})}{\partial p_{it}} < 0$. 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}.[16] i will therefore set prices p_{i1} and p_{i2} by solving

$$\max_{p_{i1},p_{i2}} p_{i1}Q_{i1}(p_{i1}) + p_{i2}Q_{i2}(p_{i2})(1 - Q_{i1}(p_{i1})) + v_i(1 - Q_{i2}(p_{i2}))(1 - Q_{i1}(p_{i1})) \tag{1}$$

[16] Q_{i2} might depend on p_{i1} if i's first period price causes some buyers to wait until the second period for i to lower his price. My formulation essentially assumes that an individual seller i is too small relative to the market for his own first period price to have a significant effect on his second period demand.

Assuming that the relevant second-order conditions are satisfied, prices will satisfy

$$p_{i2}^* = v_i - \frac{Q_{i2}(p_{i2}^*)}{\frac{\partial Q_{i2}(p_{i2}^*)}{\partial p_{i2}}} \tag{2}$$

$$p_{i1}^* = (p_{i2}^* Q_{i2}(p_{i2}^*) + v_i(1 - Q_{i2}(p_{i2}^*))) - \frac{Q_{i1}(p_{i1}^*)}{\frac{\partial Q_{i1}(p_{i1}^*)}{\partial p_{i1}}} \tag{3}$$

These conditions show that there are two reasons why prices may fall over time. First, the demand function may become more elastic causing the optimal price/mark-up to fall. Second, the opportunity cost of selling tends to fall as future selling opportunities disappear. In the last period, the opportunity cost of selling is v_i whereas in the first period it is $(p_{i2}^* Q_{i2}(p_{i2}^*) + v_i(1 - Q_{i2}(p_{i2}^*)))$ and because $p_{i2}^* > v_i$ the opportunity cost of sale must be falling. If $Q_{i1}(p_i) \equiv Q_{i2}(p_i)$ (i.e., the demand function is the same in both periods) then the opportunity cost effect will lead to falling optimal prices, just as in the theoretical literature on the dynamic pricing of perishable goods.[17]

Similar arguments apply for auction listings. If $Q_{it}(p_{it})$ is the probability of sale given the start/reserve price p_{it} ($\frac{\partial Q_{it}(p_{it})}{\partial p_{it}} < 0$) and $R_{it}(p_{it})$ is the seller's expected revenue in the event of sale with $\frac{\partial R_{it}(p_{it})}{\partial p_{it}} > 0$ then the optimal start prices will satisfy

$$\frac{\partial R_{i2}(p_{i2}^*)}{\partial p_{i2}} Q_{i2}(p_{i2}^*) + \frac{\partial Q_{i2}(p_{i2}^*)}{\partial p_{i2}} [R_{i2}(p_{i2}^*) - v_i] = 0 \tag{4}$$

$$\frac{\partial R_{i1}(p_{i1}^*)}{\partial p_{i1}} Q_{i1}(p_{i1}^*) + \frac{\partial Q_{i1}(p_{i1}^*)}{\partial p_{i1}} [R_{i1}(p_{i1}^*) - (R_{i2}(p_{i2}^*) Q_{i2}(p_{i2}^*) + v_i(1 - Q_{i2}(p_{i2}^*)))] = 0 \tag{5}$$

If the probability of sale and revenue functions are the same in both periods then declining opportunity costs will lead to declining prices. On the other hand, changing Q or R functions could also contribute to the price declines.

[17] If the Q function is linear then prices also fall increasingly quickly as the game approaches, which is the pattern that I observe in the data.

4.2 Seller Explanation 3: Learning by Sellers

Lazear's (1986) model of clearance sales provides an alternative explanation for falling prices. Lazear's basic model has a seller trying to sell one unit of an item in two periods. All customers have the same reservation value for the item, about which the seller has some prior beliefs. The optimal pricing strategy involves a high price in the first period. If the good does not sell then the seller infers that customer valuations are likely to be lower and cuts the price in the second period. By assumption, customers are unwilling or unable to substitute across periods. The key difference to the previous analysis is that prices change due to seller learning rather than perishability or changes in underlying demand, and it is useful to rule out this explanation because the rest of the analysis will assume that sellers know the demand function they are facing.

Lazear describes several observable implications of his model. First, with multiple periods, he shows that prices should decline with the time since the seller first tried to sell the good (tenure) and that prices should fall more slowly over time as tenure increases. On the other hand, if perishability drives price declines then the price declines should be related to the time until the game rather than tenure. The first six columns of Table 6 reports regression results where I include a fifth-order polynomial for tenure and seller-ticket fixed effects to look at how prices change for individual tickets.[18] For fixed price listings in both markets, the Days to Go coefficients are similar with and without the tenure variables and the tenure coefficients imply small effects (e.g., prices fall 1.9% with 10 days of tenure and 3.4% with 20 days of tenure in Market 2). The tenure effects are larger for auctions in Market 2 (start prices drop 11.3% with 10 days of tenure and 18.2% with 20 days) but the Days to Go (perishability) effects are still larger. The coefficients are almost unchanged if one includes additional polynomials in the number of times that the tickets are relisted (which may also affect learning), as well as the polynomial for the time since first listing. Second, Lazear's model predicts that the

[18] For the Stubhub data this means ticket id fixed effects and for Market 2 seller-game-section fixed effects. For Market 2 time since listing is calculated as the length of time since the seller first listed tickets for the same game and section, and for Stubhub it is calculated as the time since the ticket id was listed. As Stubhub id numbers may change when a seller changes the price, I only include ticket ids which I consider likely to represent initial listings. These are listings where the appearance of the listing id did not coincide with the disappearance of a listing id for the same game, section and row.

probability of sale in any period should remain unchanged even as prices fall (his p. 22). Figure 1(c) shows that sale probabilities tend to increase in my data, at least until the last couple of days before the game, which is consistent with sellers moving down a known demand curve as the opportunity costs of sale fall.

A possible objection is that these predictions depend on the particular assumptions of Lazear's model and that their failure reflects the inaccuracy of the assumptions rather than the absence of learning. For example, the arrival rate of consumers may increase as the game approaches, making learning and sale probabilities a function of the time until the game rather than the time since listing. However, Lazear's model also makes a cross-seller/ticket prediction which should be more robust: the tightness of sellers' priors and their rate of learning should affect observed price declines. For example, if markets are thick then there may be less learning and smaller price declines. However, the regressions in Table 5 show that listed price declines on Market 2 are similar for teams with different amounts of trade. Regressions using list prices on Stubhub and transaction prices on Market 2 generate similar results. A perhaps more convincing comparison is between sellers with different amounts of experience of selling MLB tickets. Columns (7)-(10) of Table 6 show that the sellers who sell the most MLB tickets on Market 2, and so should tend to have the most information about demand, tend to cut prices more dramatically than sellers who sell the least, at least up until 3 days before the game. This is the opposite of what a learning model would predict. On the other hand, it is consistent with an opportunity cost story if professional sellers have the greatest ability to try to relist unsold tickets, which should lead them to set high prices early on, and/or the least incentive to use tickets themselves or give them away, which should cause them to set low prices right before the game.

5 Testing the Opportunity Cost and Demand Elasticity Explanations for Why Sellers Reduce Prices

I estimate the contribution of falling opportunity costs to the observed price declines by estimating structural models of the price-setting decision. The idea is simple. Suppose that seller i uses a fixed price listing in period t. He will set price p_{it} to maximize

$$\max_{p_{it}} p_{it} Q_{it}(p_{it}) + o_{it}(1 - Q_{it}(p_{it})) \tag{6}$$

where Q_{it} is the probability of sale (or demand) function and o_{it} is the opportunity cost of sale at time t. As in (3), o_{it} will reflect his ability to try to sell an unsold ticket in future periods, possibly at different prices. Assuming second-order conditions are satisfied, the optimal price will be

$$p^*_{it} = o_{it} - \frac{Q_{it}(p_{it})}{\frac{\partial Q_{it}}{\partial p_{it}}} \tag{7}$$

and given estimates of the Q function, the opportunity cost implied by the observed price can be calculated

$$\widehat{o_{it}} = p_{it} + \frac{\widehat{Q_{it}(p_{it})}}{\widehat{\frac{\partial Q_{it}}{\partial p_{it}}}} \tag{8}$$

(7) can be used to perform counterfactuals to quantify the role of declining opportunity costs and changes in demand. Specifically, I calculate what the price of each listing would have been without any changes in demand and then compare these counterfactual prices with those observed in the data. Auction listings can be analyzed in a similar way allowing for revenues to exceed the start price in the event of a sale.

Before getting into the details, a few general comments are in order. First, unlike most of the recent structural demand and auction literature, I do not attempt to estimate underlying consumer preferences (e.g., bidder valuations). As noted by Hendricks and Porter (2007), doing so is difficult in an environment where consumers may searching across multiple listings. Second, modelling a seller as facing a static pricing problem when he chooses his price is not inconsistent with sellers being able to relist their tickets in multiple periods: this ability is reflected in the opportunity cost implied by their choice of price.[19] Third, sellers are assumed to be risk-neutral. I estimate that some sellers have negative opportunity costs, which is unrealistic given free-disposal. One interpretation of negative costs is that risk or loss aversion causes the seller to price below the expected revenue-maximizing level. An alternative interpretation is that some sellers may be constrained by state anti-scalping laws or a sense of fairness from setting prices which are above the cost or face value of the ticket. Finally, all of the analysis uses data from Market 2 as I need to observe transactions.

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 fall because of declining opportunity costs rather than changing elasticities, consistent with dynamic pricing models.

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 (demand) 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})[20]

$$Q_{it}(p_{it}) = \Phi(p_{it}, X_{it}, p_{-it}, X_{-it}, \theta^{FP})$$

[19] The structure of a dynamic model could be used to place additional restrictions on how opportunity costs evolve. Instead I show that one obtains patterns which are consistent with a theoretical dynamic model without imposing these restrictions.

[20] I do not observe shipping costs for listings which do not sell, but these costs may affect demand. I address this problem by assuming that unsold listings have (i) the average shipping cost of listings by the same seller sold in the same time period (defined in a moment) before the game and, if this is not available, (ii) the average shipping costs of tickets sold by sellers living as far from the stadium in which the game was played in the same time period prior to the game. As shipping costs are generally small I hope that these approximations will not seriously bias the results, especially once I instrument for a listing's own price.

As fixed price listings which do not sell may remain listed for different lengths of time (and I do not observe how long a sold listing would have remained listed), I define the dependent variable as whether the ticket sold within ten days of listing.[21]

As prices can differ substantially across listings because of ticket quality, the base specification uses relative prices, defined as the listed price divided by the face value of the ticket. The demand curve is allowed to vary over time by including a set of time dummies similar to those used in Section 3 and by allowing the own price coefficients to vary across four "time periods" (1-10, 11-20, 21-40 and 41 or more days before the game).[22] I control for listing quality by including the various ticket and seller characteristics variables used in Section 3 (e.g., the seller feedback dummies and the row variables). As I need to consistently estimate all of the coefficients to estimate option values I do not include game-section fixed effects, but instead include home team dummies and home team*face value and home team*expected attendance variables (based on the attendance model used in Section 3).

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.[23] I only use listings available at the time of posting as I want to estimate the seller's expected probability of sale when he chooses the price: the coefficients on these variables and the time dummies should reflect expectations about how competition will evolve once the listing has been posted. The included competition variables, defined separately for auction and fixed price listings, are the average relative price, the minimum relative price, a count of the number of listings available, a dummy for whether no listings are available and proportion of competing listings with seller feedback scores above 100.

The estimation sample consists of pure fixed price listings made in the last 90 days before the game with non-missing face value information.[24] Experimentation indicated that the price coefficients were

[21] The time dummies will control for the fact that a ticket listed in the last few days has less time to sell.

[22] I adjust the days to go dummies slightly so that they coincide with these time periods. For example, instead of 9 to 11 day and 12 to 14 day dummies I use 9 to 10 day and 11 to 14 day dummies.

[23] Additional variables based on broader definitions (e.g., all tickets for the same game) and narrower definitions (e.g., only same section) were generally insignificant when added to the specification.

[24] I include the fixed price with personal offer listings in this specification as all of the sales which I see in this format

sensitive to some listings with extremely high prices, so I exclude 8,018 listings (6.8% of the fixed price sample) where the fixed price is more than 5 times above the face value of the ticket.

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 the start price. The probability that the listing results in a sale is modeled using a probit. The observed revenue (R_{it}) in the event of a sale is modeled 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

$$R^*_{it} = f(p_{it}, X_{it}, p_{-it}, X_{-it}, \theta^R) + \varepsilon_{it} \quad \varepsilon_{it} \sim N(0, \sigma^2_R) \tag{9}$$

$$R_{it} = R^*_{it} \text{ if } R^*_{it} \geq p_{it}$$

$$= p_{it} \text{ if } R^*_{it} < p_{it}$$

and $f()$ is a linear function. I assume that, once I have controlled for the possible endogeneity of prices, there is no correlation in the residual terms in the probit and censored regression functions so that these models can consistently be estimated separately. The auction start price and revenues are both expressed relative to face values on a per seat basis including shipping costs. The control variables are the same as in the fixed price model.

The estimation sample consists of pure auction listings made in the last 90 days before the game with non-missing face value information and no secret reserve prices and which the seller did not stop before the end of the auction. To reduce the sensitivity of the specification to outliers I drop observations where the auction start price is greater than 4 times the face value of the ticket and observations where the realized revenue from the auction is more than six times the face value. These exclusions drop 3.1% of the sample.

are at the fixed price.

5.1.3 Hybrid Auction Listings

Hybrid auction listings can result in no sale, an auction sale or a fixed price sale. I therefore model the probability of each outcome as being determined by a trinomial logit model with the expected revenue in the event of an auction sale being determined by the same type of left-censored normal regression model specified above.

The estimation sample consists of hybrid auction listings made in the last 90 days before the game with non-missing face value information and which the seller did not stop before the end of the auction, and where the offered fixed price was strictly above the auction start price, a criterion which drops 36,248 listings.[25] I also drop 9.8% of listings where the fixed price was more than 5 times face value, the start price was more than 4 times face value or realized revenues were more than six times face value.

5.2 Price Endogeneity and Instruments

Price will be endogenous if there are characteristics which I do not control for which make a listing more attractive to buyers and so cause the seller to increase the price. I use instruments and a control function approach to deal with endogeneity in the context of my non-linear models.

Equation (7) implies that variables which affect or reflect a seller's opportunity cost but which do not affect a listing's attractiveness to potential buyers will be valid instruments. I define the following instruments, interacted with dummies for the time periods of interest (e.g., 1-10 and 21-40 days prior to the game).[26]

- three distance bands reflecting the distance of the seller's zipcode from the stadium of the home team (less than 40 km, 40-200 km (excluded), more than 200 km). In the cross-section distant

[25] Over 99% of sales for these listings are at the fixed price as one would expect. However, there are small number of auction sales above the start price which are impossible to rationalize.

[26] Many of these instruments are based on listings of other tickets made by the same seller. These variables are obviously not defined for sellers listing only one set of tickets. I therefore also include dummies for listings by these sellers. As I only know the seller's zipcode when he makes at least one sale of some type of event ticket I only define these instruments when the seller makes at least 10 MLB listings (in 99% of these cases I observe a zipcode somewhere in the data including from non-MLB transactions) and I include a dummy for sellers with less than 10 listings.

sellers may tend to have different characteristics to ones who are more local (e.g., season ticket holders are likely to live close by) and these groups may have different opportunity costs. My assumption is that included variables such as feedback scores will control for aspects of seller quality valued by buyers. Distant sellers are also likely to have fewer offline opportunities to dispose of tickets close to the time of the game (e.g., to sell the tickets to coworkers or to sell them outside the stadium) so are likely to cut prices more dramatically right before the game;

- the proportion of the seller's unsold listings during the same time period (for other tickets) which are relisted (at a later date) on Market 2. Frequent relisting may reflect either high opportunity costs of sale (because the costs of relisting are low) or low opportunity costs (because the seller has few opportunities to sell the tickets offline);[27]

- the proportion of listings for other tickets by the same seller in the same time period in fixed price and hybrid auction formats. Sellers with different opportunity costs might tend to use different types of listing, and they may be more willing to maintain listings unsold if they have lower costs of using that type of listing; and

- for hybrid auction listings, the average fixed price and average auction start price set by the seller in other hybrid listings during the same time period relative to the face value of the ticket. Sellers who prefer an auction sale (for example, the convenience of knowing that the auction will end on a fixed date) may set a lower start price and a higher fixed price. While one may be concerned about aspects of seller specific quality affecting these prices, these types of instrument are useful in providing separate variation for the two prices set by the seller.

The non-linearity of the models and the large number of price coefficients and other control variables require me to use a two-step control function approach (e.g., Rivers and Vuong (1988), Wooldridge (2002), p. 472ff).[28] For the fixed price probit model, the control function approach

[27] Relistings are identified by the same seller listing the same or smaller number of tickets for the same game, section and row on a date after a listing which did not result in a sale;

[28] A Full Information Maximum Likelihood (FIML) approach would be more efficient. However this is difficult to

assumes that the latent variable ($Q^*_{it}, Q_{it} = 1$ if $Q^*_{it} \geq 0$) determining the probability of sale can be expressed by

$$Q^*_{it} = \widetilde{X_{it}}\theta_1 + p_{it}\theta_2 + u_{it} \tag{10}$$

where $\widetilde{X_{it}}$ contains all the exogenous variables. Prices are assumed to be determined by linear equations of the form

$$p_{it} = \widetilde{X_{it}}\gamma_1 + Z_{it}\gamma_2 + v_{it} \tag{11}$$

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 of u and v and the normalization that $\text{var}(u) = 1$

$$u_{it} = v_{it}\theta_3 + e_{it} \tag{12}$$

where $\theta_3 = \frac{\text{Cov}(u,v)}{\text{Var}(v)}$ and e is normal and independent of $\widetilde{X}$, Z and v. In the first step OLS is used to estimate (11) yielding estimates of the vs. These $\widehat{v}$s are included in the second-step probit equation to give scaled estimates of the θ parameters.[29] 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 two-step estimation procedure. The bootstrap resamples games to allow for within-game correlations in the residuals.

A similar control function 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 trinomial logit model used to determine the probability of each outcome in the hybrid auction model is theoretically more difficult because the unobservables are assumed not to be normally distributed. Following the "practical" approach suggested by Wooldridge (2007) I specify that the latent utility-like variable associated with outcome

estimate with several endogenous variables (the different price-time period interaction coefficients). If I include only the main price effect the two-step and FIML approaches give very similar coefficients (when they are rescaled appropriately).

[29] The probit coefficients have to be scaled because the variance of e is $1-\text{corr}(u,v)^2$ rather than 1.

j as

$$u_{ijt} = \widetilde{X_{ijt}}\theta_1 + p_{ijt}\theta_2 + v_{ijt}\theta_3 + e_{ijt} \tag{13}$$

where e_{ijt} is distributed Type I extreme value and the v_{ijt}s come from price equations like (11). Given this ad-hoc assumption we can proceed as before estimating the $\widehat{v}$s in a first-step and then including them in the second stage specification.

Table 7 shows the coefficients on the instruments in the first-stage regressions. The instruments are jointly significant and most of the coefficients show plausible patterns, while providing some evidence that different types of sellers select into different mechanisms. This is not a problem as long as the selection characteristics are not valued by buyers. The distance coefficients show that as a game approaches sellers located more than 200 km from the stadium tend to cut their prices more, and sellers located within 40 km to cut them slightly less, than those located between 40 and 200 km. This is consistent with distant sellers having fewer offline opportunities to sell tickets at the last minute. Sellers who tend to use pure fixed price or hybrid auction listings tend to set higher prices than other sellers when using these listings. This is consistent with these sellers having lower costs of maintaining these listings. This price premium disappears right before the game, presumably because at that point the seller's primary concern is to sell his tickets as soon as possible, and this may be particularly true for professional sellers, who appear to make more use of fixed price listings, as they are less likely to attend games themselves. The proportion resale variables show a less consistent pattern across sale formats. For hybrid auction listings, frequent relisting is associated with higher prices a long time before the game with the premium disappearing over time. This is consistent with these sellers having low listing costs but being increasingly keen to sell as the game approaches. For fixed price listings, frequent relisting is associated with lower prices, consistent with these sellers having more limited outside opportunities than other users of fixed prices.

It is also possible to try to control for the endogeneity of competitor prices. I create instruments for these prices by taking averages of the first three types of instruments listed above across the competing listings which are used to construct the competition variables. In practice, controlling for the endogeneity of competitors' prices has only small effects on the results.

5.3 Second Stage Results, Implied Opportunity Costs and Counterfactuals

5.3.1 Fixed Price Listings

Column (1) in Table 8 shows the price coefficients from the probit specification without controlling for endogeneity. Demand slopes downwards but the average price elasticities (shown at the bottom of the table) imply that, on average, sellers are pricing below the revenue-maximizing level. This changes in column (2) when I use the control function to address price endogeneity, and the (unreported) coefficients on the $\widehat{v}$s are also positive and significant. The coefficients on the interactions between a listing's own price and the time period variables are small in magnitude, indicating that the slope of the demand curve is similar across time periods. In both specifications, the absolute value of the elasticities decrease over time, consistent with sellers moving down the demand curve as their opportunity costs fall.

The specification in column (3) also controls for the endogeneity of competitor prices. Most of the coefficients are similar to those in column (2). The coefficients on the mean relative price, number and feedback quality of competing fixed price listings are consistent with substitution across listings. The competition effects for auction listings are generally smaller in size and less significant. This is also true for the other models reported below.[30]

Figure 3(a) how the distribution of opportunity costs evolves over time, based on the Table 8 column (3) coefficients. Opportunity costs fall as the game approaches consistent with dynamic pricing models. To reduce clutter the figure only shows standard errors on the density estimates for the first time period. The density is estimated precisely and this is also true for the other time periods and models.

[30] Recall that the variables reflect the state of competition at the time the listing is posted (and the price is set) not at each point in time while the listing is available. The greater significance of the fixed price listing competition variables may reflect the fact that these listings tend to remain available (often at the same prices) for a greater period of time.

Table 9(a) reports the results of the counterfactual experiment. For each listing I take the opportunity cost implied by the estimated model and calculate what the optimal price would have been if the demand curve was the same as the one estimated 11-14 days before the game (this involves using the slope of the demand curve 11-20 days before the game and the intercept for 11-14 days before the game). As the number of competing listings also tends to increase over time and competition may also depress prices I also assume that, for all listings, the competition variables take the average of their values 11-20 days before the game. I can then compare the path of the counterfactual prices to the path of observed prices. If they are very similar, which is the case in Table 9(a), then I can conclude that changes in demand or competition are not significant causes of declining prices (because these are held fixed in the counterfactual), which must instead be explained by declining opportunity costs.

One aspect of the results which may suggest misspecification is that a relatively large proportion of implied opportunity costs are negative, especially in the period immediately before the game. An alternative specification which implies few negative opportunity costs is based on log prices because the probability of sale becomes very sensitive to price when prices are low. Figure 3(b) shows the resulting distribution of opportunity costs, and even in the immediately before the game less than 5% of opportunity costs are negative. Table 9(b) shows that the qualitative results from the counterfactual are unchanged using the log specification.[31]

5.3.2 Pure Auction Listings

Column (1) of Table 10 shows the results from the probit model used to model the probability that the listing results in a sale. In this case the price and time period interactions are statistically significant and indicate that the sale probability is less sensitive to price more than 41 days before

[31] Given these results one might prefer the log specification to the one based on relative prices. However, when the auction models are estimated using log prices a significant proportion (as high as 20% in some specifications) of the observed prices do not satisfy the second-order conditions for payoff-maximization given any opportunity costs. I therefore prefer to focus on the relative price results throughout. For auction models the qualitative counterfactual results are similar across the log and relative price specifications if one only uses observations which satisfy the second-order conditions.

the game. However, the average absolute value of the probability of sale elasticities still falls as the game approaches.[32] They are similar in the last two time periods which is consistent with auction start prices being fairly flat in the last two weeks before the game (Table 5 column (2)).

The revenue function estimates the sensitivity of expected revenues conditional on a sale to the auction start price and, on average, a \$1 increase in the start price raises expected revenues in the event of a sale by \$0.51. The negative price interaction coefficient for the final (1-10) time period implies that the revenues are less sensitive to the start price immediately before the game. This affects the estimated opportunity costs and the counterfactual (Table 9(c)): opportunity costs and counterfactual prices are both estimated to increase in the final time period, having fallen previously. While it is not obvious why the revenue function should change in the final time period, selection provides a plausible explanation for why the opportunity costs of sellers using auctions might increase. Suppose that there is a distribution of opportunity costs across sellers and the opportunity cost of each seller falls over time. If high opportunity cost sellers initially use fixed price listings, which is consistent with these listings having a relatively low probability of sale but they later switch to using auctions as they become keener to sell, while low opportunity cost sellers always use auctions then the average or median opportunity cost of sellers using auctions might increase. Consistent with this type of shift, Figure 1(c) shows that the proportion of pure auction listings resulting in sales falls in the last ten days.

5.3.3 Hybrid Auction Listings

Table 11 shows the estimated coefficients from the estimated trinomial logit and censored normal models used to model the outcomes of hybrid auction listings. In both cases the control function approach is used to control for the possible endogeneity of own and competitor prices. To save space I do not report the coefficients on the competition variables but they are qualitatively similar to those

[32] The absolute value of the sale elasticities can be less than 1 in absolute magnitude without implying that prices are below the revenue-maximizing level because in auctions expected revenues conditional on sale may not increase dollar-for-dollar with the start price.

for the earlier models.

As expected, higher auction start prices reduce the probability of auction sales, while higher fixed prices reduce the probability of fixed price sales. The revenue function coefficient on the start price interaction for the final (1-10) time period is positive, implying that a seller has more incentive to raise prices immediately before a game. This is, of course, the opposite of the effect found in the pure auction model. Higher fixed prices increase expected revenues in the event of an auction sale which is sensible because when the fixed price is higher, potential buyers with higher valuations are more likely to reject the fixed price and bid in the auction.

The median opportunity costs implied by the auction start price decline monotonically as the game approaches. One can also calculate the opportunity costs implied by the chosen fixed price. Because the estimated elasticities of sale with respect to the fixed price are relatively small and higher fixed prices increase expected auction sale revenues, observed fixed prices can only be rationalized by negative opportunity costs. They are also different from those implied by the auction model which indicates some type of misspecification. However, the implied opportunity costs still show a monotonic decline as the game approaches (the median opportunity cost relative to face value falls from -0.18 more than 41 days before the game, to -1.11, -1.92 and -2.26 in following time periods).

Table 9(d) shows the results of performing the counterfactual for auction start prices. In this case the counterfactual price declines are slightly larger than those observed in the data, which implies that changes in demand actually tend to lead prices increasing over time, while falling opportunity costs drive the declining price pattern.

5.3.4 Summary of Results

Overall the results support the hypothesis that prices decline because of falling opportunity costs, consistent with dynamic pricing models. The only exception arises for the final time period in the pure auction model, which also happens to be the one case where we do not observe a clear price decline and the proportion of listings resulting in sales actually tends to fall. This exception may reflect selection of sellers into different mechanisms.

The analysis has treated different types of listing separately. However, one can combine the opportunity cost estimates from the different models to look at what happens to costs for individual seller-ticket combinations as the game approaches. When one observes a seller listing tickets for the same game, section and row on different days, the implied opportunity cost falls over time in 68% of cases where the seller is using the same type of mechanism so the estimates come from the same model, while it falls in 66% of cases where the seller is using different mechanisms so that the estimates come from a different model. The fact that opportunity costs tend to fall in both cases is consistent with the theory and the similarity of these numbers provides some evidence in favor of the assumed specifications.

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

A potential puzzle is why some consumers choose to purchase early if prices are expected to fall. This issue has been considered in some of the most recent theoretical literature on dynamic pricing of perishable goods (e.g., Liu and van Ryzin (2008)) - previous models had assumed away the possibility of strategically timed purchases - where the roles of uncertainty about future availability, buyer risk aversion and search costs in explaining why some consumers may purchase early at higher prices have been emphasized. In this section, I examine this issue by calibrating a particular model of buyer utility. I show that early purchases can be explained by uncertainty about the future availability of particular kinds of ticket (e.g., blocks of four seats) combined with plausible valuations and return to market costs. I also show that there are some patterns in the data which are consistent with uncertainty and return to market costs being important. Throughout I assume that buyers are aware that prices tend to decline - an assessment of whether this is true or not is left to future research.

6.1 Models of Buyer Utility with Uncertain Future Availability and Prices, Search Costs and Risk/Loss Aversion

Suppose that there are two periods and that consumer i's choice is between buying a ticket which she values at v_{1i} in period 1 at price p_1 ($v_{1i} \geq p_1$) or waiting until period 2. Waiting entails a return to market cost s_i and, if she buys a ticket when she returns, she gets net surplus $v_{2i} - p_2$ which (from her perspective in period 1) has pdf $f_{2i}(v_{2i} - p_2)$. If she is risk neutral she will purchase in period 1 if and only if

$$v_{1i} - p_1 \geq -s_i + \int_0^{\infty} (v_{2i} - p_2) f_{2i}(v_{2i} - p_2) d(v_{2i} - p_2) \tag{14}$$

where the RHS reflects the fact that the ticket is only purchased in period 2 if $v_{2i} - p_2 \geq 0$. Higher search costs, lower expected availability and higher expected future prices and lower period 1 prices will make her more inclined to purchase early. Alternatively her preferences may display constant absolute risk aversion, with CARA coefficient $\alpha_i > 0$, in which case she will purchase early if and only if

$$-\frac{1}{\alpha_i} \exp(-\alpha_i(v_{1i} - p_1)) \geq -\frac{1}{\alpha_i} \exp(\alpha_i s_i) \left(\begin{array}{c} \int_0^{\infty} \exp(-\alpha_i(v_{2i} - p_2)) f_{2i}(v_{2i} - p_2) d(v_{2i} - p_2)) + \\ \int_{-\infty}^{0} f_{2i}(v_{2i} - p_2) d(v_{2i} - p_2) \end{array} \right) \tag{15}$$

and $p_2 \leq v_i$. Greater risk aversion will tend to favor an earlier purchase when future prices and availability are uncertain. Modeling consumers as being risk-averse may be unattractive in this setting because the dollar amounts involved are relatively small compared with lifetime consumption risks (Rabin and Thaler (2001), Rabin (2000)). An alternative specification therefore assumes risk-neutrality but allows for the consumer to suffer an additional utility loss l_i if she delays purchasing but ends up with a deal which is worse than the one she would have got in the first period (i.e., her preferences show a form of loss aversion)

$$v_{1i} - p_1 \geq -s_i + \int_0^{\infty} (v_{2i} - p_2) f_{2i}(v_{2i} - p_2) d(v_{2i} - p_2) - \int_{-\infty}^{v_{1i}-p_1} l_i f_{2i}(v_{2i} - p_2) d(v_{2i} - p_2) \tag{16}$$

In this section I will assess how many observed early purchase decisions (in the model people who choose to buy in period 1) can be rationalized for different values of s_i, α_i and l_i, making a variety of assumptions about consumers' valuations and their willingness to substitute across different types of listings.

6.2 Defining Consumer Preferences and Evaluating Early Purchases

Calibrating the model entails making several assumptions. In this sub-section I describe these assumptions and then explain in detail how I evaluate early purchases. All of the analysis uses data from Market 2, where I can observe actual transactions.

6.2.1 Assumptions on Preferences

When Would the Buyer Return to the Market? It is unreasonable to believe that a consumer who delays purchasing is able to constantly monitor the set of tickets which are available. I therefore assume that, if she was to delay purchasing, a buyer would return to Market 2 once five days before the game which is when availability on Market 2 is at its maximum and prices are close to their lowest level.

Which Tickets Would be Considered Available Five Days Before the Game? Five days prior the game, tickets may be available in pure auction, fixed price or hybrid auction listings. To model a buyer's beliefs about availability and prices, it is necessary to define which of these listings would be considered available, given the uncertainties involved in bidding in auctions. I assume that all fixed price and hybrid auction listings available at midnight five days before the game are available to a returning buyer at the fixed price. I consider two alternative assumptions about auction listings. The first assumption is that auctions (pure (including multi-unit) or hybrid) which end five days before the game with no bids and no secret reserve price are available at the auction start price. The alternative assumption is that the buyer would ignore all auction listings which is plausible because having waited until five days before the game she may want to guarantee that she actually gets the tickets without having to return to the market again. In practice, these different assumptions have relatively little effect on whether any tickets are available five days before the game, but they do have significant effects on prices because auction start prices tend to be low.

Which Tickets Would a Buyer Consider Substituting To? How Would She Value Them? Tickets to an individual game are differentiated products, and a person who buys a seat behind homeplate might not be willing to sit in the bleachers even if the bleacher price was very low. It is therefore necessary to define the set of tickets which the buyer would consider substituting between and how she would value them. Throughout I assume that a buyer would only consider going to the same game and buying at least as many seats as she actually bought.

The first assumption, which I will call the "better ticket" assumption, is that the buyer would only consider buying tickets at least as good as those she actually bought, where quality is defined along three dimensions: (i) the tickets must have equal or greater face value; (ii) if the face value is equal they must be in the same or a lower row; (iii) the seller must have a weakly higher feedback score[33], and that these tickets would give her the same utility (v_{1i}) as the tickets she actually bought. By ignoring the possibilities that a consumer would substitute to lower quality tickets or that she would get more utility from better tickets, this assumption will probably err in making it too unattractive for a buyer to wait.[34]

The alternative ("any ticket") assumption is that the buyer would consider any tickets but that

[33] I implement this criterion using the four feedback score categories defined in Section 3.

[34] There is some indirect evidence that the better ticket assumptions is not completely unreasonable for many buyers: when I observe people unsuccessfully bidding in auctions but later buying tickets to the same game (223,503 cases), 74% of them buy from a sellers with at least as high feedback score and 68% of them buy tickets with at least as high face value.

the value she gets from these tickets varies dollar-for-dollar with their face value. Row and seller feedback are ignored under this assumption. For example, if I observe a consumer purchasing a seat with \$60 face value for \$40 and I assume that she values it at \$50 then I would assume that she would value a seat with a \$40 face value at \$30. As buyers are likely to purchase seats which are particularly good matches for their preferences, this assumption is likely to err on the side of making it too attractive for a buyer to wait.

How Does A Buyer Value The Tickets She Buys? The final assumption concerns how a buyer values the tickets she is observed to buy in the first period (i.e., $v_{1i} - p_1$). When tickets are valued more highly, a buyer will be more inclined to purchase early if future availability is uncertain. I allow $v_{1i} - p_1$ to take on values of \$10, \$25, \$50 and \$75 per seat.

6.2.2 Evaluating Early Purchases

I now explain the steps involved in evaluating early purchases under the "better ticket" assumption. In the case of risk-neutrality it is useful to express the right-hand side of (14) as $-s_i + q_i \int_0^{v_{1i}} (v_{1i} - p_2) g_{2pi}(p_2) dp_2$, where q_i is the consumer's belief that a better ticket will be available and $g_{2_{pi}}(p_2)$ is the density of the price of the cheapest available better ticket. Utilities under risk aversion and loss aversion can be expressed in similar ways.

Step 1: Estimating a Consumer's Expectations About Ticket Availability (q_i) I estimate a consumer's expectation of whether a better ticket will be available using a probit model, where the explanatory variables are game, ticket and listing characteristics of the tickets which the consumer actually purchased. The sample consists of all 289,784 sets of tickets with non-missing face value information which I observe ever being purchased in the Market 2 data. The dependent variable is whether a better ticket is available five days before the game.

Step 2: Estimating a Consumer's Expectations About Future Ticket Prices Under the assumption that a consumer receives utility v_{1i} from any better ticket, she will purchase the cheapest better ticket available. I model the price of the cheapest better ticket (conditional on a better ticket being available) as being drawn from a two-parameter gamma distribution where the parameters are linear functions of observed ticket, listing and game characteristics

$$p_2 \sim \Gamma(k, \theta) \text{ where } k = \exp(X_0\beta_0), \theta = \exp(X_1\beta_1)$$

I estimate the parameters using the 255,885 observations on ever purchased tickets with non-missing face value information where a better ticket was available five days before the game. The price is defined per seat purchased so that if two seats were bought but the only available better tickets are in a three seat listing for \$180 then the price per seat purchased would be \$90.

Table 12 shows some of the coefficients from the estimated probit and gamma models, assuming that both fixed price and auction listings (with no bidders) are available. On average, better tickets are available for 88% of listings (this high availability reflects the fact that most purchased tickets are for popular games which have a lot of listings), and the average price of the cheapest available better ticket is \$42.59 per seat. The coefficients themselves show a sensible pattern with, for example, less availability and higher prices for purchased listings with more seats, higher face values (at least for face values covered by almost all of the data) and better rows. Interestingly, 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).

Step 3: Evaluating Observed Early Purchases The predicted availability of better tickets from the estimated probit model and the estimated price distribution are used to evaluate the inequalities (14), (15) and (16) using assumed values for $v_{1i} - p_1$, s_i, α_i and l_i for each observed early purchase. I define early purchases as those being made more than ten days before the game is played. If the inequality holds then the early purchase is said to be rationalized.

6.2.3 Results Under the Better Ticket Assumption

The top section of Table 13 presents the results of the analysis assuming that a waiting buyer would consider auction listings with no bidders to be available. The first line shows the proportion of early purchases which can be rationalized with no search costs, risk neutrality and no loss aversion for different buyer valuations. If a buyer gets a surplus of \$25 per seat from the tickets she actually buys then 41% of observed early purchase decisions are rationalized. These are a combination of buyers who purchase early but happen to find relatively low prices and buyers who purchase tickets for which substitutes are relatively unlikely to be available at a later date. For example, 79% of early purchases of three or more seats are rationalized if surplus is \$25 per seat, compared with only 35% of purchases of pairs. As surplus increases, buyers stand to lose more if tickets are not available so a greater proportion of purchases are rationalized.

The next three lines show how the results change as return to market costs are increased, with risk neutrality and no loss aversion. When return to market costs are above \$25 the vast majority of early purchases can be rationalized even without needing to assume that consumers get high surplus. This reflects the fact that the expected price gain to delaying until five days before the game is generally less than \$25. The final four lines show the effects of introducing risk or loss aversion without return to market costs and then combining \$25 per seat return to market costs with some risk or loss aversion. With a coefficient of absolute risk aversion of 0.05 a person would be indifferent to accepting a gamble with a 0.62 probability of winning \$10 and a 0.38 probability of losing \$10. Risk aversion has a particularly large effect on the desire to purchase early when buyers are assumed to get a lot of surplus. On the other hand, when combined with return to market costs, both risk and loss aversion can rationalize almost all observed early purchasing even when surplus is lower (e.g., \$25 or \$50 per ticket).

The next section of the table shows the effects of assuming that only fixed price listings are available. Making this assumption actually only has a small average effect on predicted availability (the average $\widehat{q_i}$ falls by around one percentage point) but it has a large effect on expected prices because fixed prices are generally higher than the start prices of auctions (even those with no bidders) so the cheapest better ticket price tends to increase. As a result the majority of observed purchases are rationalized for lower return to market costs or risk/loss aversion parameters.

6.2.4 Results Under the Any Ticket Assumption

The last two sections of Table 13 present the results under the assumption that consumers would consider purchasing any ticket to the same game with the same number of seats, and that their valuations of tickets would vary one-for-one with face values. As a result, a waiting consumer would buy the ticket with the lowest price relative to the ticket's face value (i.e., the lowest $p_2^{MKT\ 2} - p_2^{FACE}$). This relative price can be negative so I model the lowest price as being drawn from a normal rather than a gamma distribution. As before, ticket availability is modeled using a probit although under the any ticket assumption average availability is very high (the average $\widehat{q_i}$ is 0.98 even when only tickets at fixed prices are considered to be available).

The result of allowing consumers to substitute to a wider variety of tickets is that fewer early purchases are rationalized for any value of the return to market, risk or loss aversion parameters. The main insight is that plausible values of risk or loss aversion alone cannot rationalize the majority of purchases for plausible values of buyer surplus. This is especially true for two seat purchases which make up the vast majority of the sample (for 4 or more seats 40% of purchases are still justified with \$25 surplus and no return to market costs or risk or loss aversion). On the other hand, once one allows for \$50 return to market costs or \$25 return to market costs combined with some risk aversion around two-thirds of early purchases can be rationalized.

6.3 Supporting Evidence: Who Buys Early?

The calibration exercise showed that early purchasing can be rationalized by return to market costs of \$25-\$50 per seat or high valuations for tickets where there is a reasonable probability that substitute tickets may not be available close to the game (e.g., people buying four or more seats). This leads to testable implications about which types of buyers should buy tickets early (those likely to have high return to market costs) and the types of tickets which should be purchased earlier (those which are likely to have fewer substitutes for some subset of consumers).

For online markets the time costs involved in returning to the market at a later date are likely to be relatively small. However, there may be significant other costs involved in waiting to buy. For example, "complementary investments" (booking hotels or plane tickets, finding baby-sitters, coordinating with friends) which must be made to attend the game may be more significantly expensive (or difficult) if they are made at the last minute and when ticket availability is not certain people will be unwilling to make these investments before buying game tickets. A plausible assumption is that people who live further away from the stadium tend to have to make larger complementary investments, on average, to attend a game. Consistent with this story, early purchasers tend to live further away from the stadium where the game is played. Table 14(a) shows the results of regressing the log of the distance that buyers live from the stadium on the same variables that were used in the price regressions in Section 3 including game-section fixed effects. The mean (median) distance is 295 (59) km.[35] On average, buyers who buy 30-32 days before a game live 73% further away from the stadium than people who buy 0-2 days before the game. The proportional effect is similar using different fixed effects, a least absolute deviations estimator to look at median distances and when controlling for buyer experience. An interesting finding which suggests that early purchasing is not driven purely by ignorance of observed price declines, is that controlling for distance, more experienced buyers are not significantly more likely to buy closer to the game.

[35] The regression excludes 3,821 observations where I was unable to calculate the distance either because the buyer zipcode was missing or I was unable to calculate the distance (e.g., Canadian buyers).

Table 14(b) reports the results of regressing the number of days to go when the transaction takes place on ticket and game characteristics (controlling for buyer distance effects using a third-order polynomial in distance and a dummy for buyers living within 40 km of the stadium). Four and six seat listings are less likely to be available than pairs and consistent with the model these listings tend to be purchased earlier. Three and five seat listings show the opposite effect, but this may be due to people who want smaller listings (two or four seats) buying these listings close to the game when they fear that suitable listings for their ideal number of seats will not become available. Better rows (first or second row, or lower row number) also tend to be purchased earlier (even though Figure 1(d) shows that the average row quality of available listings tends to increase as the game approaches) consistent with some consumers having strong preferences to sit at the front of a section. One surprising feature is that higher face value tickets tend to be purchased closer to the game.

Controlling for team effects, tickets to games with higher expected attendance tend to be purchased earlier. This is consistent with buyers perceiving that there is more competition for these tickets, combining the primary and secondary markets, even though these games have more secondary market listings. There may also be more consumers with very high valuations for these games which would also rationalize earlier purchasing.

7 Conclusion

This paper has examined a striking feature of prices in online resale markets for MLB tickets: they tend to fall significantly as a game approaches. The falling price pattern exists for both posted and transaction prices and it is similar across teams, demand conditions and cheap and expensive seats and across different trading mechanisms. Consistent with theoretical models of dynamic pricing for perishable goods, sellers cut prices as a game approaches because their future selling opportunities disappear. My finding that these theoretical models accurately describe the behavior of sellers who do not typically employ complex revenue management systems, contrasts with the results of previous attempts to test these models using data from the airline industry.

The paper also examines why some buyers purchase a long time before the game when prices are expected to fall. Until very recently, this question has been ignored by the theoretical literature which assumed that buyers could not time their purchases strategically. Under the assumption that consumers are aware of the expected price declines, I show that the majority of observed early purchase decisions can be justified by plausible ticket valuations and return to market costs, possibly combined with some degree of risk- or loss-aversion.

Two questions seem ripe for further analysis. First, why are pricing patterns in this market different from those observed in airline markets and possibly markets for other perishable goods such as hotel rooms and spots on radio and television stations? A possible demand-side explanation is that, compared with resale markets for MLB tickets, it may be much more likely that a customer arriving close to the end will have high a valuation. This seems particularly plausible for airlines and hotels. An alternative supply-side explanation is that market concentration and repeated interaction between the same buyers and sellers provides incentives for sellers to commit or build reputations for not reducing their prices, and I have heard this type of argument made for the sale of spots by radio stations.

The second question concerns what affects sellers' choices over which market and which trading mechanism to use. A nice feature of my data is that I observe sellers switching from one mechanism to another as the game approaches, presumably because some mechanism characteristics, such as the price flexibility offered by auctions, are more valuable when sellers are really keen to sell. On the other hand, buyers may prefer the certainty offered by fixed price purchases when there is little time remaining. Understanding how different trading mechanisms are valued by both buyers and sellers potentially has implications far beyond the type of online resale market considered here.

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Table 1: Summary Statistics By Team

	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	Market 2 Mean, Median # of Days Purchase Prior to Game		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
Atlanta Braves	0.63	150,956	15,913	8,124	260	41.80	35.34	18.3	9	103.3
Baltimore Orioles	0.55	146,770	17,159	6,889	83	62.73	37.20	32.3	14	70.4
Boston Red Sox	0.99	342,658	65,016	35,907	39	106.38	38.25	37.8	18	56.1
Chicago White Sox	0.85	257,272	33,701	15,440	150	42.33	34.57	34.5	12	24.9
Chicago Cubs	0.96	485,003	52,508	25,755	13	67.52	29.45	24.1	11	42.9
Cincinnatti Reds	0.59	32,426	16,882	7,968	151	40.63	27.73	22.7	10	67.4
Cleveland Indians	0.68	57,438	15,306	7,879	218	40.34	29.06	19.1	9	46.8
Colorado Rockies	0.59	33,714	3,484	1,815	226	45.38	N/A	21.8	11	53.1
Detroit Tigers	0.85	227,020	36,595	17,276	97	41.10	23.16	23.6	9	36.5
Florida Marlins	0.40	8,134	1,673	859	666	36.01	33.74	7.9	5	22.3
Houston Astros	0.85	100,240	10,225	5,650	82	48.02	31.32	14.1	6	27.2
Kansas City Royals	0.48	19,928	4,702	2,237	223	41.57	22.89	18.1	8	54.8
Los Angeles Angels	0.94	238,824	34,485	16,605	54	38.39	24.50	16.9	6	19.5
Los Angeles Dodgers	0.85	216,623	43,382	21,730	121	38.24	45.33	17.2	6	19.7
Milwaukee Brewers	0.78	27,650	14,743	8,845	202	34.36	26.40	17.9	8	51.7
Minnesota Twins	0.59	23,173	3,170	1,523	297	36.65	32.32	11.6	6	27.7
New York Mets	0.84	201,669	30,964	13,051	52	52.11	34.27	18.2	8	24.4
New York Yankees	0.96	579,124	103,569	41,192	26	54.19	56.63	28.4	12	44.6
Oakland Athletics	0.68	37,773	4,343	1,845	109	46.59	33.71	15.5	8	42.6
Philadelphia Phillies	0.85	92,735	11,323	5,993	66	60.23	33.43	21.0	10	28.7
Pittsburgh Pirates	0.58	20,992	2,871	1,972	286	30.69	22.79	23.5	12	39.7
San Diego Padres	0.77	82,755	11,399	5,078	166	55.37	35.34	19.3	6	31.3
San Francisco Giants	0.91	334,489	28,349	12,744	45	46.04	34.05	21.9	8	45.9
Seattle Mariners	0.71	62,792	5,423	2,883	156	51.82	37.39	15.3	9	42.8
St Louis Cardinals	0.95	260,886	42,521	19,418	48	50.33	35.51	27.6	12	91.4
Tampa Bay Devil Rays	0.45	14,445	2,518	1,245	298	50.88	39.53	18.6	8	63.0
Texas Rangers	0.58	47,675	12,035	5,261	227	34.45	33.35	13.6	6	28.8
Toronto Blue Jays	0.58	19,606	2,161	698	862	44.91	44.07	24.1	11	196.3
Washington Nationals	0.60	117,399	5,914	2,251	204	34.55	44.20	17.6	7	24.7
Totals		4,331,927	637,217	298,128						

Notes: HHI is calculated based on the number of transactions. Mean face value is calculated based on seating sections for which single-game prices can be identified. Transaction price is the price paid by buyers including shipping.

Table 2: Summary Statistics

Number of Seats Per Listing			
No. of Seats in Listing	Stubhub # listings	Market 2 # listings	Market 2 # transactions
1	50,490	5,314	2,576
2	1,708,002	554,038	260,216
3	231,889	10,908	4,928
4	1,863,810	56,794	29,443
5	88,985	3,077	1,245
6	388,751	3,907	1,971

Sales Mechanism on Market 2	No. of Listings	No. of Transactions
Single-Unit Auction		
Auction no BIN option	235,075	146,122
Auction with BIN option	207,221	
sold by BIN option		51,711
sold by auction		48,878
Multi-Unit Auction	8,129	1,541
Personal Offer	7,926	1,525
(all sold at fixed price)		
Fixed Price Format		
Store Fixed Price	46,864	7,861
Non-Store Fixed Price	128,823	42,741

	Secondary Market Prices, $ per seat					Primary Market (Face Value) Prices, $ per seat					Secondary/Primary Price	
Stubhub Listings	**No. of Obs.**	**Mean**	**Std Dev**	**Min**	**Max**	**No. of Obs.**	**Mean**	**Std Dev**	**Min**	**Max**	**Mean**	**Std Dev**
Buyer Price	67,517,910	102.17	87.8	3.05	999.75	66,236,993	38.96	26.87	5	312	2.74	1.89
Seller Price	67,517,910	75.47	67.83	0.0085	769.25	66,236,993	38.96	26.87	5	312	1.99	1.45
Market 2 Transactions												
Buyer Price	300,379	54.94	53.75	0.0025	959.5	290,360	36.48	32.8	5	312	1.77	1.64
Seller Price	300,379	49.46	51.38	0.0023	918.39	290,360	36.48	32.8	5	312	1.57	1.56
Market 2 Listing Prices												
Auction Start Price	450,425	34.93	50.94	0.0017	1000	432,661	36.67	33.7	5	312	1.04	1.39
Fixed Price	390,834	69.88	71.28	0.005	1000	376,325	39.64	39.98	5	312	2.13	1.99
excluding seller commission	390,834	67.13	68.82	0.0045	967.38	376,325	39.64	39.98	5	312	2.04	1.92

Notes: seller prices exclude commissions. Buyer prices include commissions paid by buyer and shipping costs. Primary market prices are calculted based on sections for which single-game prices can be identified.

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 * Games to Go	-0.0000741***	-0.0000174	-0.00642***	-0.0000157	-0.0000939*	0.000183***	-0.0000889***	0.0000205	-0.0000116	0.000191***	0.0000657
	(0.0000)	(0.0000)	(0.0016)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
Games Back * Games to Go	0.000102***	0.0000970***	0.00259***	0.0000814***	0.000108***	0.000166***	0.0000662***	0.0000653***	0.0000302**	0.000119***	0.0000980***
	(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 specifications include dummies for the number of seats in the listing (1-6), dummies for ticket characteristics (e.g., piggy back seats), away team form variables. Specifications with game-section fixed effects include row quality control variables. Standard errors in parentheses clustered on the listing id number. ***,** and * denote significance at the 1, 5 and 10% levels. Within R2 does not include fixed effects. Buyer prices include shipping costs and commissions. Seller prices exclude commissions.

Table 4: Market 2 Transactions

	(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)
12 to 14 days	0.136***	0.145***	0.114***	0.153***	0.208***	0.124***	0.119***	0.149***	0.125***	0.0846***	0.168***
	(0.0057)	(0.0084)	(0.0077)	(0.0055)	(0.0100)	(0.0110)	(0.0130)	(0.0092)	(0.0110)	(0.0160)	(0.0110)
15 to 17 days	0.169***	0.175***	0.162***	0.181***	0.239***	0.168***	0.122***	0.183***	0.173***	0.105***	0.191***
	(0.0062)	(0.0089)	(0.0084)	(0.0060)	(0.0110)	(0.0120)	(0.0140)	(0.0099)	(0.0120)	(0.0170)	(0.0120)
18 to 20 days	0.189***	0.204***	0.187***	0.200***	0.243***	0.203***	0.119***	0.180***	0.168***	0.171***	0.242***
	(0.0067)	(0.0093)	(0.0091)	(0.0065)	(0.0110)	(0.0130)	(0.0150)	(0.0100)	(0.0130)	(0.0200)	(0.0140)
21 to 23 days	0.203***	0.226***	0.199***	0.212***	0.270***	0.216***	0.158***	0.192***	0.197***	0.187***	0.238***
	(0.0073)	(0.0100)	(0.0099)	(0.0071)	(0.0120)	(0.0140)	(0.0170)	(0.0110)	(0.0150)	(0.0210)	(0.0150)
24 to 26 days	0.228***	0.219***	0.224***	0.230***	0.287***	0.247***	0.183***	0.224***	0.222***	0.157***	0.283***
	(0.0077)	(0.0110)	(0.0100)	(0.0075)	(0.0120)	(0.0150)	(0.0180)	(0.0120)	(0.0150)	(0.0220)	(0.0160)
27 to 29 days	0.224***	0.221***	0.224***	0.222***	0.280***	0.237***	0.197***	0.190***	0.242***	0.186***	0.269***
	(0.0082)	(0.0110)	(0.0110)	(0.0080)	(0.0130)	(0.0160)	(0.0190)	(0.0130)	(0.0160)	(0.0240)	(0.0160)
30 to 32 days	0.249***	0.236***	0.250***	0.245***	0.269***	0.283***	0.169***	0.219***	0.262***	0.238***	0.277***
	(0.0087)	(0.0110)	(0.0120)	(0.0084)	(0.0140)	(0.0170)	(0.0200)	(0.0140)	(0.0180)	(0.0240)	(0.0180)
33 to 35 days	0.247***	0.250***	0.257***	0.240***	0.249***	0.283***	0.190***	0.220***	0.241***	0.250***	0.293***
	(0.0091)	(0.0120)	(0.0120)	(0.0089)	(0.0140)	(0.0170)	(0.0200)	(0.0140)	(0.0190)	(0.0270)	(0.0190)
36 to 38 days	0.243***	0.242***	0.249***	0.241***	0.285***	0.250***	0.189***	0.213***	0.274***	0.204***	0.268***
	(0.0099)	(0.0130)	(0.0130)	(0.0096)	(0.0160)	(0.0190)	(0.0240)	(0.0150)	(0.0200)	(0.0290)	(0.0200)
39 to 41 days	0.264***	0.262***	0.269***	0.252***	0.278***	0.300***	0.211***	0.225***	0.288***	0.250***	0.310***
	(0.0100)	(0.0130)	(0.0140)	(0.0100)	(0.0160)	(0.0190)	(0.0240)	(0.0150)	(0.0210)	(0.0290)	(0.0230)
42 to 44 days	0.255***	0.266***	0.266***	0.246***	0.269***	0.267***	0.171***	0.206***	0.271***	0.249***	0.317***
	(0.0110)	(0.0140)	(0.0150)	(0.0100)	(0.0160)	(0.0210)	(0.0240)	(0.0160)	(0.0210)	(0.0300)	(0.0240)
45 to 47 days	0.242***	0.245***	0.247***	0.234***	0.259***	0.255***	0.195***	0.218***	0.274***	0.189***	0.263***
	(0.0110)	(0.0140)	(0.0150)	(0.0110)	(0.0170)	(0.0210)	(0.0260)	(0.0160)	(0.0230)	(0.0310)	(0.0250)
48 to 50 days	0.235***	0.225***	0.244***	0.232***	0.270***	0.288***	0.142***	0.217***	0.236***	0.171***	0.297***
	(0.0120)	(0.0150)	(0.0160)	(0.0110)	(0.0180)	(0.0230)	(0.0280)	(0.0180)	(0.0240)	(0.0340)	(0.0250)
51 to 55 days	0.228***	0.223***	0.229***	0.214***	0.254***	0.264***	0.153***	0.189***	0.243***	0.184***	0.299***
	(0.0100)	(0.0130)	(0.0140)	(0.0097)	(0.0150)	(0.0190)	(0.0230)	(0.0150)	(0.0200)	(0.0300)	(0.0230)
56 to 60 days	0.230***	0.236***	0.241***	0.221***	0.258***	0.235***	0.224***	0.198***	0.249***	0.168***	0.289***
	(0.0110)	(0.0140)	(0.0140)	(0.0100)	(0.0170)	(0.0210)	(0.0240)	(0.0150)	(0.0210)	(0.0330)	(0.0250)
61 to 70 days	0.225***	0.216***	0.222***	0.225***	0.286***	0.258***	0.193***	0.202***	0.235***	0.171***	0.268***
	(0.0087)	(0.0120)	(0.0120)	(0.0084)	(0.0140)	(0.0170)	(0.0200)	(0.0120)	(0.0180)	(0.0270)	(0.0210)
71 to 80 days	0.209***	0.208***	0.195***	0.206***	0.272***	0.224***	0.229***	0.170***	0.241***	0.241***	0.204***
	(0.0092)	(0.0120)	(0.0120)	(0.0089)	(0.0140)	(0.0180)	(0.0210)	(0.0130)	(0.0190)	(0.0300)	(0.0220)
81 plus	0.147***	0.155***	0.122***	0.150***	0.233***	0.184***	0.168***	0.115***	0.161***	0.124***	0.195***
	(0.0071)	(0.0110)	(0.0096)	(0.0069)	(0.0120)	(0.0140)	(0.0170)	(0.0100)	(0.0150)	(0.0220)	(0.0190)
Home Team Form Variables											
Games Ahead	0.00769***	0.0067	0.00730**	0.0120***	0.0132***	0.00952	0.0173***	0.00781***	0.0039	-0.0288**	0.0258***
	(0.0026)	(0.0041)	(0.0035)	(0.0025)	(0.0040)	(0.0065)	(0.0052)	(0.0030)	(0.0097)	(0.0140)	(0.0080)
Games Back	-0.0269***	-0.0258***	-0.0326***	-0.0268***	-0.0161***	-0.0187***	-0.0167***	-0.0416***	-0.0329***	-0.0282***	-0.0157***
	(0.0011)	(0.0018)	(0.0015)	(0.0011)	(0.0020)	(0.0026)	(0.0024)	(0.0032)	(0.0024)	(0.0026)	(0.0020)
Games Ahead *	-0.0000308	-0.0000227	-0.0000282	-0.0000559**	-0.0000847**	0.0000207	-0.000201***	-0.0000803***	-0.0000166	0.000319**	-0.00000522
Games to Go	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)
Games Back *	-0.00000882	0.00000926	-0.0000117	-0.0000115	-0.0000329	-0.0000805***	-0.0000856***	0.0000862***	0.0000416	-0.00000963	-0.0000242
Games to Go	(0.0000)	(0.0000)	(0.0000)	(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	Game-Section	Game-Section	Game-Section	Game-Section	Game-Section	Game-Section	Game-Section	Game-Section
Sale Format Dummies	No	No	No	Yes	No	No	No	No	No	No	No
Average Buyer Price $	54.94	54.94	54.94	54.94	65.06	29.82	89.53	80.31	48.71	40.46	39.81
Within R^2	0.08	0.05	0.0475	0.06	0.09	0.09	0.05	0.07	0.08	0.07	0.11
Observations	300,379	300,379	300,379	300,379	103,838	89,308	74,140	92,520	86,208	48,071	73,580

Notes: all specifications include dummies for the number of seats in the listing (1-6), the feedback score of the seller (4 dummies), dummies for ticket and listing characteristics (e.g., piggy back seats), away team form variables and dummies for if feedback or shipping cost information is missing (1,352 observations). Specifications with game-section fixed effects also include row quality control variables. Standard errors in parentheses. ***,** and * denote significance at the 1, 5 and 10% levels. Within R2 does not include fixed effects. Buyer prices include shipping costs. Seller prices exclude commissions.

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)
Date Used	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 *	-0.000036	0.000393***	-0.0000221	0.000393***	-0.0000209	0.000422***	0.0000501	0.000552*
Games to Go	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Games Back *	0.0000734***	0.000285***	0.0000658***	0.000290***	0.000129***	0.000375***	0.0000221	0.000137
Games to Go	(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: see Table 4. 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. Prices do not include shipping costs.

Table 6: Testing the Lazear (1986) Explanation for Falling Prices

	(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 Auctions Experienced	Market 2 Fixed Prices Inexperienced	Market 2 Auctions 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)
56 to 60 days	0.730***	0.686***	1.350***	1.025***	0.330***	0.302***	0.723***	0.729***	0.381***	0.562***
	(0.007)	(0.007)	(0.023)	(0.027)	(0.003)	(0.003)	(0.021)	(0.081)	(0.030)	(0.097)
61 to 70 days	0.738***	0.692***	1.373***	1.011***	0.338***	0.305***	0.753***	0.803***	0.329***	0.529***
	(0.006)	(0.007)	(0.021)	(0.026)	(0.003)	(0.003)	(0.021)	(0.077)	(0.028)	(0.086)
71 to 80 days	0.747***	0.697***	1.457***	1.047***	0.344***	0.306***	0.781***	0.983***	0.353***	0.385***
	(0.006)	(0.007)	(0.022)	(0.029)	(0.003)	(0.003)	(0.021)	(0.081)	(0.031)	(0.098)
81 plus	0.781***	0.719***	1.635***	1.069***	0.364***	0.307***	0.838***	1.294***	0.342***	0.432***
	(0.005)	(0.007)	(0.021)	(0.033)	(0.003)	(0.003)	(0.021)	(0.082)	(0.026)	(0.078)
Days Since First Listing										
Tenure	-	-0.00229***	-	-0.0142***	-	-0.0000950**	-	-	-	-
		(0.000)		(0.001)		(0.000)				
Tenure^2/100	-	0.00313***	-	0.0325***	-	-0.00194***	-	-	-	-
		(0.000)		(0.003)		(0.000)				
Tenure^3/(10^4)	-	-0.00160***	-	-0.0396***	-	0.00224***	-	-	-	-
		(0.000)		(0.004)		(0.000)				
Tenure^4/(10^6)	-	0.000274	-	0.0191***	-	-0.00109***	-	-	-	-
		(0.000)		(0.002)		(0.000)				
Tenure^5/(10^8)	-	-0.00000859	-	-0.00323***	-	0.000182***	-	-	-	-
		(0.000)		(0.000)		(0.000)				
Fixed Effects	Seller-Game-Section	Seller-Game-Section	Seller-Game-Section	Seller-Game-Section	Ticket Id	Ticket Id	Game-Section	Game-Section	Game-Section	Game-Section
Sale Format Dummies	Yes	Yes	Yes	Yes	No (one format)	No (one format)	Yes	Yes	Yes	Yes
Observations	390,834	390,834	450,425	450,425	1,965,659	1,965,659	118,187	74,454	76,887	139,974

Notes: see Tables 4 and 5. Specifications also include home team form variables.

Table 7: Regressions of Market 2 Prices on Instruments

Listing Sample	Pure Fixed Price	Pure Auction	Hybrid Auction	
Price (relative to face value)	Fixed Price	Auction Start	Auction Start	Fixed Price
Seller Within 40 km	-0.0218	0.018	-0.0329*	-0.0375*
	(0.024)	(0.028)	(0.020)	(0.023)
* 1-10 Days Prior to Game	0.0482	0.023	0.0291	0.0298
	(0.030)	(0.029)	(0.021)	(0.025)
* 11-20 Days Prior to Game	0.0223	-0.016	0.0357***	0.0349*
	(0.028)	(0.028)	(0.023)	(0.029)
* 21-40 Days Prior to Game	-0.0224	-0.019	0.00393	0.0384**
	(0.028)	(0.028)	(0.022)	(0.028)
Seller More than 200 km	0.163***	-0.0493**	-0.0366*	-0.0294
	(0.023)	(0.022)	(0.020)	(0.023)
* 1-10 Days Prior to Game	-0.229***	-0.0477**	-0.00819	-0.0304
	(0.029)	(0.023)	(0.021)	(0.025)
* 11-20 Days Prior to Game	-0.133***	-0.038	-0.015	0.0102
	(0.026)	(0.024)	(0.021)	(0.026)
* 21-40 Days Prior to Game	-0.0566**	0.007	-0.0368*	-0.0283
	(0.027)	(0.023)	(0.021)	(0.025)
Proportion of Seller's Unsold Listings	-0.118***	-0.0538*	0.137***	0.0700***
During Time Period Relisted on Market 2	(0.033)	(0.030)	(0.025)	(0.031)
* 1-10 Days Prior to Game	-0.0901*	0.284***	-0.173***	-0.172***
	(0.050)	(0.033)	(0.029)	(0.037)
* 11-20 Days Prior to Game	-0.131**	0.146***	-0.119***	-0.137***
	(0.063)	(0.035)	(0.031)	(0.042)
* 21-40 Days Prior to Game	-0.424***	0.256***	-0.0354	-0.0648**
	(0.050)	(0.038)	(0.034)	(0.042)
Proportion of Seller's Other Listings	-0.101*	0.232***	0.149***	0.153***
in Hybrid Auction Format	(0.056)	(0.052)	(0.034)	(0.039)
* 1-10 Days Prior to Game	0.162**	-0.045	-0.0470	-0.116***
	(0.067)	(0.056)	(0.035)	(0.042)
* 11-20 Days Prior to Game	0.270***	-0.007	-0.0426*	-0.0293
	(0.072)	(0.055)	(0.038)	(0.043)
* 21-40 Days Prior to Game	0.0918*	-0.046	-0.00315	-0.0511
	(0.071)	(0.056)	(0.040)	(0.048)
Proportion of Seller's Other Listings	0.138***	0.476***	0.119***	0.218***
in Pure Fixed Price Formats	(0.040)	(0.049)	(0.043)	(0.052)
* 1-10 Days Prior to Game	-0.226***	-0.602***	-0.0927*	-0.234***
	(0.047)	(0.054)	(0.048)	(0.060)
* 11-20 Days Prior to Game	0.0388	-0.476***	-0.119**	-0.172**
	(0.052)	(0.055)	(0.055)	(0.068)
* 21-40 Days Prior to Game	0.016	-0.351***	-0.0117	-0.0334
	(0.054)	(0.061)	(0.053)	(0.062)
		-		
Average Relative Fixed Price in	-		-0.202***	0.391***
other Hybrid Auction Listings		-	(0.012)	(0.014)
* 1-10 Days Prior to Game	-		0.0678***	0.0453***
		-	(0.013)	(0.017)
* 11-20 Days Prior to Game	-		0.0904***	0.0207**
		-	(0.021)	(0.023)
* 21-40 Days Prior to Game	-		0.0701***	-0.0644*
			(0.016)	(0.035)
		-		
Average Relative Start Price	-		0.599***	-0.128***
in other Hybrid Auction Listings		-	(0.014)	(0.016)
* 1-10 Days Prior to Game	-		0.0530***	0.0793***
		-	(0.019)	(0.021)
* 11-20 Days Prior to Game	-		0.00197	0.0429*
		-	(0.023)	(0.025)
* 21-40 Days Prior to Game	-		-0.0430**	0.0845**
			(0.022)	(0.036)
Observations	109,296	182,302	115,406	115,406
F-statistic on the instruments	15.71	47.75	231.84	76.43

Notes: Specifications also include competition variables, dummies for number of seats, seller feedback scores, ticket and listing characteristics, row quality controls, home team dummies, home team*face value interactions, home team*game expected attendance interactions and dummies for sellers with 1 and less than 10 listings. Standard errors in parentheses clustered on the game. ***,** and * denote significance at the 1, 5 and 10% levels

Table 8: Fixed Price Probability of Sale Model

	(1) Probit Model	(2) Probit Model With Control Function to Address Own Price Endogeneity	(3) Probit Model With Control Function to Address Own and Competitor Price Endogeneity
<u>Own Price Coefficients</u>			
Relative Fixed Price	-0.200***	-0.895***	-0.805***
	(0.014)	(0.045)	(0.049)
1-10 Days Prior to Game*Relative Price	0.072***	0.007	-0.018
	(0.016)	(0.020)	(0.022)
11-20 Days Prior to Game*Relative Price	0.066***	0.012	-0.003
	(0.016)	(0.022)	(0.024)
21-40 Days Prior to Game*Relative Price	0.0351**	-0.019	-0.051**
	(0.018)	(0.020)	(0.025)
<u>Competition Coefficients</u>			
Mean Relative Price for Fixed Price Listings	0.092***	0.258***	0.398***
	(0.012)	(0.021)	(0.086)
Mean Relative Start Price for Auction Listings	0.028**	0.080***	0.070
	(0.014)	(0.017)	(0.064)
Minimum Relative Price for Fixed Price Listings	0.000	0.049***	-0.247**
	(0.011)	(0.016)	(0.107)
Minimum Relative Price for Auction Listings	-0.041**	-0.080***	-0.146**
	(0.015)	(0.017)	(0.073)
Dummy Variable for No Competing	0.275***	0.689***	0.344***
Fixed Price Listings	(0.029)	(0.043)	(0.124)
Dummy Variable for No Competing	-0.091***	-0.146***	-0.142***
Auction Listings	(0.023)	(0.023)	(0.036)
Number of Competing Fixed Price Listings	-0.007***	-0.012***	-0.020***
	(0.002)	(0.002)	(0.004)
Proportion of Competing Fixed Price Listings with	-0.053	0.035	-0.190**
Seller Feedback Scores Above 100	(0.040)	(0.041)	(0.087)
Number of Competing Auction Listings	0.001	0.004*	0.002
	(0.002)	(0.002)	(0.003)
Proportion of Competing Auction Listings with	-0.018	-0.078***	-0.031
Seller Feedback Scores Above 100	(0.023)	(0.022)	(0.028)
<u>Mean Probability of Sale Elasticities at Observed Prices</u>			
1-10 Days Prior to Game	-0.190	-1.660	-1.482
11-20 Days Prior to Game	-0.280	-2.350	-2.075
21-40 Days Prior to Game	-0.460	-3.270	-2.949
More than 41 Days Prior to Game	-0.750	-4.300	-3.735
Number of observations	109,296	109,296	109,296

Notes: Specifications also include dummies for number of seats, seller feedback scores, ticket and listing characteristics, row quality controls, home team dummies, home team*face value interactions, home team*game expected attendance interactions and dummies for sellers with 1 and less than 10 listings. Standard errors in parentheses clustered on the game (for control function models they are estimated using a bootstrap with 200 repetitions). ***,** and * denote significance at the 1, 5 and 10% levels. Coefficients in columns (2) and (3) have been rescaled to be comparable with those in column (1).

Table 9: Counterfactuals Using Estimated Pricing Models

(a) Counterfactuals for Fixed Price Model
Relative Price Specification

	Days Prior to Game			
	1-10	**11-20**	**21-40**	**41 plus**
<u>Observed</u>				
Mean Price $	53.58	60.93	65.81	69.44
Median Price $	40.63	49.50	54.20	58.50
<u>Counterfactual:</u> demand parameters same as 11-14 days prior to game; competition variables same as average 11-20 days before game				
Mean Price $	50.26	59.41	65.66	68.99
Median Price $	39.78	49.35	55.13	59.40

(b) Counterfactuals for Fixed Price Model
Log Price Specification

	Days Prior to Game			
	1-10	**11-20**	**21-40**	**41 plus**
<u>Observed</u>				
Mean Price $	53.58	60.93	65.81	69.44
Median Price $	40.63	49.50	54.20	58.50
<u>Counterfactual:</u> demand parameters same as 11-14 days prior to game; competition variables same as average 11-20 days before game				
Mean Price $	50.58	58.39	64.33	69.40
Median Price $	40.95	49.38	54.95	59.89

(c) Counterfactual for Single Unit Pure Auction Model
Relative Price Specification

	Days Prior to Game			
	1-10	**11-20**	**21-40**	**41 plus**
<u>Observed</u>				
Mean Price $	20.95	21.59	25.91	31.14
Median Price $	11.50	11.95	14.87	23.32
<u>Counterfactual:</u> demand/revenue parameters same as 11-14 days prior to game; competition variables same as average 11-20 days before game				
Mean Price $	24.60	21.68	25.15	28.85
Median Price $	15.96	11.70	13.78	20.47

(d) Counterfactual for Auction Start Prices in Hybrid Auction Model
Relative Price Specification

	Days Prior to Game			
	1-10	**11-20**	**21-40**	**41 plus**
<u>Observed</u>				
Mean Price $	31.21	34.39	41.92	52.25
Median Price $	23.76	27.00	33.99	44.78
<u>Counterfactual:</u> demand/revenue parameters same as 11-14 days prior to game; competition variables same as average 11-20 days before game				
Mean Price $	36.34	39.65	49.16	61.79
Median Price $	27.63	30.60	39.60	50.60

Table 10: Single Unit Auction Listing Models

	(1) Probability of Sale With Control Function to Address Own and Competitor Price Endogeneity (Probit)	(2) Revenue Function With Control Function to Address Own and Competitor Price Endogeneity (Censored Normal)
<u>Own Price Coefficients</u>		
Relative Fixed Price	-1.177***	0.300***
	(0.068)	(0.086)
1-10 Days Prior to Game*Relative Price	-0.247***	-0.172***
	(0.056)	(0.061)
11-20 Days Prior to Game*Relative Price	-0.251***	-0.021
	(0.055)	(0.055)
21-40 Days Prior to Game*Relative Price	-0.266***	0.001
	(0.050)	(0.058)
<u>Competition Coefficients</u>		
Mean Relative Price for Fixed Price Listings	0.272***	0.526***
	(0.096)	(0.171)
Mean Relative Start Price for Auction Listings	0.012	0.310**
	(0.078)	(0.139)
Minimum Relative Price for Fixed Price Listings	0.102	-0.37*
	(0.138)	(0.211)
Minimum Relative Price for Auction Listings	-0.029	-0.445**
	(0.106)	(0.182)
Dummy Variable for No Competing	0.718***	0.642***
Fixed Price Listings	(0.076)	(0.154)
Dummy Variable for No Competing	-0.027	-0.182**
Auction Listings	(0.033)	(0.071)
Number of Competing Fixed Price Listings	-0.050	-0.337***
	(0.066)	(0.129)
Proportion of Competing Fixed Price Listings with	-0.004	0.056
Seller Feedback Scores Above 100	(0.027)	(0.057)
Number of Competing Auction Listings	0.015	0.076
	(0.024)	(0.082)
Proportion of Competing Auction Listings with	-0.020	-0.371***
Seller Feedback Scores Above 100	(0.074)	(0.127)
Standard Deviation		0.852***
		(0.017)
<u>Mean Probability of Sale Elasticities at Observed Prices</u>		
1-10 Days Prior to Game	-0.86	
11-20 Days Prior to Game	-0.84	
21-40 Days Prior to Game	-1.13	
More than 41 Days Prior to Game	-1.37	
<u>Median Opportunity Costs Relative to Ticket Face Values</u>		
1-10 Days Prior to Game	0.50	
11-20 Days Prior to Game	0.20	
21-40 Days Prior to Game	0.41	
More than 41 Days Prior to Game	0.59	
Number of observations	182,302	122,609

<u>Notes:</u> Specifications also include dummies for number of seats, seller feedback scores, ticket and listing characteristics, row quality controls, home team dummies, home team*face value interactions, home team*game expected attendance interactions and dummies for sellers with 1 and less than 10 listings. Standard errors in parentheses clustered on the game estimated using a bootstrap with 200 repetitions. ***,** and * denote significance at the 1, 5 and 10% levels.

Table 11: Hybrid Auction Listing Models

	(1) Probability of Sale With Control Function to Address Own and Competitor Price Endogeneity (Trinomial Logit)	(2) Revenue Function With Control Function to Address Own and Competitor Price Endogeneity (Censored Normal)
<u>Own Price Coefficients</u>		
Relative Auction Start	-2.291***	0.005
	(0.096)	(0.028)
1-10 Days Prior to Game*Relative Start Price	0.061***	0.213***
	(0.098)	(0.028)
11-20 Days Prior to Game*Relative Start Price	-0.177***	0.180***
	(0.121)	(0.031)
21-40 Days Prior to Game*Relative Start Price	-0.040	0.125***
	(0.093)	(0.040)
Relative Fixed Price	-1.124***	0.677***
	(0.123)	(0.033)
1-10 Days Prior to Game*Relative Fixed Price	0.296***	-0.155***
	(0.089)	(0.027)
11-20 Days Prior to Game*Relative Fixed Price	0.167*	-0.140***
	(0.097)	(0.027)
21-40 Days Prior to Game*Relative Fixed Price	0.090	-0.060***
	(0.077)	(0.032)
Standard Deviation	-	0.535***
		(0.008)
<u>Mean Probability of Sale Elasticities wrt Auction Start Price at Observed Prices</u>		
1-10 Days Prior to Game	-0.46	
11-20 Days Prior to Game	-0.57	
21-40 Days Prior to Game	-0.76	
More than 41 Days Prior to Game	-1.00	
<u>Mean Probability of Sale Elasticities wrt Fixed Price at Observed Prices</u>		
1-10 Days Prior to Game	-0.26	
11-20 Days Prior to Game	-0.30	
21-40 Days Prior to Game	-0.39	
More than 41 Days Prior to Game	-0.50	
<u>Median Opportunity Costs Relative to Ticket Face Values Implied by Auction Start Prices</u>		
1-10 Days Prior to Game	0.004	
11-20 Days Prior to Game	0.116	
21-40 Days Prior to Game	0.516	
More than 41 Days Prior to Game	0.809	
Number of observations	115,406	37,567

<u>Notes:</u> Specifications also include competition variables, number of seat and feedback dummies, ticket and listing characteristics, row quality controls, home team dummies, home team*face value interactions, home team*game expected attendance interactions and dummies for sellers with 1 and less than 10 listings. Standard errors in parentheses clustered on the game estimated using a bootstrap with 200 repetitions. ***,** and * denote significance at the 1, 5 and 10% levels.

Table 12: Models for Ticket Availability and Expected Prices Five Days Prior to Game

under assumption that buyer only considers tickets wihch are better than those she bought and that she considers auction listings which close 5 days before the game with no bidders to be available

	Probit Model for Ticket Availability	Gamma Model for Prices of Available Tickets Shape Parameters	Scale Parameters
Monday	0.110***	0.1179***	-
	(0.017)	(0.006)	
Tuesday	0.246***	0.088***	-
	(0.017)	(0.006)	
Wednesday	0.304***	0.1378***	-
	(0.017)	(0.006)	
Thursday	-0.139***	0.1876***	-
	(0.017)	(0.007)	
Friday	-0.0797***	0.1205***	-
	(0.014)	(0.005)	
Saturday	-0.204***	0.1173***	-
	(0.014)	(0.005)	
Feedback 10-100	-0.0616**	0.0484***	-
	(0.028)	(0.009)	
Feedback 100-1000	-0.278***	0.1365***	-
	(0.027)	(0.008)	
Feedback Greater Than 1000	-1.016***	0.4668***	-
	(0.027)	(0.008)	
Two Seats	0.0273	0.1265***	-0.8503***
	(0.049)	(0.026)	(0.034)
Three Seats	-1.561***	0.677***	-0.7061***
	(0.054)	(0.035)	(0.044)
Four Seats	-1.675***	0.7307***	-0.9805***
	(0.050)	(0.028)	(0.036)
Five Seats	-2.594***	1.0927***	-1.2669***
	(0.067)	(0.069)	(0.081)
Six Seats	-2.832***	0.8063***	-1.1756***
	(0.061)	(0.065)	(0.077)
Front Row	-0.106***	0.0016	0.0225
	(0.014)	(0.009)	(0.011)
Second Row	-0.0950***	-0.0037***	0.0191***
	(0.015)	(0.010)	(0.012)
Row Number	0.0224***	-0.0064***	-0.0004***
	(0.001)	(0.001)	(0.001)
Row N/A	0.860***	0.1774***	-0.5532***
	(0.064)	(0.022)	(0.025)
No Row Listed	0.766***	-0.2904***	0.0253***
	(0.020)	(0.011)	(0.013)

	Probit Model for Ticket Availability	Gamma Model for Prices of Available Tickets Shape Parameters	Scale Parameters
Main Effects (Arizona Diamondbacks)			
Constant	-4.346***	-1.5174***	0.8612***
	(0.920)	(0.436)	(0.075)
Log(Face Value)	2.311***	*0.3982*	0.9191***
	(0.510)	*(0.260)*	(0.039)
Log(Face Value)^2	-0.469***	-0.0124	-0.071***
	(0.074)	(0.039)	(0.006)
Expected Attendance	5.157***	0.3841***	1.5181***
	(0.360)	(0.148)	(0.014)
Interaction Effects for Selected Teams (not reported for other teams)			
Boston Red Sox Interactions			
Constant	0.839	6.9176***	-
	(1.020)	(0.463)	
Log(Face Value)	0.607	-2.8615***	-
	(0.560)	(0.272)	
Log(Face Value)^2	-0.066	0.4391***	-
	(0.079)	(0.041)	
Expected Attendance	-3.184***	-2.6557***	-
	(0.390)	(0.156)	
Chicago Cubs Interactions			
Constant	-7.267***	0.1359	-
	(1.210)	(0.522)	
Log(Face Value)	3.160***	-0.7041**	-
	(0.700)	(0.314)	
Log(Face Value)^2	-0.576***	0.1888***	-
	(0.100)	(0.047)	
Expected Attendance	2.269***	-0.4126***	-
	(0.450)	(0.166)	
Average Availiability Data, Predicted	0.88, 0.88		
Average Prices Data, Predicted		42.59, 42.17	
Std Deviation Prices Data, Predicted		58.78, 58.20	
Log-Likelihood	-58,168.2	-1,120,320.5	
Number of Observations	289,784	255,885	

Notes: Standard errors in parentheses. ***,** and * denote significance at the 1, 5 and 10% levels. Specification also includes month of game dummies.

Table 13: Rationalizing Observed Early Purchase Decisions

table shows the proportion of purchases taking place more than 10 days prior to the game which can be rationalized for different values of the parameters

Search/Return to Market Cost	CARA Coefficient	Loss Aversion Cost	Valuation of Tickets Above Price Paid			
			$10	$25	$50	$75
Assumption 1: Substitution Only to Better Tickets, Valued Same as Purchased, Auction Listings Available						
$0	Risk Neutral	$0	29%	41%	49%	52%
$10	Risk Neutral	$0	52%	58%	62%	65%
$25	Risk Neutral	$0	71%	73%	75%	77%
$50	Risk Neutral	$0	86%	86%	87%	87%
$0	0.05	$0	42%	66%	84%	92%
$0	Risk Neutral	$25	61%	64%	66%	68%
$25	0.05	$0	87%	92%	96%	98%
$25	Risk Neutral	$25	76%	77%	78%	79%
Assumption 2: Substitution Only to Better Tickets, Valued Same as Purchased, Only Fixed Price Available						
$0	Risk Neutral	$0	46%	57%	62%	65%
$10	Risk Neutral	$0	66%	70%	73%	74%
$25	Risk Neutral	$0	80%	81%	83%	83%
$50	Risk Neutral	$0	90%	91%	91%	91%
$0	0.05	$0	58%	74%	84%	89%
$0	Risk Neutral	$25	72%	74%	75%	76%
$25	0.05	$0	90%	92%	95%	97%
$25	Risk Neutral	$25	83%	84%	84%	85%
Assumption 3: Substitution Only to All Tickets, Value Varies with Face Value, Auction Listings Available						
$0	Risk Neutral	$0	2%	6%	10%	12%
$10	Risk Neutral	$0	7%	12%	17%	19%
$25	Risk Neutral	$0	24%	31%	35%	36%
$50	Risk Neutral	$0	58%	59%	59%	59%
$0	0.05	$0	11%	24%	34%	38%
$0	Risk Neutral	$25	17%	21%	24%	25%
$25	0.05	$0	56%	59%	61%	62%
$25	Risk Neutral	$25	34%	38%	41%	41%
Assumption 4: Substitution Only to All Tickets, Value Varies with Face Value, Only Fixed Price Available						
$0	Risk Neutral	$0	3%	8%	15%	18%
$10	Risk Neutral	$0	9%	18%	26%	29%
$25	Risk Neutral	$0	35%	43%	47%	48%
$50	Risk Neutral	$0	66%	67%	67%	67%
$0	0.05	$0	17%	36%	47%	51%
$0	Risk Neutral	$25	26%	31%	36%	37%
$25	0.05	$0	64%	67%	69%	70%
$25	Risk Neutral	$25	46%	50%	52%	53%

Table 14(a): Timing of Purchases

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

Notes: 3,821 observations with non-US buyers or missing zip code information are excluded. Specification also includes the same controls as specifications in Table 4. Standard errors in parentheses. ***,** and * denote significance at the 1, 5 and 10% levels.

Table 14(b): Ticket Characteristics and the Timing of Purchases

Dep. Var	Number of Days Prior to Game Ticket Purchased
Number of Seats (one seat excluded)	
Two Seats	1.346
	(0.840)
Four Seats	2.557***
	(0.900)
Six Seats	17.10***
	(1.730)
Three Seats	-3.753***
	(0.920)
Five Seats	-2.858***
	1.1
Face Value	
Face Value ($)	-0.042***
	(0.003)
Row Variables	
First Row Dummy	1.627***
	(0.340)
Second Row Dummy	1.647***
	(0.340)
Number of Row	-0.048***
	(0.014)
Game Variables	
Expected Attendance as Propn of Capacity	27.57***
(function of team form)	(1.080)
Observations	286,656
R^2	0.06

Notes: specification also includes third-order polynomial in the distance the buyer lives from the stadium of the home team, a dummy for buyers within 40 km and home team fixed effects. Standard errors in parentheses clustered on the game. ***,** and * denote significance at the 1, 5 and 10% levels.

Figure 1: Evolution of Listings, Sales Mechanisms, Sale Probabilities and Ticket Quality As Game Approaches

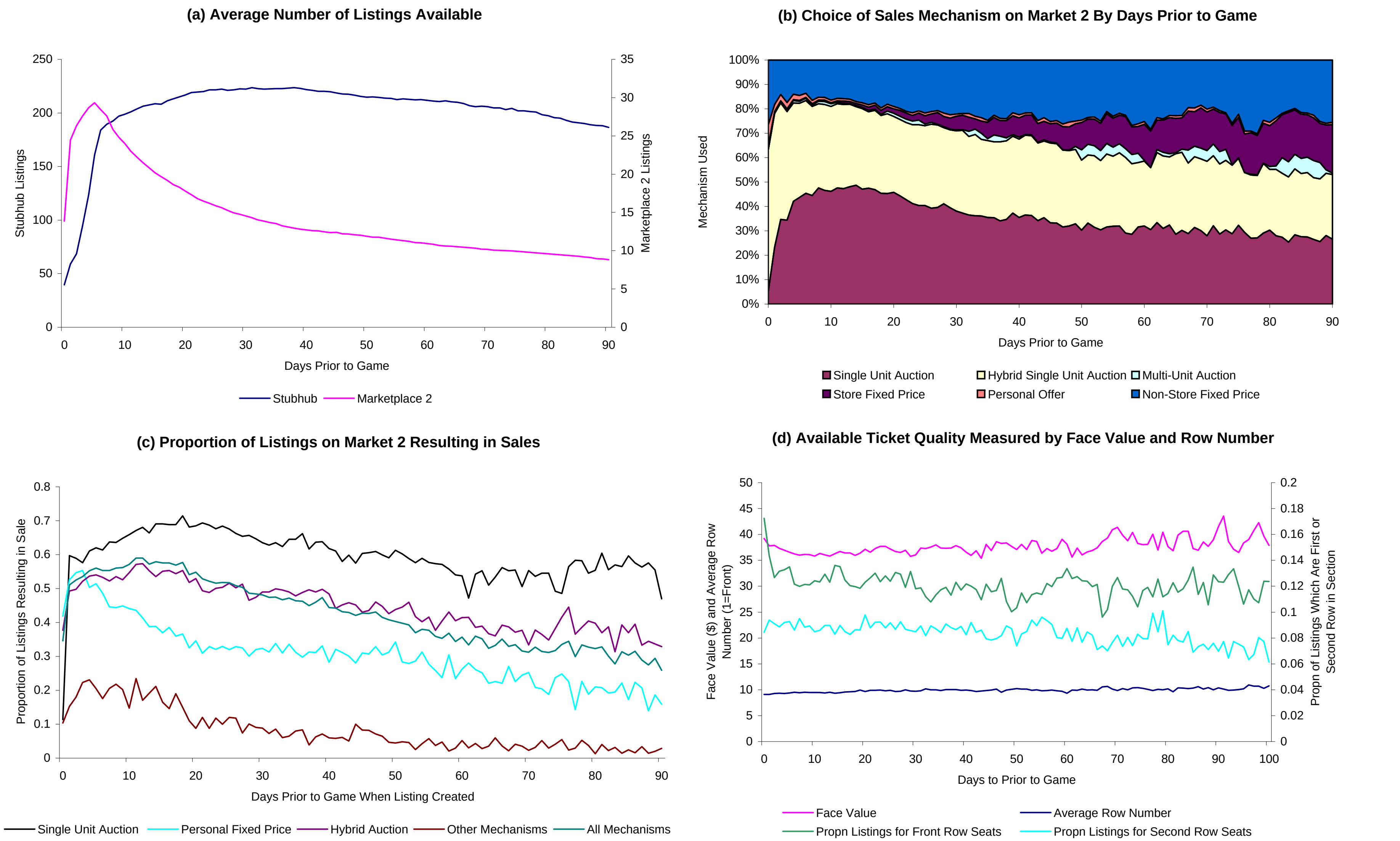
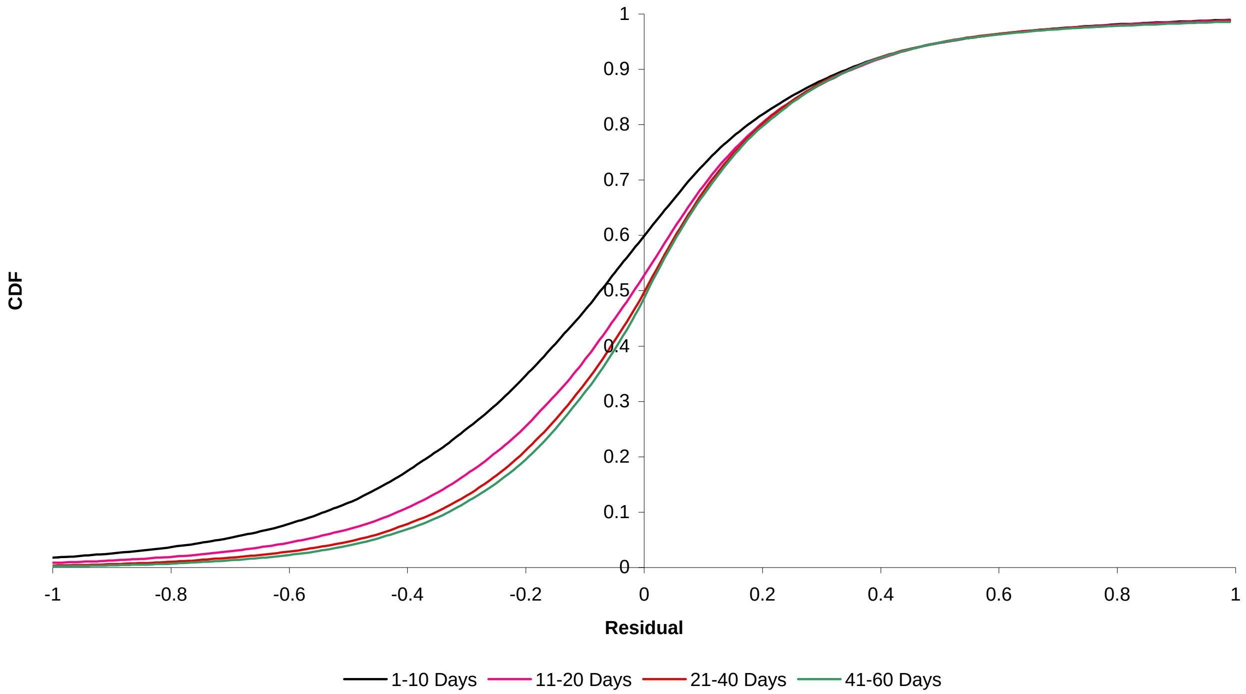


Figure 2(a): CDFs of Residuals from Regression of Log(Seller Price) on Ticket Characteristics and Game-Section Fixed Effects Using Stubhub Data



(b) CDF of Residuals from Regression of Log(Seller Transaction Price) on Ticket Characteristics and Game-Section Fixed Effects Using Market 2 Data

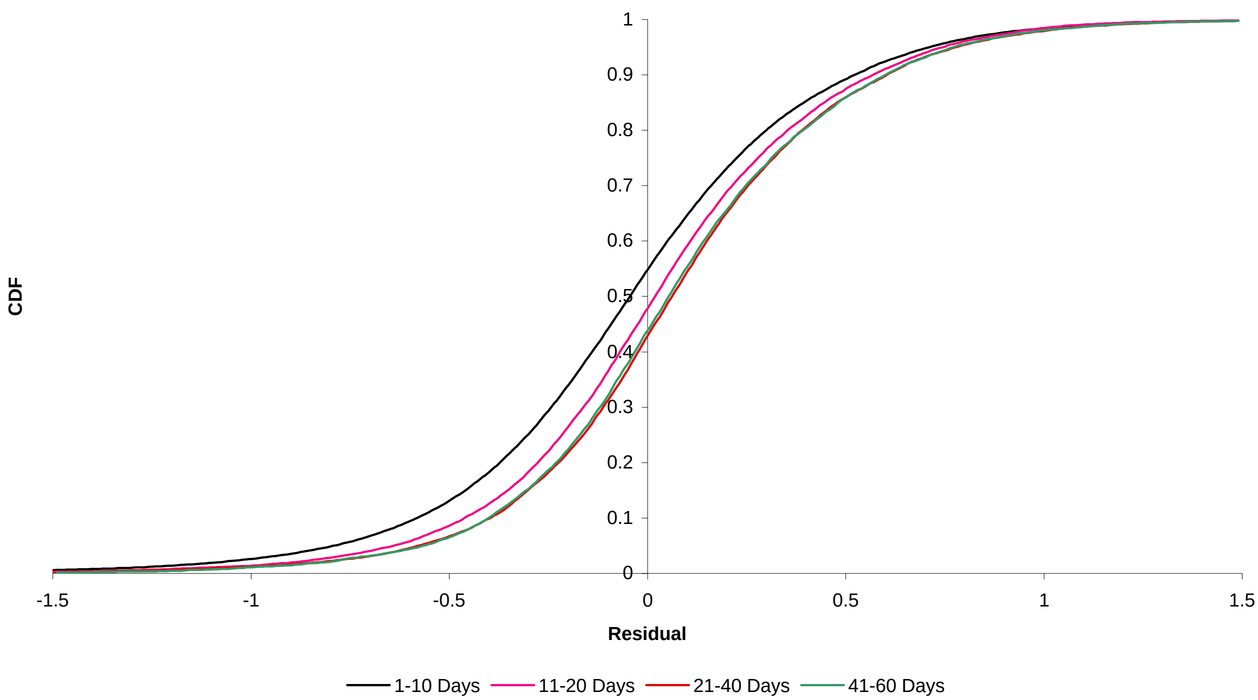
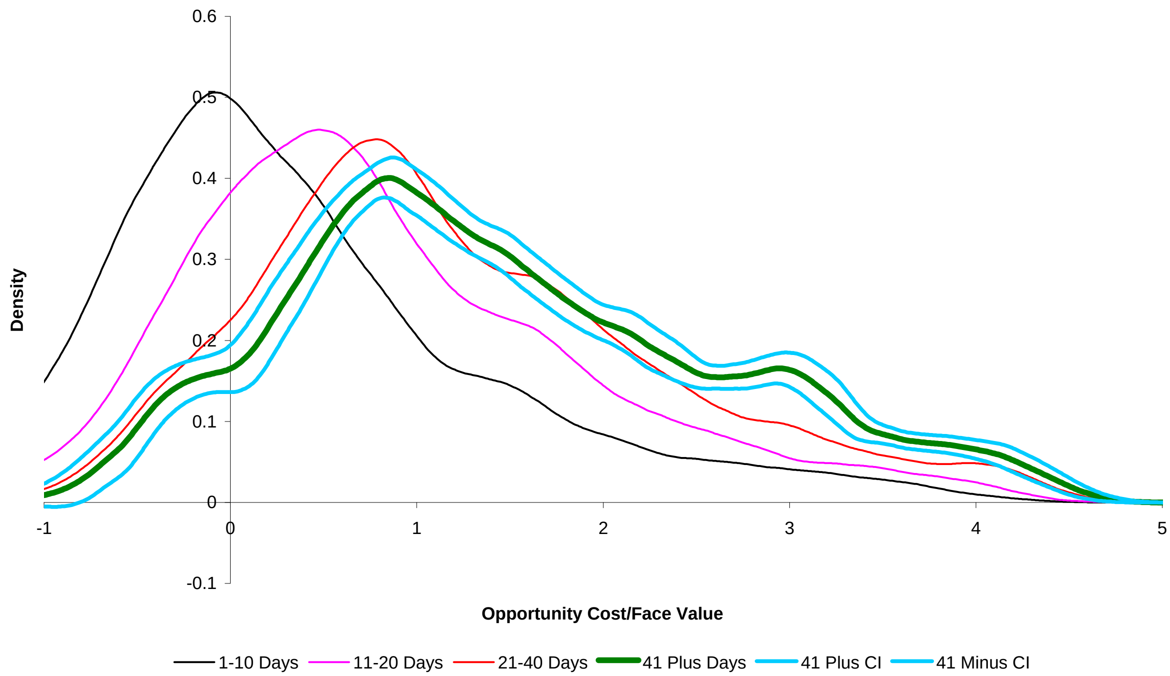


Figure 3
Opportunity Costs Implied by Fixed Price Listing Models Using Control Function to Address the Endogeneity of Own and Competitor Prices

(a) Relative Price Model



(b) Log Price Model