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 vast majority of observed early purchasing can be rationalized by plausible values of risk aversion and search costs given the vertically differentiated nature of tickets and uncertainty about the future availability of particular types of tickets.

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1 Introduction

This paper analyzes the dynamics of prices in two online resale markets for Major League Baseball (MLB) tickets. The most relevant characteristics of tickets for price dynamics is that they are perishable products (i.e., they have no value once the game is played) that can only be consumed on a particular date (the day of the game) independent of when they are purchased. *A priori*, several dynamic patterns seem plausible. For example, the possibility of arbitrage might keep expected prices roughly constant over time, while either discounting or the revelation of information concerning the value of the game to consumers might cause expected prices to increase over time. Prices might also tend to increase if consumers who arrive just before the game tend to have inelastic demands, just like business travellers buying airline tickets close to the day of departure. Alternatively prices may tend to fall as the moment the tickets perish approaches because sellers become increasingly desperate to find buyers.

I show that, in the days and weeks leading up to the game, prices tend to fall. The average price declines are large (e.g., 20-50% in the last six weeks prior to the game), common across different sales mechanisms and very robust to considering different sub-samples of the data (for example, games with different levels of expected demand and cheap and expensive seats) and different ways of controlling for seat quality. Moreover, the entire distribution of prices tends to fall as well as the mean.

As well as establishing this new stylized fact, I also examine *why* prices tend to fall. Revenue management models of perishable goods pricing (e.g., McAfee and te Velde (2006), Gallego and van Ryzin (1994)) predict that prices should tend to decline because the value of holding onto inventory (i.e., the opportunity cost of selling) declines as the moment of perishability approaches and future selling opportunities disappear. Alternative theories involve demand becoming more elastic over time (i.e., the opposite of the business traveller story) or sellers initially experimenting with high prices to learn about demand (e.g., Lazear (1986)). I show, using a combination of reduced-form and structural analysis, that the declining opportunity cost story is the one that fits the data. This is a potentially important contribution because there is little empirical evidence supporting revenue management models of perishable goods pricing.

A possible objection to the claim that declining prices should be the equilibrium outcome is that buyers might want to delay purchasing if prices are expected to fall, which would lead sellers to set lower prices in early periods. In line with very recent theoretical work examining the behavior of strategic buyers (e.g., Aviv and Pazgal (2008), Liu and van Ryzin (2008), Dasu and Tong (2008), Levin et al. (2008)), I consider whether factors such as buyer risk aversion, uncertainty about ticket availability, search costs and preferences for particular types of ticket can explain why some people buy early. I find that given product differentiation and uncertain availability of particular types of ticket, the vast majority of observed early purchasing can be rationalized for small and plausible values of risk aversion and search costs.

1.1 Relationship to the Existing Literature

Theoretical models concerning the dynamic pricing of perishable goods have attracted attention from both economists and operations researchers, motivated by the optimal pricing problems facing, amongst others, airlines, hotels and radio and television stations selling commercial time. The models which are most closely relevant to those in the current paper are those where the seller can freely adjust prices over time rather than committing to a price schedule at the beginning (McAfee and te Velde (2006), Gallego and van Ryzin (1994) and Bitran and Mondschein (1993)).[1] The standard version of these models has a single seller with multiple units of inventory which can be sold during a fixed time interval. Customers arrive stochastically and their valuations for one unit of the good are drawn from a distribution which does not vary over time. Customers either buy at once or exit the market. The seller's optimal price at any point is determined by the probability that a current sale

[1] These models are the most relevant to my paper as 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.

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

There has been almost no empirical work testing these models.[4] The airline industry has received most attention (McAfee and te Velde (2006), Escobari and Gan (2007)), but the declining price prediction has been rejected. The observation that prices tend to increase can be rationalized by the fact that most consumers who discover they want to travel close to the day of departure have relatively inelastic demand. A possible complementary explanation is that airlines may also want, and have the ability, to commit to a dynamic pricing schedule which affects when strategic consumers will purchase. The small size of sellers relative to the market in my setting tends to make commitment stories implausible.

An alternative explanation for why prices may fall is provided by Lazear's (1986) model of seller learning. In this model, sellers do not know consumers' reservation values and set initially high prices and then sequentially cut prices if the product does not sell as they infer that valuations are likely to be lower. This model has received empirical support from housing markets (Herrin et al. (2004)) but, while I cannot rule out that there is some learning taking place, I show that several of its predictions

[2] I have also looked at the small number of sellers who have multiple listings of different but similar tickets. Most of these sellers list their tickets at the same time at the same price, sometimes in multi-unit listings. There is evidence that prices sometimes increase after some units sell but the sample is too small to generate significant and robust results.

[3] Strategic consumer behavior has, of course, played an important role in the durable goods literature (Coase (1972), Stokey (1979), Besanko and Winston (1990)).

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

about how prices should decline do not match my data.

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

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

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

2 Data

2.1 Secondary Market Data

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

2.1.1 Stubhub.com

The first dataset contains data on *list prices* from Stubhub.com, collected using an automated script.[5] 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 accounts 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.

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

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

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

The limitation of the Stubhub data is that it contains data only on posted prices and not on transactions. While I observe tickets which cease to be listed I do not know whether this is because they are sold on Stubhub or sold elsewhere, possibly at a 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.

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 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 for the auction.

Sellers pay a small listing fee and a small commission (between 1% and 7%) which varies with the transaction price. 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

[6] 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.

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.[7] 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 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.[8] 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. The exclusion of listings with more than six seats drops and those with prices above \$1,000 or shipping costs above \$40 drops 0.7% of the Market 2 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 record (form) of each team. Stadium capacities are measured using the maximum observed attendance each year as these exceed

[7] 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 make only a few MLB listings.

[8] 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.

recorded capacities for many teams. The single game price (face value) for each game and section was collected from team websites. Some teams, such as the Boston Red Sox, charge the same prices irrespective of the opposition, whereas others, like the New York Mets, have several pricing tiers which depend on the opposition and the day of the week. Face value information is missing for some season ticket only sections and for all Colorado Rockies games. No MLB teams practised dynamic pricing in the primary market.

2.3 Summary Statistics

Table 1 shows how the listings are distributed across MLB teams and, based on transactions observed on Market 2, some additional measures of pricing, market concentration and the timing of sales. Listings may be available for multiple days: on Stubhub the average listing lasts 16 days compared with 4.5 days for auction listings on Market 2 and 19 days for non-auction listings. Stubhub has more listings than Market 2 for every team, although the ratio of listings shows some variation across teams. The teams with the most listings and highest secondary market prices on both sites tend to be those in the largest cities with the highest realized attendances, which is consistent with secondary markets existing partly because of excess demand in the primary market. For MLB they also serve the purpose of allowing season ticket holders to sell tickets to the games they do not wish to attend (a full season ticket covers 81 home games). Consistent with there being many small sellers, the HHI measures of seller concentration for each team are very small. 63% of sellers have only one or two listings 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 do cannot identify face values for premium season ticket only sections for some teams. 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).[9] In terms of dynamics the table shows that the majority of listings happen in the last two to three weeks before the game, although the average days before the game when a transaction takes place is significantly higher. The final column also shows the median distance that buyers live (based on the shipping zipcode) from the stadium where the game is played. Even looking only at the team level, there is a positive correlation (0.4) between the median distance and the median days before the game is played, which is consistent with people who have to make more plans to attend the game wanting to purchase tickets earlier.

Table 2 provides some more detailed statistics on listings. Listings for two seats are the most common on Market 2, while four seat listings are also common on Stubhub. However, 93% of these four seat Stubhub 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 seats, are relatively rare. A higher proportion of single-unit pure auctions result in sales than other formats.

The lower part of Table 2 provides further summary statistics on primary and secondary market prices. The average face value of tickets listed on the two sites is similar. The large difference between buyer and seller prices 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 easiest 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). As a proportion of face value, these prices are similar. Of course, a seller's expected return on either site also depends on the probability of sale.

[9] 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.

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

3 Robust Evidence of Price Declines

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

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

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

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

A game refers to a particular fixture between two teams scheduled to be played on a particular day (e.g., Seattle Mariners at the New York Yankees on May 6). A game-section fixed 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 sections defined in this way. A game-face value fixed effect groups together those sections for a particular game which have the same face value in the primary market (in my example, odd numbered Loge Boxes 473 to 545 and even numbered Loge Boxes 474 to 548, with a face value price of $55). When using game-face value fixed effects I do not include those sections for which no face value can be identified. A game-section-row fixed effect is a dummy for a particular row within the section (e.g., Loge Box 512 Row D for the Seattle Mariners at the New York Yankees on May 6). Obviously seats closer to the field tend to be preferred so when I do not include game-section-row fixed effects I include controls for the quality of the row (specifically, dummies for the first and second rows, a linear count variable for the row number and separate dummies for the identity of the row not being available and the row not being relevant (e.g., open seating bleachers)). I also include dummies for the listing indicating that the seats are not in the same row (e.g., "piggy back" seats), on an aisle or if parking is included.[12]

3.1 Stubhub

Table 3 shows results from a number of linear fixed effects regressions using list prices from Stubhub.com. The price is defined as the price per seat. The regressions use daily observations on available prices 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). I use a sample of game-sections as there are too many daily listings (over 67 million) to estimate the regressions using all observations, but I have checked that the results are very similar using different random samples. The price declines are also *larger* if I use only use observations when listings change prices or first appear. As individual listings are available for multiple days I cluster standard errors on the Stubhub

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

listing identification number. I do not report coefficients on ticket characteristics such as the piggy dummy, the row variables (where applicable), dummy variables for the number of tickets available in a listing which are interacted with a dummy variable for whether it is possible to buy less than the full number of seats and the form variables for the away team.

The specification in column (1) includes game-section fixed effects so that the coefficients are identified from seats in the same section which are listed at different prices. The dependent variable is the natural log of the seller price per seat. The highly significant "Days to Go" coefficients indicate that, on average, list prices decline substantially before a game. For example, prices are 22% higher 30-32 days before the game than 0-2 days before.[13] The estimated price decline is quite smooth and it accelerates in the final two weeks. The home team form coefficients have plausible signs: when a team slips further back from the top of its division (the Games Back variable increases) prices tend to fall and the effect of division position is smaller when there are more games left in the season. The unreported row variable coefficients are also sensible with prices falling by 1% for each row ones moves back and a 10% front row premium. The pattern of price declines can also be seen within individual listing ids, where 89% of price changes are price *reductions*.

Column (2) includes game-section-row fixed effects to control in a more comprehensive way for row quality. The estimated percentage price declines are a little larger than in column (1) but the qualitative pattern is the same. In the remaining Stubhub regressions I use game-section-row fixed effects. The specification in Column (3) uses the dollar value of the seller price, with the estimated average decline in the seller price in the last 30-32 days before the game being $14.66. 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

[13] 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 if only use observations from the last three months prior to a game for all games.

can be identified being dropped. In the last two days before a game list prices are, on average, 56% above face value. The regression coefficients indicate that prices are 94% above face value 30-32 days before the game.

Having established that prices fall as the game approaches, 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 into different groups based on the expected attendance at the game (as a % of capacity). Expected attendance 90 days prior to a game is predicted using a censored regression model estimated using data on all games played from 2000 to 2007.[14] Prices decline for all levels of expected attendance with larger percentage decreases for lower demand games. One possible explanation is that sellers of tickets for high demand games are more confident of being able to sell their remaining tickets (perhaps offline, either to friends or at the stadium) even when the game is only a few days away.

3.2 Market 2

Table 4 and 5 reports results using both list and transaction prices from Market 2. Table 4 uses data on transactions. There is one observation per listing per buyer so that there may be more than one observation for listings where more than one unit is sold (e.g., multi-unit auctions). The dependent variable is the log of the buyer price which includes shipping costs, and the column (1) specification includes game-section fixed effects, ticket characteristics and the row variables. It also includes additional seller characteristics, such as the seller's feedback score, which are likely to be valued by potential buyers. As feedback scores cover a huge range I use four dummies to represent different levels (less than 10, 11 to 100, 101 to 1000 and greater than 1000). Buyer prices tend to fall as the game approaches, declining by 25% on average in the last 30-32 days before the game. The

[14] The model contains the form variables 90 days before the game is played, 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).

form variables again have sensible signs, and the unreported row coefficients indicate that transaction prices fall by 0.3% for each row one moves away from the field, with a 13% front row premium. There are, however, two 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, although most of the deviations from monotonicity are small and not statistically significant. Second, there is evidence that prices increase by a small amount prior to 50 days before the game. I return to the question of why this may be happening in a moment.

The column (2) 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. Twenty days before a game, they average \$3.69 per seat. The average increases to a maximum of \$4.30 per seat 4 days before a game but falls to only \$1.49 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 observations 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 make sure that changes in the mix of mechanism do not explain the price declines. Including these dummies has almost no effect on the estimated price declines. However, further analysis reveals that the transaction price increases between 80 and 50 days before the game result 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 only marginally significant at the 1% level). In contrast, in an unreported regression using only auction sales prices 39-41 days before the game (coefficient 0.278), whereas the 61-70 and 81 plus coefficients are 0.208 and 0.132.

The remaining transaction price regressions repeat the specification in column (1) for several subsets of the data which are similar to those used in the Stubhub regressions. The number of observations is smaller in these regressions so that the price declines in the last 40 days are less monotonic, although the deviations from monotonicity are generally not statistically significant. Similar to the Stubhub regressions, price declines are smaller in percentage terms for more expensive tickets, although, unlike for Stubhub, there is no clear pattern that price declines are larger for games with higher expected attendance.

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 and the game. As more expensive fixed price listings (conditional on quality) are likely to remain unsold and so stay on the site for longer, prices tend to fall by less using this definition.[15] For auctions, the price declines continue until about a week before the game, although they increase in the last few days. A noticeable feature of the auction results is that even though transaction prices in auctions appear to be *increasing* by a small amount more

[15]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 quite similar to the estimate in Table 3 column (1) using the Stubhub data.

than 50 days before a game, auction start prices are *declining* at the same time, just like fixed prices. This suggests that transaction prices may be increasing because, a long time before the game, people 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.[16] Columns (5)-(8) report the 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. For auction start prices, the declines from around 40 to 6 days before the game are also pretty similar, although prices increase in the last five days before the game for the teams with fewer listings.

4 Theoretical Explanations for Why Sellers Cut Prices

The rest of the paper examines why the equilibrium outcome involves price declines. Both theoretically and empirically, it is useful to break the problem into two parts: first, why do sellers tend to cut prices/accept lower expected revenues over time given some general formulation of demand? and second, why are some people willing to purchase early when prices are expected to fall? At first sight, this separation may seem inappropriate because equilibrium outcomes must depend on the interaction of demand and supply. But the split is appropriate because I am going to analyze the pricing and purchase decisions of individual buyers and sellers taking the behavior of other agents as given. In addition, individual buyers and sellers are so small relative to the total market they can be safely assumed to ignore how their decisions will affect the future behavior of other agents. This might not be true in other settings: for example, an airline might be concerned that if it sets lower prices close to departure this will cause more travellers to wait to purchase in the future with possible negative effects on profits.

Before describing three plausible explanations for price cutting by sellers, two explanations can be disposed of immediately. First, in some markets buyer impatience might lead to some early purchasing at premium prices. However, this is because early purchasing allows them to consume

[16] 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.

earlier, which is not true of event tickets. Second, discounting might affect behavior in the timeframes I consider. But it would tend to make buyers willing to pay more for later transactions and sellers willing to accept less for earlier transactions, and so would rationalize prices that were increasing not decreasing.

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

The first two explanations can be described in a single framework. Suppose that a risk-neutral seller i has a single ticket to sell and that there are two time periods before the game, $t = 1, 2$, where period 1 happens first. The sellers get a payoff of $\$v_i$ if the ticket is unsold after period 2. This payoff could be the utility from going to the game or giving the ticket to a friend, or the expected price from selling the ticket offline. For now I assume that the seller sets a fixed price p_{it} in each period and that the probability that the ticket sells is $Q_{it}(p_{it})$ where $\frac{\partial Q_{it}(p_{it})}{\partial p_{it}} < 0$. 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}.[17] i will therefore set prices p_{i1} and p_{i2} by solving

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

Assuming that the relevant second-order conditions are satisfied, prices will be given by

$$Q_{i2}(p^*_{i2}) + \frac{\partial Q_{i2}(p^*_{i2})}{\partial p_{i2}}[p^*_{i2} - v_i] = 0 \tag{2}$$

$$Q_{i1}(p^*_{i1}) + \frac{\partial Q_{i1}(p^*_{i1})}{\partial p_{i1}}[p^*_{i1} - (p^*_{i2}Q_{i2}(p^*_{i2}) + v_i(1 - Q_{i2}(p^*_{i2})))] = 0 \tag{3}$$

[17] 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.

These are the standard price-setting formulae for sellers with marginal costs of selling of v_i in the second period and $p_{i2}Q_{i2}(p_{i2}) + v_i(1 - Q_{i2}(p_{i2}))$. In what follows I will call these costs the "opportunity cost" of selling the ticket and it increases with future selling opportunities. Equation (2) implies that $p_{i2}^* > v_i$. If $Q_{i1}(p_i) \equiv Q_{i2}(p_i)$ (i.e., the demand function is the same in both periods) then it also follows that $p_{i1}^* > p_{i2}^*$ and prices tend to fall over time and, of course, the same logic applies with more periods.[18] Just like in the revenue management models of perishable goods pricing, prices tend to fall as the moment the good perishes approaches because the seller becomes increasingly keen to sell the product. However, an alternative possible cause of falling prices is that demand becomes more elastic over time.

The same arguments can be made for tickets sold through auctions. 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 be given by

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

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

If probability of sale and revenue functions are the same in each period then declining opportunity costs over time will lead to declining prices. Alternatively, prices or revenues could decline because of changes in the Q or R functions.

4.2 Seller Explanation 3: Learning by Sellers

Lazear's (1986) model of clearance sales provide 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

[18] In the case of a linear Q function one can also show that prices would fall increasingly quickly as the game approaches, which is the pattern I observe in the data.

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.

Lazear describes several observable implications of his model which I am able to compare with my data. First, in a multi-period extension of the model, 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. In contrast, if perishability drives price declines then the price declines should be related to the time until the game rather than tenure. Table 6 reports regression results where I include a fifth-order polynomial of the time since listing and seller-ticket fixed effects to look at how prices change for individual tickets.[19] 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. Second, Lazear's model predicts that the probability of sale in any period should remain unchanged even as prices fall (his p. 22). Figure 1 showed that in fact the probability of sale tends to increase in my data at least until the last couple of days before the game consistent with sellers moving down a known demand curve.

Third, the model predicts that factors which affect the tightness of a seller's prior or the 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

[19] 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.

prices on Stubhub and transaction prices on Market 2 generate similar results. The specifications in columns (7)-(10) of Table 6 compare price declines in Market 2 list prices depending on the level of experience of the seller based on sales of MLB tickets in 2007. The quartile of tickets sold by the most experienced sellers show larger price declines (at least up until 3 days before the game) than the quartile sold by the least experienced sellers. Assuming that the most experienced sellers have the tightest priors this is contrary to what a learning model would predict. One possible explanation, consistent with the option value story, is that professional sellers have the greatest ability to try to resell tickets close to the game so that they have higher values of holding onto tickets when the game is further away.

5 Testing the Option Value and Demand Elasticity Explanations for Why Sellers Reduce Prices

I distinguish between the declining opportunity cost of selling and the changing elasticity of demand explanations for declining prices by estimating structural models of the price-setting decision. The basic idea can be seen most clearly by considering a seller i using a fixed price listing in period t. He will set price p_{it} to maximize

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

where Q_{it} is the probability of sale (or demand) function and o_{it} is the opportunity cost of selling which should reflect the ability of the seller to try to sell the ticket in the future if it does not sell now. Under some regularity conditions, the optimal price is

$$p_{it}^{*} = o_{it} - \frac{Q_{it}(p_{it})}{\frac{\partial Q_{it}}{\partial p_{it}}} \tag{6}$$

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

$$\widehat{o_{it}} = p_{it} + \frac{\widehat{Q_{it}(p_{it})}}{\widehat{\frac{\partial Q_{it}}{\partial p_{it}}}} \tag{7}$$

and, using (6), the separate roles of declining opportunity costs and changing demand elasticities in causing prices to fall over time can be identified. Observable variables which affect opportunity costs but not consumer valuations are potential instruments for prices. Auction listings can be analyzed in a similar way except that the price received by the seller in the event of a sale may be above the price set, so it is also necessary to estimate how expected revenues change with the start price.

Before getting into details, a few general comments are in order. First, unlike most of the recent structural demand and auction literature, I estimate demand and expected revenue functions rather than attempting to estimate the underlying distribution of consumer valuations. Estimating valuations would require me to have a reliable measure of how many consumers consider purchasing each listing, which would be hard to construct when many consumers are likely to be looking at many listings possibly on different websites and offline.[20] My approach has the limitation that when I consider what a seller would do if she had different opportunity costs I have to assume that the demand and revenues functions would stay the same. This assumption is reasonable when considering individual sellers who are generally small. Second, sellers are assumed to face a static pricing problem when they switch. The possibility of listing at different prices in future periods will be reflected in the estimated opportunity costs. Third, sellers are assumed to know the probability of sale and expected revenue functions and to be risk-neutral. I estimate that some sellers have negative opportunity costs, which is unrealistic given free-disposal, and one interpretation is that these assumptions are violated for these sellers. Fourth, I estimate separate models for three types of mechanism (pure fixed prices, pure auctions and hybrid auctions) and do not directly consider the choice between different mechanisms. Finally, all of the analysis uses data from Market 2 as I need to observe transactions.

[20] Hendricks and Porter (2008) note that the development of tractable but realistic dynamic models of consumer behavior and search on sites such as EBay is an important direction for future research whuch is beyond the current research frontier.

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

5.1 Empirical Specifications

5.1.1 Pure Fixed Price Listings

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

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

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]

Prices can be defined in various ways: for example, in levels, logs or as a proportion of the face value. Own price elasticities are 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 using the variables used in Section 3, such as format dummies (e.g., store or other fixed price), dummies for four levels of seller feedback, dummies for the number of seats, the team form variables, the row variables and indicators for whether the listing includes parking or is highlighted. As the formulation is non-linear and I need consistent estimates of all of the coefficients to calculate option values I do

[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.

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

Competition variables are defined based on listings for the same number of tickets, to the same game and with the same face value which were available at the time the listing was posted. I only use listings available at the time of posting as I want to estimate the seller's expected probability of sale when he chooses the price: the coefficients on these variables and the time dummies should reflect expectations about how he expects competition to evolve once the listing has been made. Additional variables based on broader definitions (e.g., all tickets for the same game) and narrower definitions (e.g., only same section) were tried but these were generally insignificant. The included competition variables, defined separately for auction and fixed price listings, are the average price, the minimum price, a count of the number of listings available, a dummy for whether no listings are available and proportion of how many competing listings have seller feedback scores above 100.

The estimation sample consists of pure fixed price listings made in the 90 days before the game with non-missing face value information.[23] Experimentation indicated that the price elasticities were sensitive to some listings with extremely high prices, so I exclude 8,018 listings (about 7% of the fixed price sample) where the fixed price is more than 5 times above the face value. A final problem is that I do not observe shipping costs for listings which do not sell, but these costs may affect demand. I partially address this problem by assuming that unsold tickets have the average shipping costs of tickets which were sold by sellers living as far from the stadium in which the game was played and in the same time period prior to the game (e.g., 1-10 or 21-40 days before the game). As shipping costs are generally small I hope that this approximation will not seriously bias the results, especially as I instrument for a listing's own price.

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

5.1.2 Pure Auction Listings

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

$$\begin{aligned} R_{it}^{*} &= f(p_{it}, X_{it}, p_{-it}, X_{-it}, \theta^{R}) + \varepsilon_{it} \quad \varepsilon_{it} \sim N(0, \sigma_{R}^{2}) \\ R_{it} &= R_{it}^{*} \text{ if } R_{it}^{*} \geq p_{it} \\ &= p_{it} \text{ if } R_{it}^{*} < p_{it} \end{aligned} \tag{8}$$

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

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

5.1.3 Hybrid Auction Listings

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

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

From the estimation sample I exclude listings where the fixed price is more than five times face value. I also drop 36,248 observations (or 23% of hybrid auction listings) where the fixed price is equal to the auction start price as hybrid auctions only make sense if the fixed price is above the auction start price.[25]

5.2 Price Endogeneity and Instruments

A potential problem is that sellers will set higher prices for listings which are more likely to sell because of unobserved (or uncontrolled for) characteristics. I address this endogeneity in this context of these non-linear models by defining instruments and using a control function approach.

From equation (6) it is clear that variables which affect or reflect a seller's opportunity cost but which do not affect the attractiveness of the listing to consumers 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.). All else equal sellers who are further away are likely to have fewer opportunities to sell tickets offline, especially close to the time of the game. Distance may also distinguish between different types of seller who will have different opportunity costs (for example, season ticket holders are more likely to be local), and distance will also provide a valid instrument in this case as long as measures such as feedback scores, which are included in the specifications, control for aspects of seller quality which matter to buyers;
- the proportion of the seller's unsold listings during the same time period (for other tickets) which

[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 observations where the variables are not defined. 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) and include a dummy for observations with less than 10 listings.

are relisted (at a later date) on Market 2. A high proportion of relistings could reflect either high opportunity costs of selling (because the costs of relisting must be low) or low opportunity costs (because the seller must have few offline opportunities to sell them). 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;

- the proportion of listings for other tickets by the same seller in the same time period in fixed price and hybrid auction formats. Sellers may have lower marginal costs of listing in the formats which they are more used to using; 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 requires me to take a two-step control function approach (e.g., Rivers and Vuong (1988), Wooldridge (2002), p. 472ff) to estimation.[27] For the fixed price probit model, the control function approach assumes that the latent variable ($Q^*_{it}, Q_{it} = 1$ if $Q^*_{it} \geq 0$) determining the probability of sale can be expressed by

$$Q^*_{it} = \widetilde{X_{it}}\theta_1 + p_{it}\theta_2 + u_{it} \tag{9}$$

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

$$p_{it} = \widetilde{X_{it}}\gamma_1 + Z_{it}\gamma_2 + v_{it} \tag{10}$$

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

where Z_{it} are the instruments excluded, by assumption, from the Q^*_{it} function. u_{it} and v_{it} are mean zero bivariate normal, and prices are endogenous if u_{it} and v_{it} are correlated. The two-step procedure exploits the fact that under joint normality and the normalization that $\text{Var}(u) = 1$

$$u_{it} = v_{it}\theta_3 + e_{it} \tag{11}$$

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

A similar approach can be used for the probit and censored regression (Wooldridge (2002), p. 530) models used for pure auction listings, and the censored regression model used for hybrid auction listings. Addressing endogeneity in the context of the multinomial logit model used to determine the probability of each outcome in the hybrid auction model is theoretically more difficult because the residuals in the logit model are not normal. I follow the "practical" approach suggested by Wooldridge (2007). This involves specifying that the latent utility-like variable associated with outcome j as

$$u_{ijt} = \widetilde{X_{ijt}}\theta_1 + p_{ijt}\theta_2 + v_{ijt}\theta_3 + e_{ijt} \tag{12}$$

where e_{ijt} is distributed Type I extreme value and the v_{ijt}s come from price equations like (10). Given this ad-hoc assumption we can proceed as before estimating the $\widehat{v}$s in a first-step and them including them in the second stage specification.

Table 7 shows how the results of first-stage regressions where the dependent variables are the prices chosen by the seller relative to the face value of the ticket (i.e., the relative price would be 2 if the chosen price per seat was twice the face value of the ticket). Many of the coefficients on the instruments have a sensible pattern, although there is also some evidence that there may be selection of different types of seller into different types of mechanism (which is not necessarily a problem as long as the selection characteristics are not valued by buyers). The distance coefficients show that as 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 seller's located between 40 and 200 km.. This is consistent with distant sellers having fewer opportunities to sell tickets at the last minute. Sellers who tend to use pure fixed price and hybrid 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. The proportion resale variables show a less consistent pattern across sale formats. For hybrid auction listings, a higher tendency to relist is associated with higher prices a long way before the game with the premium disappearing over time (consistent with low listing costs and keenness to sell). For fixed price listings, people who tend to relist more always tend to set lower prices, consistent with relisters having limited outside opportunities relative to other users of fixed prices, and their prices also tend to fall more over time. For auctions, sellers who relist a lot tend to set relative prices which increase over time, which suggests that amongst auction sellers, relisters may have better outside opportunities.

5.3 Results

5.3.1 Fixed Price Listings

[I AM IN THE PROCESS OF REDOING THESE RESULTS WITH RELATIVE PRICE (I.E. RELATIVE TO FACE VALUE WHICH APPEAR TO GIVE MORE SENSIBLE RESULTS FOR THE AUCTION MODEL AND SIMILAR FOR THE FIXED PRICE MODEL TO THOSE REPORTED HERE]

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

The own price coefficients and the price elasticities clearly show that taking account of the endogeneity of the seller's own price matters. As usual, addressing endogeneity increases the elasticity of demand. In fact, without controlling for endogeneity the average price elasticities could only be rationalized by negative option values which would not make sense given free disposal. The coefficients on the own price $\widehat{v}$s in the control function specifications are also positive (higher prices associated with higher quality) and they are jointly significant at the 0.01% level. A common feature across all of the specifications is that the coefficients on the own price-time period interactions are positive indicating that falling prices are unlikely to be explained by increasing elasticities of demand.

The remaining coefficients have sensible signs and most of them are statistically significant. For example, there is greater demand for tickets with better sellers (higher feedback scores, although the big difference is with sellers with very low scores) and better rows (lower row numbers or the front row). Higher feedback scores for other listings also tend to reduce demand.

The fixed price competition variables have larger coefficients than the auction competition variables (some of which have the wrong sign), suggesting that there is more competition between fixed price listings than between fixed price listings and auction listings. This is plausible as the different formats might attract different buyers. The large positive coefficients on the mean log(competitor fixed price) and the negative coefficient on the minimum log(competitor fixed price) suggest that competition price effects may be non-linear (each coefficient is positive when only one of the variables is included). Allowing for the possible endogeneity of competitors' prices has only small effects on the own price coefficients and the elasticities of demand, and as these are critical in what follows I use the coefficients from column (2) below.

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

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

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

In the first counterfactual I recompute optimal prices using (6), given the estimated option value for each ticket, removing any demand effect by making both the intercept and the slope of the demand curve the same as they are estimated to be 41 to 44 days before the game. Optimal prices in this 4 day period are the same as those observed in the data and the remaining prices in first time period change only slightly due to small changes in the demand intercept. In the later time periods, counterfactual prices are slightly lower than observed prices because (in the data) demand becomes less elastic as the game approaches. Therefore changes in the demand elasticity actually tend to increase not decrease prices, with falling option values causing the price declines.

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

5.3.2 Auction Listings

5.3.3 Initial Results

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

The implied distribution of option values (calculated using the first order condition for the auction start price) in each of three time periods [NOTE: I will change this to four] is shown in Figure 3. As before only a small proportion of option values are estimated to be less to zero, although a much greater proportion are close to zero than in the fixed price case. The distributions for 0-10 and 11-20 days before the game are also very similar. This is not surprising as the results in Section 3 showed the fall in auction start prices is complete by 14 days prior to the game. The fall in option values from the first to the last two periods is, however, clear.

[NOTE: will repeat counterfactuals for the new auction model results]

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

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

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

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

$$u(v_i, p, \alpha_i) = -\frac{1}{\alpha_i}\exp(-\alpha_i(v_i - p)),\ \alpha_i > 0$$

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

Now suppose that there are two periods and that i's choice is between buying this ticket in period 1 at a price of p_1 or waiting until period 2. If she waits, then a ticket will be available in period 2 with probability q ($0 \leq q \leq 1$), its price (if available) will have pdf $f_2(p_2)$ and she will also have to

[28] As seen in Table 1 *most* purchases in Market 2 happen in the last week or so before the game by which time most of the observed price declines have already occurred. Therefore, even if early purchasing is a puzzle it is only a puzzle which applies to a subset of the data.

[29] I assume throughout that buyers are aware of the price declines. Given that these patterns seem surprising to many economists it is quite possible that some early purchasers are not aware of them. Quantifying the extent of consumer awareness is an interesting topic for future research.

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

$$-\frac{1}{\alpha_i}\exp(-\alpha_i(v_i-p_1)) \geq -\frac{1}{\alpha_i}\exp(-\alpha_i s_i)\left(\begin{array}{c} q\int_0^{v_i}\exp(-\alpha_i(v_i-p_2))f_2(p_2)dp_2+ \\ (1-q)+q\int_{v_i}^{\infty}f_2(p_2)dp_2 \end{array}\right) \tag{13}$$

The RHS reflects the fact that she will only buy in period 2 if a ticket is both available and $p_2 \leq v_i$. Inspection of (13) shows that i will be more willing to purchase early if expected future availability (q) is lower or future prices (p_2), search costs (s_i) or the coefficient of absolute risk aversion (α_i) are higher.

I use inequality (13) to calculate the degree of risk aversion required to rationalize observed early purchases in Market 2. I estimate q and $f_2(p_2)$ from the data making assumptions about which tickets a buyer would consider to be substitutes, which listings are available and at what prices. Given these estimates, I then calculate the α_i required to make (13) hold for each early purchase in the data given a variety of alternative assumptions on v_i and s_i.

6.2 Defining Substitute Tickets, Availability and Prices

Tickets to an individual game are differentiated products and people who buy the best seats might not be interested in bleacher seats even if their price is very low. Throughout the rest of the analysis I assume that someone who makes an early purchase would, if she instead waited, only consider buying tickets which are both to the same game and weakly "better" than those she actually bought along each of 4 dimensions: (i) at least as many seats; (ii) equal or greater face value; (iii) if the face value is equal they must be in the same or a lower row; (iv) seller has a weakly higher feedback score.[30] I also assume that if she did wait and buy better tickets she would only get the same utility (v_i) from these tickets as those she actually bought, so she would buy the cheapest better ticket available. These assumptions will, of course, tend to make waiting less attractive but, at least as a starting

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

point for considering a question which has not really been considered empirically before, they are not implausible especially for people buying high quality seats.

It is also necessary to make assumptions about which tickets would be viewed as available if a buyer returned to the market.[31] In particular, a buyer might be outbid for tickets sold in auctions. I therefore define tickets as being available on a particular day if they could be purchased at fixed prices (including hybrid auctions) at the beginning of the day or if they were sold in an auction which ended that day with no bidders and no secret reserve price.[32] In the latter case I assume that the tickets could have been bought at the auction start price. These assumptions will also tend to make waiting look less attractive because all tickets sold in auctions with secret reserves or actual bidding are treated as being completely unavailable.

Under these definitions, how many people would find better tickets to be available if they visited the market at a particular date? The answer to this question is shown in the upper section of Figure 4. For the 289,784 sets of tickets with non-missing face value information which were actually purchased I check whether better tickets were available on a set of days (80, 75, 70, ..., 5 and 1) before the game. The average availability is high (around 85%), partly because most tickets are sold for the most popular teams which also have the highest availability, and it peaks between 5 and 10 days before the game. The diagram also shows the average price of the cheapest available better ticket on a given day, together with the 10^{th} and 90^{th} percentiles of the distribution of this price. Prices are 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 would be $90. I exclude shipping costs as these are not available for listings which never sell. [NOTE: I will change this so that imputed shipping costs are included]. Consistent with the earlier results but also driven by increasing availability, the average cheapest better ticket price and the entire distribution of cheapest better ticket prices tend to fall as the game approaches.

[31] I assume that someone observed purchasing early in Market 2 would only return to Market 2 and not Stubhub or an offline market.

[32] Units which are unsold in multi-unit auctions are also considered to be available.

These facts alone suggest that if a buyer was only able to visit the market once then she choose to do so between 5 and 10 days before the game, when availability is highest and prices are lowest. For this reason I focus on early purchasers choosing between purchasing early and returning to the market five days before the game. Their decision not to wait should be driven by the expected gains from waiting being sufficiently small. The bottom diagram in Figure 4 shows the average $ per seat potential gain from waiting (in terms of a lower price) *if tickets are available* for people who actually purchased on different dates, together with the proportion of these buyers for whom better tickets would have been available. 88% of people buying 30-34 days before a game would have found better tickets available had they waited until five days before the game and, for these buyers, waiting would have allowed them to pay $13.44 less per seat on average..

6.3 Specification of f_2 and q

In inequality (13) $f_2(p_2)$ and q represent an early buyer's expectations about the availability and prices of better tickets if they return to the market 5 days prior to the game. To control for the considerable heterogeneity in tickets across games and sections, I estimate parametric specifications for these functions using the better ticket data constructed above.[33]

q is estimated as a probit function. The dependent variable is equal to 1 if a "better" ticket is available 5 days prior to the game. The regressors include the full set of home team dummies, and the interactions of these dummies with the log of the ticket's face value, the squared log of the ticket's face value, the game's expected attendance (the latent variable from the attendance model in Section 3). The other included variables are the row variables and dummies for the number of seats, the month and day of week of the game and the seller's feedback score. The sample includes all 289,784 listings ultimately purchased with non-missing face value information.

Table 11 shows some of the estimated coefficients, and they show a reasonable pattern. In particular, better tickets are less likely to be available later when the purchased listing has more seats,

[33] An implicit assumption here is that if an individual early purchaser was to delay buying then this would not change the availability and prices of listings at later dates.

a higher face value (at least for the face values covered by almost all of the data), a better row and a better seller. Availability is higher for games with higher expected attendance indicating that the supply curve in the secondary market is upward sloping, although, conditional on expected attendance, it is lower on weekends than during the week (which is consistent with season ticket holders having more time to go to games on weekends). Consistent with Figure 4, the average predicted q is 0.88.

The distribution of cheapest available better ticket prices five days before the game, conditional on availability, is estimates as a 2 parameter gamma distribution i.e.,

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

p_2 is the price per seat of the cheapest available better ticket and the estimation sample includes the 255,885 (of the 289,784) listings where better tickets were available 5 days before the game. X_0 (affecting the shape parameter) contains the full set of variables included in the probit model. X_1 (affecting the scale parameter) contains a constant, the log of the ticket face value and its square, the expected attendance, the number of seat dummies and the row variables.[34] The parameters were estimated using maximum likelihood with an analytic gradient and Hessian.

Table 11 shows some of the estimated coefficients. The interaction of the shape and scale parameters makes interpreting them slightly harder than in the case of the probit availability model, but simulations show that expected prices are increasing in face value, expected attendance and the quality of the row. The estimated model matches the first two moments of the price distribution very closely.

[34] The fit of the model (measured by the match to the aggregate distribution of prices) did not improve significantly adding more variables to the scale function and it was reduced when more variables were included in the scale function than the shape function. Models based on other distributions, including exponentials, normals and mixtures of exponentials, also provided an inferior fit.

6.3.1 Assumptions on v_i and s_i and the Calculation of α_i

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

To understand the calculation of the coefficient of absolute risk aversion (α_i) consider an example. Suppose that a pair of Loge Box 512 Row D tickets to the Seattle Mariners at the New York Yankees on May 6 is purchased 30 days before the game for $80 per seat ($p_1 = 80$). These characteristics are used to calculate the expected availability of better tickets and the distribution of the price of the cheapest available better ticket using the probit and gamma models. Suppose that I assume that the valuation is 50% more than the price paid ($v_i = 120$) and that there are no search costs ($s_i = 0$), then these values and distributions can be plugged into (13) and a simple computation will find the lowest value of α_i (risk aversion) for which the inequality holds and early purchasing is rationalized. $\widehat{\alpha_i}$ is set equal to 0 if the purchase is rationalized by risk neutrality.

6.4 Results

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

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

[35] In the proportional valuation case I assume that valuations are at least $10. This addresses a small number of cases with low purchases prices (e.g. $4 per seat) where (otherwise) exceptionally high levels of risk averion are required to rationalize purchasing.

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

To interpret the figure it is necessary to have some idea of what levels of risk aversion are plausible. Suppose that a person is offered a gamble where if she wins she gets \$10 and otherwise she has to pay \$10. For coefficients of absolute risk aversion of 0.01, 0.05, 0.1 or 0.5 she will accept the gamble if the probability of winning is 0.53, 0.62, 0.73 or 0.99 respectively. Introspection suggests to me that coefficients greater than 0.1 are implausible. On this basis, 90% of early purchases are rationalized with plausible risk aversion if surplus is more than 50% of the purchase price.

The second diagram uses valuations which are a \$ amount above purchase prices. This formulation has the advantage that it does not assume a smaller surplus when the buyer finds an unusually low price. Over 90% of early purchases are rationalized by plausible levels of risk aversion if surplus is more than \$20 per seat. Combining the results in the first and second diagram 95% of purchases are rationalized if the buyer's surplus is the greater of \$20 or 50% of the purchase price.

The final diagram presents the results when I allow for the presence of "search costs" that a buyer has to pay if she returns to the market at a later date. I assume that these costs have to be paid whether or not an acceptable ticket is available. Consideration of these costs is reasonable because the typical value of the gain from waiting (e.g., \$30 for a pair of tickets) could easily be dominated by the opportunity cost of time involved from returning to the market at a later date.[36] Even when surplus is only 10% of the purchase price, 96% of early purchases are rationalized by risk neutrality or plausible risk aversion if search costs are \$20 per seat. If surplus is 50% of the purchase price, 99% of early purchases are rationalized by plausible risk aversion if search costs are \$10.

[36] For this reason I have chosen not to present the results of an analysis using the availability and prices of tickets which are *ever* available after the date of purchase. In this case the gains from waiting look very large (averaging \$40 per seat on average) but it seems very implausible that anyone would search the site every day. For this reason I assume that they could revisit once and that they would do so at the time when availability is highest and prices are lowest.

Costs of return of \$10 or \$20 per seat may seem high for a market which is readily accessible online. However, the fixed costs of waiting may include more than just the costs of clicking on some links. In particular, some buyers may have to make "complementary investments" or plans to attend the game and these investments may be cheaper if they are made in advance. For example, it may be hard to find baby-sitters or hotel rooms may be more expensive if booked at the last minute. When future ticket availability and prices are uncertain, people may be unwilling to make these investments without having the tickets and may be willing to pay a premium for tickets in order to make plans when it is cheaper for them to do so.[37]

It is plausible that people who live further away from the stadium have to make more investments on average to attend a game, particularly of the sort (plane tickets, hotel rooms) which are likely to become more expensive if purchased at the last minute. Consistent with this story, early buyers tend to live further away from the stadium. Table 12 shows the results of regressing the log(distance) 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.[38] 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 size of this effect is similar using different fixed effects, controlling for buyer experience and median incomes in the home zipcode of the buyer and when using the least absolute deviations estimator to look at the effect on the median distances.[39]

[37] A simple model illustrates the point. Consider a risk-neutral potential buyer who values tickets at \$200. Seats are available in period 1 at \$80 and will be available in period 2 with probability q in which case the price will be \$50. The buyer has to make a complementary investment to attend the game. If the investment is made in the period 1 it costs \$100 and if it is made in period 2 it costs $\$100 + c, c \geq 0$. The buyer has three potentially strategies which are optimal for some values of c and q: (1) buy and invest in period 1, (2) buy and invest in period 2 if a ticket is available or (3) invest in period 1 and buy a ticket in period 2 if one is available. If it is not available then the investment is wasted. For example if $c = 20$ then: if $q \leq \frac{2}{3}$ then (1) is optimal; if $\frac{2}{3} < q \leq \frac{5}{6}$ then (2) is optimal and if $q > \frac{5}{6}$ then strategy (3) is optimal. As one would expect, when availability is more certain it is more attractive to wait to buy in period 2 and if it is very certain then it can also makes sense to invest in period 1 when investment is cheaper. As c (the additional cost of investing in period 2) increases the range of qs for which it is optimal to buy tickets in period 1 increases.

[38] 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).

[39] I have also examined whether early buyers tend to be less experienced at buying event tickets or come from zipcodes with higher or lower incomes. There are no systematic or large effects in either case.

7 Conclusion

This paper has examined a striking stylized fact about the dynamics of prices in online resale markets for MLB tickets: prices tend to fall 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. Sellers reduce prices as a game approaches because of the value they have of holding onto tickets tends to fall, consistent with event tickets being perishable products. This example therefore provides clear evidence in favour of recent theoretical models of dynamic pricing of perishable goods.

The paper also addresses the question of why some buyers purchase a long time before the game when prices are expected to fall. This question is ignored (by assumption) in the theoretical literature which assumes that buyers enter exogenously and must either buy at once or exit. I show that many observed early purchase decisions can be justified given uncertainty about the future availability and prices of tickets, together with plausible amounts of risk aversion. The fact that people who live further away from the stadium tend to purchase earlier is also consistent with stories where it is more difficult or expensive to make complementary investments closer to the game. It is also possible that for some buyers the costs of staying in the market to search for cheaper tickets are too large to justify waiting.

Two questions seem ripe for further analysis. First, the pattern of declining prices is clearly different from those typically observed in markets for airline tickets. Based on conversations with station executives, I also understand that prices for perishable advertising time on radio and television stations also tend to increase. What explains these differences? At least two explanations are plausible. The first explanation is that demand becomes less elastic over time so that a seller's optimal price increases. This seems particularly plausible for the airline example as, for exogenous reasons, businesspeople may only be able to plan trips a few days before they need to travel. The second explanation is that in markets where sellers are more concentrated and less anonymous, sellers have dynamic incentives to commit to increasing prices. This argument has been mentioned to me by station executives and seems plausible in the context of concentrated local broadcasting markets.

The second question concerns what factors drive sellers' choices over which market and which trading mechanism to use as the day of the game approaches. For sellers' an auction may be more attractive when a game is only a few days away because it allows prices to be flexible in response to realizations of demand. On the other hand, buyers might prefer fixed price listings which remove the uncertainties involved with bidding. Understanding how and why buyers and sellers value different trading mechanisms, using the exogenous variation in preferences created by the approach of the game, potentially has important implications beyond the type of online resale markets considered here.

References

[1] Ackerberg, Daniel, Keisuke Hirano and Quazi Shahriar (2006), "The Buy-It-Now Option, Risk Aversion and Impatience in an Empirical Model of EBay Bidding", mimeo, UCLA

[2] Aguirregabiria, Victor (1999), "The Dynamics of Markups and Inventories in Retailing Firms", *Review of Economic Studies*, 66(2), 275-308

[3] Ashenfelter, Orley (1989), "How Auctions Work for Wine and Art", *Journal of Economic Perspectives*, 3(3), 23-36

[4] Aviv, Yossi and Amit Pazgal (2008), "Optimal Pricing of Seasonal Products in the Presence of Forward-Looking Consumers", *Manufacturing Service Operations Management*, forthcoming

[5] Beggs, Alan and Kathryn and Graddy (1997), "Declining Values and the Afternoon Effect: Evidence from Art Auctions", *RAND Journal of Economics*, 28(3), 544-565

[6] Bitran, Gabriel R. and Susana V. Mondschein (1993), "Pricing Perishable Products: An Application to the Retail Industry", mimeo, MIT Sloan

[7] Black, Jane and David De Meza (1993), "Systematic Price Differences Between Successive Auctions are No Anomaly", *Journal of Economics and Management Strategy*, 1(4), 607-628

[8] Burdett, Kenneth, and Kenneth L. Judd, "Equilibrium Price Dispersion," *Econometrica*, LI (1983), 955–969

[9] Cachon, Gerard P. and Robert Swinney (2007), "Purchasing, Pricing and Quick Response in the Presence of Strategic Consumers", mimeo, Wharton School, University of Pennsylvania

[10] Courty, Pascal (2003), "Some Economics of Ticket Resale", *Journal of Economic Perspectives*, 17(2), 85-97

[11] Courty, Pascal (2003), "Ticket Pricing Under Demand Uncertainty", *Journal of Law and Economics*, XLVI, 627-652

[12] Courty, Pascal (2000), "An Economic Guide to Ticket Pricing in the Entertainment Industry", *Louvain Economic Review*, 66(2), 167-192

[13] Dana, James D. (1998), "Advance-Purchase Discounts and Price Discrimination in Competitive Markets", *Journal of Political Economy*, 106(2), 395-422

[14] Dana, James D. (1999), "Equilibrium Price Dispersion under Demand Uncertainty: The Roles of Costly Capacity and Market Structure", *RAND Journal of Economics*, 30(4), 632-660

[15] Dasu, Sriram and Chuyang Tong (2008), "Dynamic Pricing When Consumers are Strategic: Analysis of a Posted Price Scheme", *Operations Research*, forthcoming

[16] Engelbrecht-Wiggans, Richard (1994), "Sequential Auctions of Stochastically Equivalent Objects", *Economics Letters*, 44, 87-90

[17] Escobari, Diego and Li Gan (2007), "Price Dispersion under Costly Capacity and Demand Uncertainty", NBER working paper no. 13075

[18] Forrester Research (2008), "The Future of Online Secondary Ticket Markets", February 6 2008, Cambridge, MA

[19] Gale, Ian L. and Donald B. Hausch (1994), "Bottom-Fishing and Declining Prices in Sequential Auctions", *Games and Economic Behavior*, 7, 318-331

[20] Gale, Ian L. and Thomas J. Holmes (1992), "The Efficiency of Advance-Purchase Discounts in the Presence of Aggregate Demand Uncertainty", *International Journal of Industrial Organization*, 10(3), 413-437

[21] Gale, Ian L. and Thomas J. Holmes (1993), "Advance-Purchase Discounts and Monopoly Allocation of Capacity", *American Economic Review*, 83(1), 135-146

[22] Gallego, Guillermo and Garrett van Ryzin (1994), "Optimal Dynamic Pricing of Inventories with Stochastic Demand over Finite Horizons", *Management Science*, 40(8), 999-1020

[23] Ginsburgh, Victor (1998), "Absentee Bidders and the Declining Price Anomaly in Wine Auctions", *Journal of Political Economy*, 106(6), 1302-1319

[24] Herrin, William E., John R. Knight, C.F. Sirmans (2004), "Price Cutting Behavior in Residential Markets", *Journal of Housing Economics*, 13(3), 195-207

[25] Karp, Larry and Jeffrey M. Perloff (2005), "When Promoters Like Scalpers", *Journal of Economics and Management Strategy*, 14(2), 477-508

[26] Levin, Yuri, Jeff McGill and Mikhail Nediak (2008), "Optimal Dynamic Pricing of Perishable Items By a Monopolist Facing Strategic Consumers", mimeo, Queen's University

[27] Lazear, Edward P. (1986), "Retail Pricing and Clearance Sales", *American Economic Review*, 76(1), 14-32

[28] Leslie, Phillip and Alan Sorensen (2007), "The Welfare Effects of Ticket Resale", mimeo, Stanford University

[29] Liu, Qian and Garrett van Ryzin (2008), "Strategic Capacity Rationing to Induce Early Purchases", *Management Science*, forthcoming

[30] McAfee, R. Preston and Daniel Vincent (1993), "The Declining Price Anomaly", *Journal of Economic Theory*, 60, 191-212

[31] McAfee, R. Preston and Vera te Velde (2006), "Dynamic Pricing in the Airline Industry" in *Handbook on Economics and Information Systems*, volume 1, edited by T.J. Hendershott, Elsevier

[32] Zhou, Yong-Pin, Ming Fan and Minho Cho (2006), "Strategic Consumer Response to Dynamic Pricing of Perishable Products", mimeo, University of Washington Business School

[33] Rivers, Douglas and Quang Vuong (1988), "Limited Information Estimators and Exogeneity Tests for Simultaneous Probit Models", *Journal of Econometrics*, 39, 347-366

[34] Sass, Tim R. (1988), "A Note on Optimal Price Cutting Behavior under Demand Uncertainty", *Review of Economics and Statistics*, 336-339

[35] Sorensen, Alan (2000), "Equilibrium Price Dispersion in Retail Markets for Prescription Drugs", *Journal of Political Economy*, 108(4), 833-850

[36] Stigler, George (1961), "The Economics of Information", *Journal of Political Economy*, 69(3), 213-225

[37] van den Berg, Gerard, Jan C. van Ours and Menno P. Pradhan (2001), "The Declining Price Anomaly in Dutch Rose Auctions", *American Economic Review*, 91(4), 1055-1062

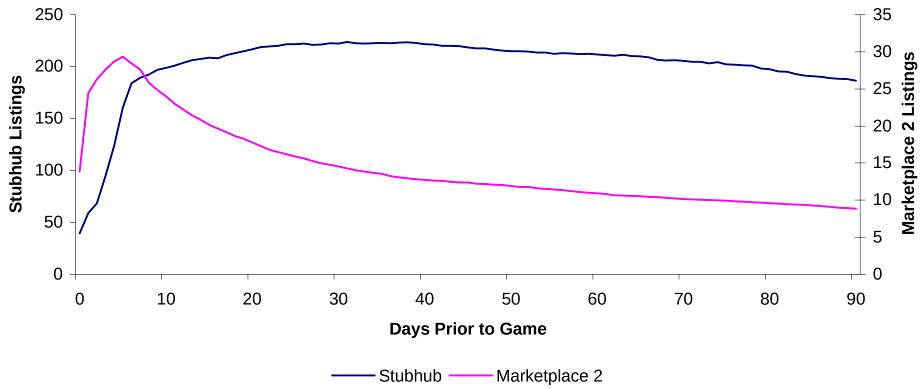
[38] Wooldridge, Jeffrey M. (2002), *The Econometric Analysis of Panel Data*, Cambrdige, MA: MIT Press

[39] Wooldridge, Jeffrey M. (2007), "Control Functions and Related Methods", lecture as part of NBER series "What's New in Econometrics?"

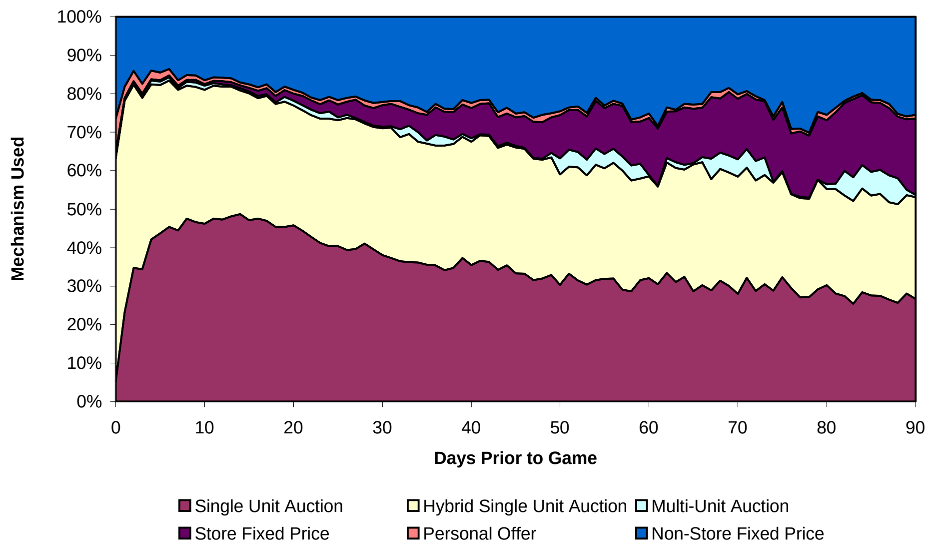
[40] Zeithammer, Robert (2006), "Forward-Looking Bidding in Online Auctions", *Journal of Marketing Research*, XLIII, 462-476

Figure 1

Availiability of Listings on Stubhub and Market 2



Choice of Sales Mechanism on Market 2 By Days Prior to Game



Proportion of Listings on Market 2 Resulting in Sales

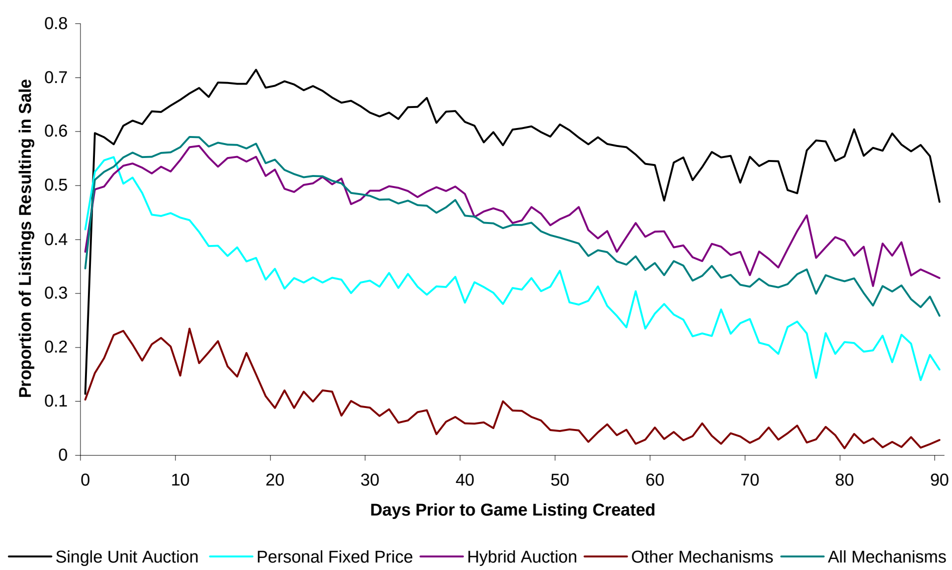


Figure 2: Option Values Implied By the Fixed Price Model

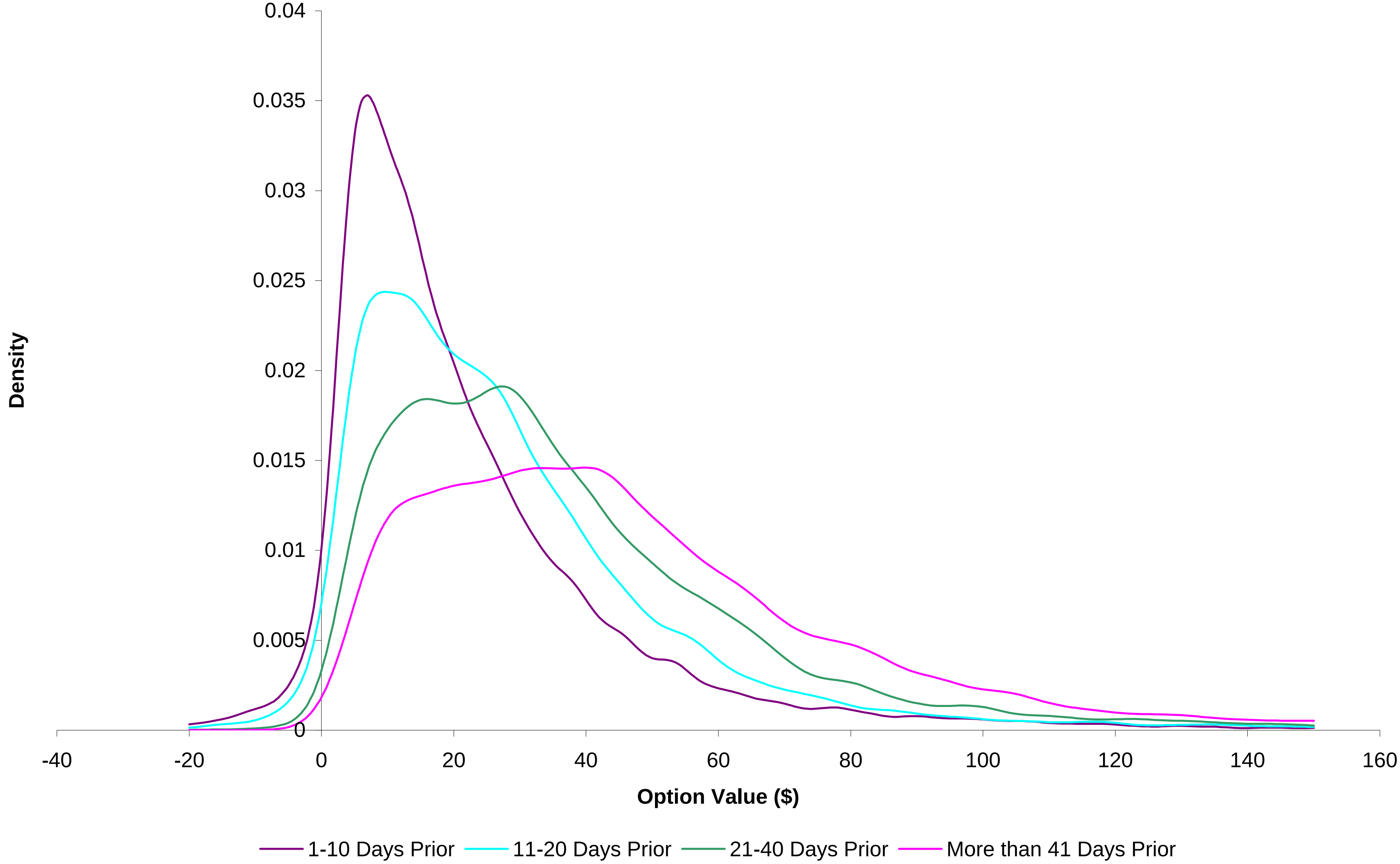


Figure 3: Distribution of Option Values Implied by Control Function Auction Model (Log Specification)

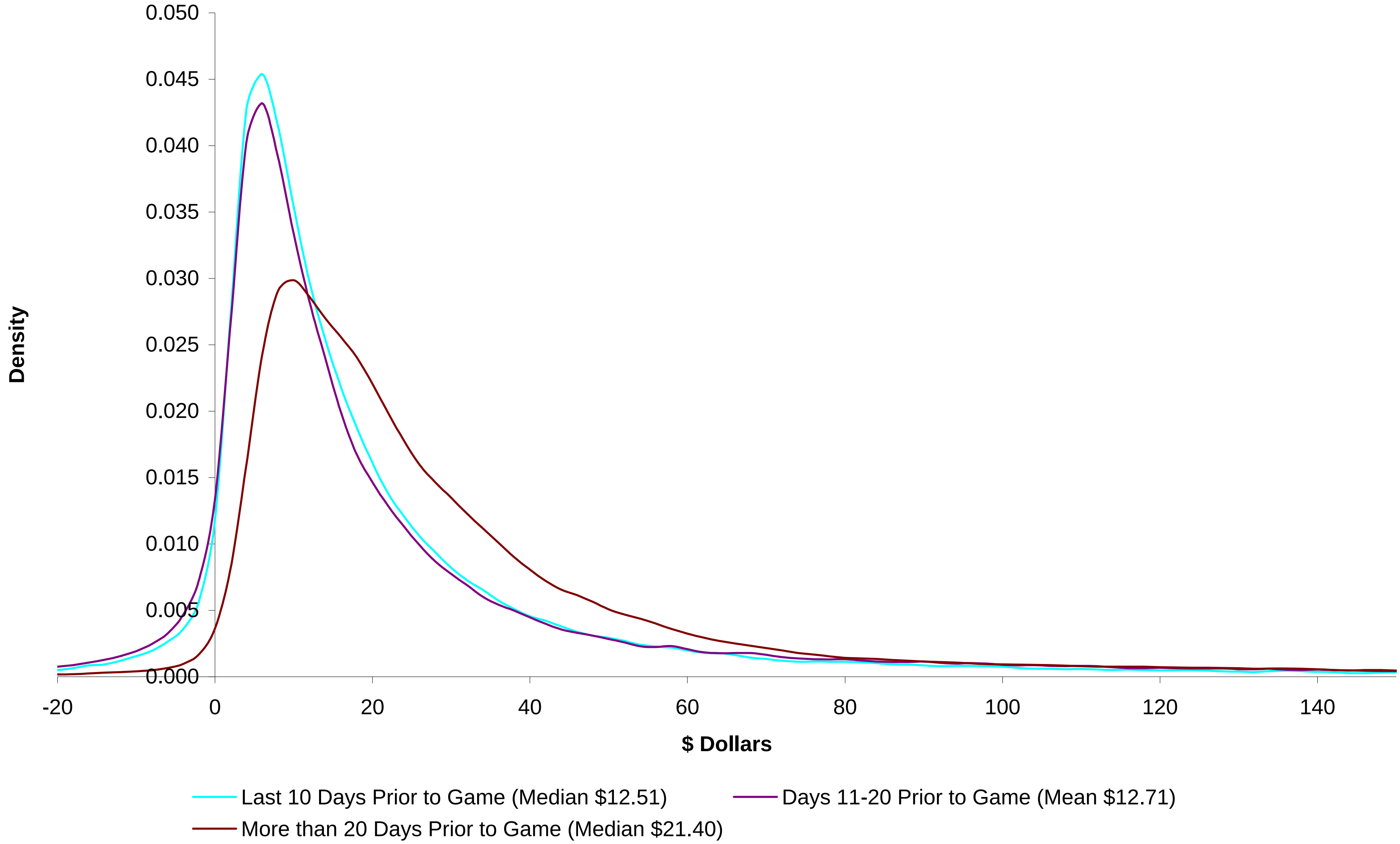
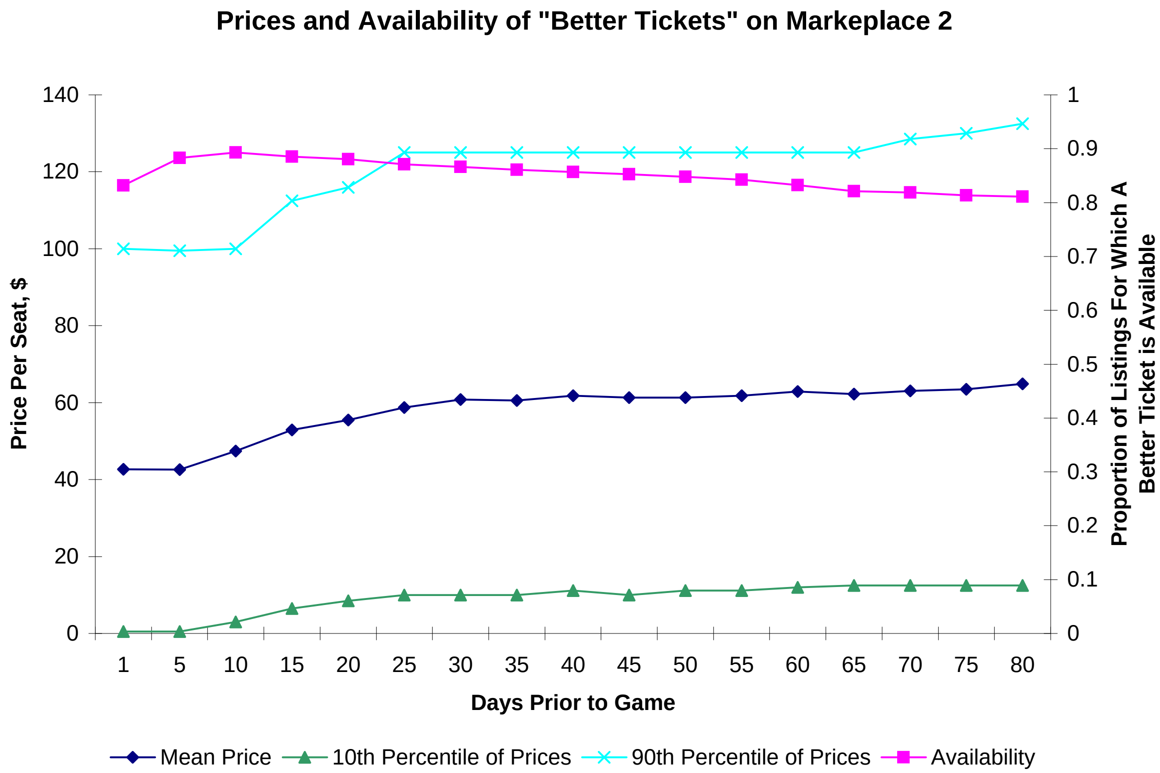


Figure 4: Analysis of Prices and Availability of "Better" Tickets



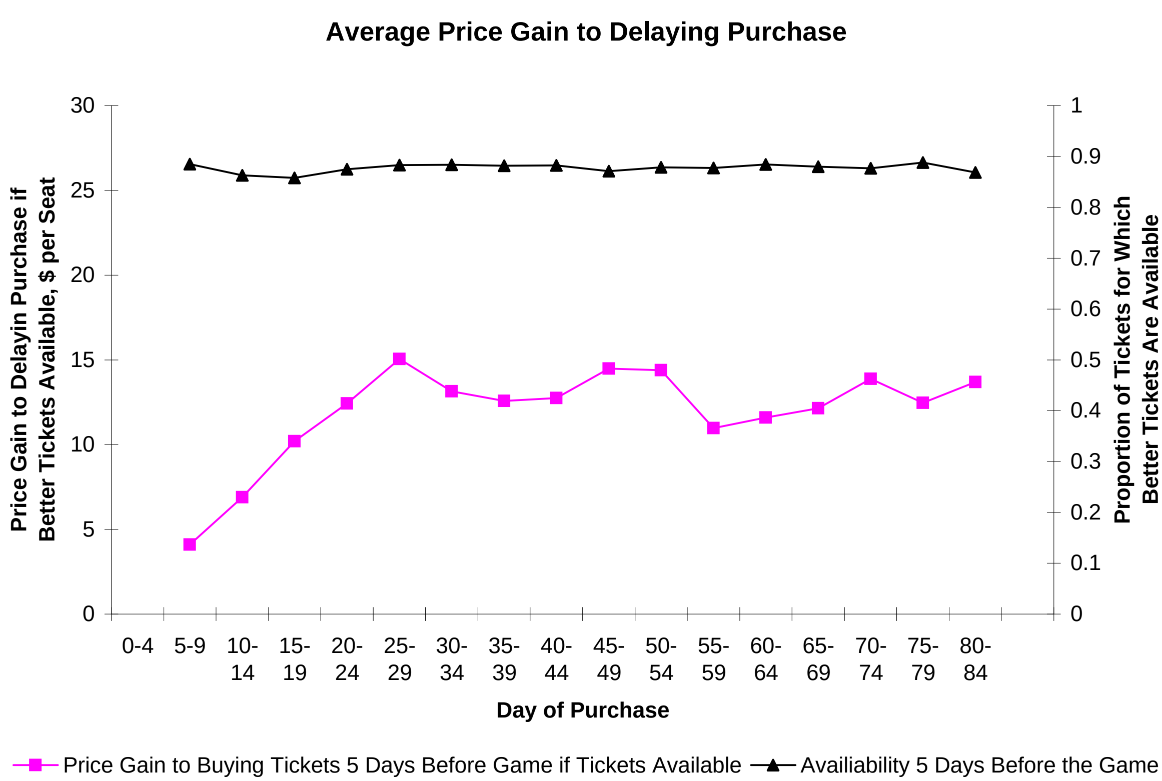
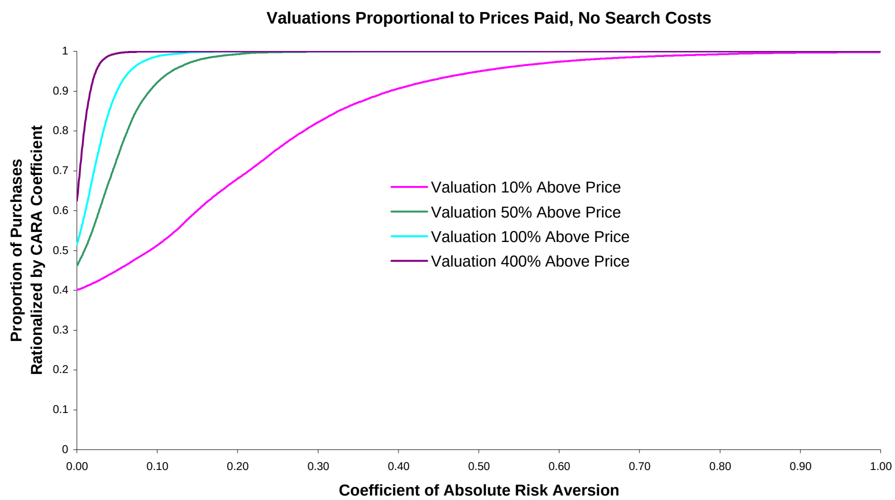
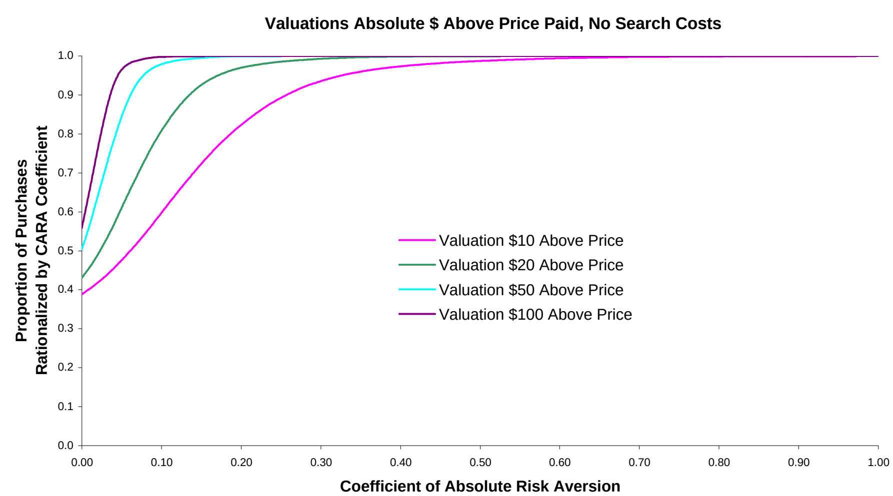


Figure 5

Coefficients of Absolute Risk Aversion Required to Rationalize Observed Early Purchasing When Alternative is to Return to Market 2 5 Days Before the Game

Sample Includes All Tickets Purchased More than 10 Days Before the Game for More than $10 Per Seat





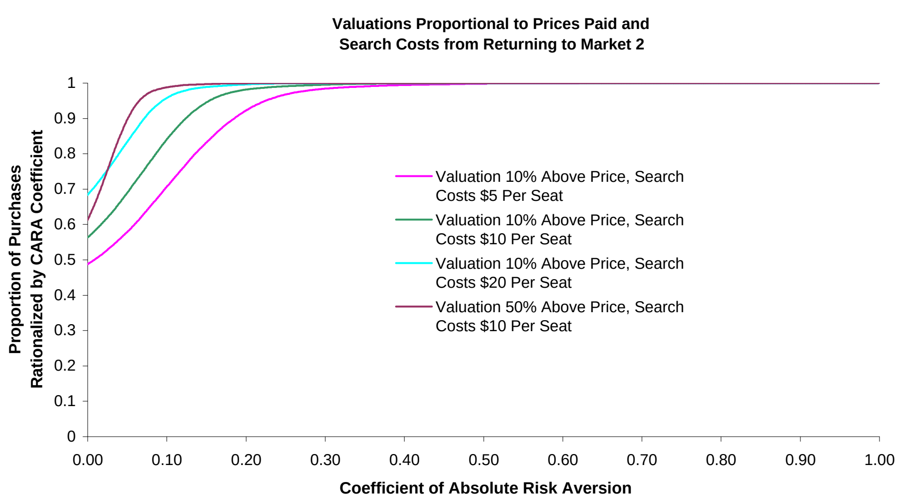


Table 1: Summary Statistics By Team

	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		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
LA 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 transactions rather than listings, and is based on quantity rather than revenue shares. Mean face value is calculated based on seating sections for which single-game pricing information is available. Transaction prices is the buyer price 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 Prices, $ per seat					Secondary/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

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

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

Table 5: Market 2 Listings

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample	Fixed Prices	Auctions	Fixed Prices	Auctions	Fixed Prices	Auctions	Fixed Prices	Auctions
Teams	All	All	All	All	Most Listed	Most Listed	Less Listed	Less Listed
Dep. Var	Log(Fixed Price)	Log(Auction Start)	Log(Fixed Price)	Log(Auction Start)	Log(Fixed Price)	Log(Auction Start)	Log(Fixed Price)	Log(Auction Start)
DTG Counted	Listing Start Date	Listing Start Date	Listing End Date	Listing End Date	Listing Start Date	Listing Start Date	Listing Start Date	Listing Start Date
Day to Go Dummies (0-2 excluded)								
3 to 5 days	0.134***	0.0228	0.114***	-0.0409***	0.142***	0.0382*	0.103***	-0.0494
	(0.007)	(0.018)	(0.005)	(0.014)	(0.007)	(0.020)	(0.013)	(0.037)
6 to 8 days	0.200***	-0.0356*	0.165***	-0.0663***	0.206***	-0.00264	0.173***	-0.178***
	(0.007)	(0.019)	(0.005)	(0.017)	(0.008)	(0.022)	(0.013)	(0.040)
9 to 11 days	0.264***	0.00351	0.205***	0.0900***	0.271***	0.0443*	0.237***	-0.172***
	(0.007)	(0.020)	(0.006)	(0.019)	(0.008)	(0.023)	(0.014)	(0.043)
12 to 14 days	0.302***	-0.0153	0.233***	0.204***	0.306***	0.0122	0.281***	-0.144***
	(0.007)	(0.021)	(0.006)	(0.020)	(0.008)	(0.024)	(0.014)	(0.043)
15 to 17 days	0.327***	0.107***	0.256***	0.319***	0.331***	0.167***	0.308***	-0.121**
	(0.007)	(0.023)	(0.006)	(0.022)	(0.009)	(0.026)	(0.014)	(0.048)
18 to 20 days	0.365***	0.242***	0.267***	0.326***	0.364***	0.264***	0.357***	0.125**
	(0.007)	(0.024)	(0.007)	(0.025)	(0.009)	(0.028)	(0.014)	(0.050)
21 to 23 days	0.382***	0.344***	0.288***	0.346***	0.385***	0.385***	0.365***	0.164***
	(0.008)	(0.025)	(0.007)	(0.028)	(0.009)	(0.028)	(0.015)	(0.055)
24 to 26 days	0.386***	0.371***	0.287***	0.351***	0.384***	0.412***	0.383***	0.188***
	(0.008)	(0.028)	(0.007)	(0.028)	(0.009)	(0.032)	(0.017)	(0.060)
27 to 29 days	0.405***	0.366***	0.297***	0.380***	0.410***	0.394***	0.385***	0.233***
	(0.008)	(0.030)	(0.008)	(0.030)	(0.010)	(0.034)	(0.016)	(0.059)
30 to 32 days	0.413***	0.388***	0.302***	0.518***	0.417***	0.388***	0.394***	0.357***
	(0.009)	(0.031)	(0.008)	(0.030)	(0.010)	(0.036)	(0.017)	(0.062)
33 to 35 days	0.416***	0.411***	0.323***	0.537***	0.418***	0.430***	0.405***	0.308***
	(0.009)	(0.033)	(0.008)	(0.031)	(0.010)	(0.038)	(0.018)	(0.062)
36 to 38 days	0.422***	0.462***	0.318***	0.567***	0.425***	0.494***	0.406***	0.309***
	(0.009)	(0.033)	(0.008)	(0.034)	(0.010)	(0.038)	(0.020)	(0.065)
39 to 41 days	0.440***	0.552***	0.303***	0.642***	0.440***	0.584***	0.431***	0.403***
	(0.010)	(0.034)	(0.008)	(0.036)	(0.011)	(0.039)	(0.021)	(0.070)
42 to 44 days	0.440***	0.601***	0.313***	0.551***	0.437***	0.665***	0.449***	0.321***
	(0.010)	(0.035)	(0.009)	(0.037)	(0.012)	(0.040)	(0.019)	(0.070)
45 to 47 days	0.440***	0.587***	0.307***	0.621***	0.436***	0.610***	0.451***	0.493***
	(0.009)	(0.038)	(0.010)	(0.038)	(0.011)	(0.043)	(0.019)	(0.077)
48 to 50 days	0.434***	0.659***	0.320***	0.611***	0.433***	0.716***	0.432***	0.412***
	(0.010)	(0.040)	(0.009)	(0.039)	(0.011)	(0.045)	(0.023)	(0.077)
51 to 55 days	0.430***	0.625***	0.305***	0.706***	0.431***	0.652***	0.418***	0.511***
	(0.009)	(0.034)	(0.008)	(0.033)	(0.010)	(0.038)	(0.020)	(0.069)
56 to 60 days	0.447***	0.710***	0.321***	0.694***	0.446***	0.718***	0.445***	0.664***
	(0.009)	(0.035)	(0.008)	(0.035)	(0.010)	(0.040)	(0.019)	(0.065)
61 to 70 days	0.464***	0.741***	0.341***	0.752***	0.462***	0.751***	0.460***	0.698***
	(0.008)	(0.030)	(0.007)	(0.030)	(0.009)	(0.035)	(0.018)	(0.059)
71 to 80 days	0.479***	0.806***	0.357***	0.761***	0.482***	0.814***	0.458***	0.780***
	(0.009)	(0.033)	(0.008)	(0.032)	(0.009)	(0.037)	(0.020)	(0.064)
81 plus	0.521***	0.907***	0.385***	0.892***	0.528***	0.897***	0.483***	0.952***
	(0.008)	(0.029)	(0.008)	(0.028)	(0.009)	(0.032)	(0.017)	(0.060)
Home Team Form Variables								
Games Ahead	0.0109***	-0.0374***	0.00814***	-0.0374***	0.00961***	-0.0431***	0.00162	-0.0509
	(0.003)	(0.013)	(0.003)	(0.013)	(0.003)	(0.013)	(0.011)	(0.032)
Games Back	-0.0208***	-0.0222***	-0.0199***	-0.0221***	-0.0288***	-0.0354***	-0.00874***	-0.000856
	(0.001)	(0.004)	(0.001)	(0.004)	(0.002)	(0.005)	(0.002)	(0.008)
Games Ahead *	-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: all regressions include dummies for the number of seats in the listing (1-6), the feedback score of the seller (4 dummies), whether the seller is a store owner, dummies for ticket characteristics (piggy back, aisle seats and whether parking included) and a dummy for if seller feedback is missing. Regressions with game-section fixed effects also include variables to control for row quality (row number, first row and second row dummies and dummies for if row information is not available or not applicable). Standard errors in parentheses. ***,** and * denote significance at the 1, 5 and 10% levels.

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

Cluster

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 Fixed Prices Experienced	Market 2 Fixed Prices Inexperienced	Market 2 Fixed Prices Inexperienced
Dep. Var	Log(Fixed Price)	Log(Fixed Price)	Log(Auction Start)	Log(Auction Start)	Log(Fixed Price)	Log(Fixed Price)	Log(Fixed Price)	Log(Auction Start)	Log(Fixed Price)	Log(Auction Start)
Day to Go Dummies (0-2 excluded)										
3 to 5 days	0.197***	0.194***	0.165***	0.142***	0.0990***	0.0979***	0.235***	-0.310***	0.0912***	0.0632
	(0.004)	(0.004)	(0.013)	(0.013)	(0.003)	(0.003)	(0.019)	(0.063)	(0.014)	(0.041)
6 to 8 days	0.323***	0.316***	0.296***	0.251***	0.138***	0.136***	0.370***	-0.191***	0.158***	0.0720*
	(0.005)	(0.005)	(0.014)	(0.014)	(0.003)	(0.003)	(0.019)	(0.065)	(0.016)	(0.043)
9 to 11 days	0.408***	0.398***	0.470***	0.401***	0.168***	0.166***	0.468***	0.167**	0.230***	0.0824*
	(0.005)	(0.005)	(0.015)	(0.015)	(0.003)	(0.003)	(0.019)	(0.071)	(0.017)	(0.046)
12 to 14 days	0.468***	0.455***	0.614***	0.524***	0.193***	0.189***	0.516***	0.207***	0.268***	0.0714
	(0.005)	(0.005)	(0.015)	(0.016)	(0.003)	(0.003)	(0.019)	(0.066)	(0.018)	(0.048)
15 to 17 days	0.521***	0.505***	0.706***	0.596***	0.214***	0.209***	0.568***	0.363***	0.299***	0.130**
	(0.005)	(0.005)	(0.016)	(0.017)	(0.003)	(0.003)	(0.020)	(0.068)	(0.019)	(0.054)
18 to 20 days	0.564***	0.545***	0.832***	0.703***	0.232***	0.225***	0.618***	0.580***	0.313***	0.222***
	(0.005)	(0.006)	(0.017)	(0.018)	(0.003)	(0.003)	(0.020)	(0.068)	(0.019)	(0.056)
21 to 23 days	0.586***	0.565***	0.923***	0.777***	0.247***	0.239***	0.620***	0.541***	0.344***	0.324***
	(0.006)	(0.006)	(0.017)	(0.019)	(0.003)	(0.003)	(0.020)	(0.068)	(0.021)	(0.059)
24 to 26 days	0.605***	0.581***	0.976***	0.814***	0.263***	0.253***	0.625***	0.590***	0.359***	0.338***
	(0.006)	(0.006)	(0.018)	(0.020)	(0.003)	(0.003)	(0.019)	(0.081)	(0.027)	(0.066)
27 to 29 days	0.620***	0.594***	1.027***	0.848***	0.273***	0.262***	0.647***	0.517***	0.342***	0.369***
	(0.006)	(0.006)	(0.019)	(0.021)	(0.003)	(0.003)	(0.020)	(0.076)	(0.026)	(0.069)
30 to 32 days	0.641***	0.612***	1.053***	0.857***	0.282***	0.270***	0.663***	0.579***	0.354***	0.299***
	(0.006)	(0.006)	(0.020)	(0.022)	(0.003)	(0.003)	(0.021)	(0.077)	(0.024)	(0.072)
33 to 35 days	0.655***	0.624***	1.116***	0.906***	0.290***	0.276***	0.666***	0.627***	0.381***	0.475***
	(0.006)	(0.007)	(0.020)	(0.022)	(0.003)	(0.003)	(0.021)	(0.083)	(0.026)	(0.078)
36 to 38 days	0.669***	0.636***	1.135***	0.912***	0.298***	0.282***	0.671***	0.585***	0.387***	0.424***
	(0.007)	(0.007)	(0.022)	(0.024)	(0.003)	(0.003)	(0.021)	(0.076)	(0.027)	(0.083)
39 to 41 days	0.676***	0.641***	1.219***	0.982***	0.305***	0.287***	0.675***	0.673***	0.384***	0.433***
	(0.007)	(0.007)	(0.022)	(0.025)	(0.003)	(0.003)	(0.022)	(0.082)	(0.028)	(0.084)
42 to 44 days	0.679***	0.642***	1.223***	0.972***	0.310***	0.291***	0.692***	0.729***	0.406***	0.515***
	(0.007)	(0.007)	(0.023)	(0.025)	(0.003)	(0.003)	(0.022)	(0.082)	(0.030)	(0.091)
45 to 47 days	0.699***	0.662***	1.230***	0.962***	0.315***	0.294***	0.712***	0.810***	0.437***	0.495***
	(0.007)	(0.007)	(0.024)	(0.027)	(0.003)	(0.003)	(0.021)	(0.097)	(0.033)	(0.100)
48 to 50 days	0.700***	0.661***	1.275***	0.995***	0.320***	0.297***	0.689***	0.739***	0.404***	0.443***
	(0.007)	(0.008)	(0.024)	(0.027)	(0.003)	(0.003)	(0.022)	(0.095)	(0.034)	(0.110)
51 to 55 days	0.707***	0.666***	1.303***	0.999***	0.325***	0.300***	0.710***	0.793***	0.388***	0.458***
	(0.006)	(0.007)	(0.022)	(0.026)	(0.003)	(0.003)	(0.022)	(0.080)	(0.031)	(0.097)
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 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: all regressions include dummies for the number of seats in the listing (1-6), the feedback score of the seller (4 dummies), whether the seller is a store owner, dummies for ticket characteristics (piggy back, aisle seats and whether parking included) and a dummy for if seller feedback is missing. Regressions with game-section fixed effects also include variables to
control for row quality (row number, first row and second row dummies and dummies for if row information is not available or not applicable). Standard errors in parentheses. ***,** and * denote significance at the 1, 5 and 10% levels.
Fixed price sample includes pure fixed price, personal offer and hybrid auction listings. Auction sample includes pure single unit auctions, hybrid auctions and multiple unit auctions.

Cluster

Table 7: First Stage Regressions for Own Listing Prices: Coefficients on the Instruments

Listings	Pure Fixed Price	Pure Auction	Hybrid Auction	
Price (relative to face value)	Fixed Price	Auction Start	Auction Start	Fixed Price
Seller Distance from Stadium Less than 40km	-0.0218	0.000816	-0.0329***	-0.0375***
	(0.014)	(0.011)	(0.011)	(0.014)
* 1-10 Days Prior to Game	0.0482***	0.0362***	0.0291**	0.0298*
	(0.018)	(0.013)	(0.012)	(0.017)
* 11-20 Days Prior to Game	0.0223	-0.00146	0.0357***	0.0349*
	(0.021)	(0.013)	(0.013)	(0.018)
* 21-40 Days Prior to Game	-0.0224	0.00597	0.00393	0.0384**
	(0.020)	(0.014)	(0.014)	(0.019)
Seller Distance from Stadium More than 200km	0.163***	-0.0525***	-0.0366***	-0.0294**
	(0.012)	(0.009)	(0.010)	(0.013)
* 1-10 Days Prior to Game	-0.229***	-0.0410***	-0.00819	-0.0304*
	(0.018)	(0.011)	(0.012)	(0.016)
* 11-20 Days Prior to Game	-0.133***	-0.0248**	-0.015	0.0102
	(0.019)	(0.012)	(0.013)	(0.017)
* 21-40 Days Prior to Game	-0.0566***	0.0199	-0.0368***	-0.0283
	(0.018)	(0.013)	(0.013)	(0.018)
Proportion of Seller's Unsold Listings	-0.118***	-0.0240*	0.137***	0.0700***
During Time Period Relisted on Market 2	(0.020)	(0.013)	(0.016)	(0.022)
* 1-10 Days Prior to Game	-0.0901***	0.245***	-0.173***	-0.172***
	(0.034)	(0.018)	(0.020)	(0.027)
* 11-20 Days Prior to Game	-0.131***	0.128***	-0.119***	-0.137***
	(0.046)	(0.020)	(0.024)	(0.032)
* 21-40 Days Prior to Game	-0.424***	0.217***	-0.0354	-0.0648**
	(0.034)	(0.020)	(0.023)	(0.032)
Proportion of Seller's Other Listings	-0.101***	0.196***	0.149***	0.153***
in Hybrid Auction Format	(0.038)	(0.021)	(0.020)	(0.027)
* 1-10 Days Prior to Game	0.162***	-0.0377	-0.0470**	-0.116***
	(0.046)	(0.024)	(0.023)	(0.031)
* 11-20 Days Prior to Game	0.270***	0.00219	-0.0426*	-0.0293
	(0.053)	(0.026)	(0.024)	(0.033)
* 21-40 Days Prior to Game	0.0918*	-0.0737***	-0.00315	-0.0511
	(0.052)	(0.028)	(0.026)	(0.035)
Proportion of Seller's Other Listings	0.138***	0.310***	0.119***	0.218***
in Pure Fixed Price Formats	(0.026)	(0.019)	(0.025)	(0.034)
* 1-10 Days Prior to Game	-0.226***	-0.438***	-0.0927***	-0.234***
	(0.033)	(0.026)	(0.031)	(0.042)
* 11-20 Days Prior to Game	0.0388	-0.329***	-0.119***	-0.172***
	(0.037)	(0.028)	(0.034)	(0.046)
* 21-40 Days Prior to Game	0.016	-0.284***	-0.0117	-0.0334
	(0.036)	(0.028)	(0.035)	(0.047)
Average Relative Fixed Price in	-	-	-0.202***	0.391***
other Hybrid Auction Listings			(0.006)	(0.009)
* 1-10 Days Prior to Game	-	-	0.0678***	0.0453***
			(0.007)	(0.010)
* 11-20 Days Prior to Game	-	-	0.0904***	0.0207**
			(0.008)	(0.010)
* 21-40 Days Prior to Game	-	-	0.0701***	-0.0644***
			(0.008)	(0.011)
Average Relative Start Price	-	-	0.599***	-0.128***
in other Hybrid Auction Listings			(0.007)	(0.010)
* 1-10 Days Prior to Game	-	-	0.0530***	0.0793***
			(0.009)	(0.012)
* 11-20 Days Prior to Game	-	-	0.00197	0.0429***
			(0.010)	(0.013)
* 21-40 Days Prior to Game	-	-	-0.0430***	0.0845***
			(0.010)	(0.013)
Observations	109,296	179,055	115,406	115,406
F-statistic on the instruments	47.5	105.6	1332.2	674.1

Note: coefficients not reported for the following variables: home team dummies, home*face value dummies, home*expected attendance, row variables, seller and listing characteristics (e.g., feedback score dummies, highlighted listing), prices and characteristics of contemporaneous listings, day to go dummies, sale format dummies (for fixed price), auction duration dummies, game day of week dummies

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

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

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

Table 9: Counterfactual Prices ($) Using Probit Control Function Demand Model For Fixed Price Listings

	Days Prior to the Game			
	1-10	**11-20**	**21-40**	**More than 41**
Actual				
Mean Price	52.21	58.29	63.21	66.20
Std Dev Price	(49.93)	(50.68)	(50.36)	(51.13)
Counterfactual 1: demand 41-44 days prior to game applies throughout				
Mean Price	49.29	51.66	57.60	66.91
	(1.87)	(1.88)	(1.58)	(0.49)
Std Dev Price	41.96	38.76	42.65	51.68
	(2.98)	(2.58)	(2.32)	(0.98)
Counterfactual 2: mean of option value distribution same as in "more than 41 days prior to game period"				
Mean Price	74.87	77.05	73.50	66.20
	(3.32)	(2.98)	(2.83)	(N/A)
Std Dev Price	47.86	50.18	50.22	51.13
	(4.55)	(3.76)	(3.57)	(N/A)
Number of observations	31,510	20,515	24,327	31,973

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

Table 10: Auction Model (Preliminary Results)

Multinomial Logit Model Using Control Function - Coefficients on Own Prices

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

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

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

Table 11: Models for Ticket Availability and Expected Prices Five Days Prior to Game

	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)
Selected Team Effects			
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	-58168.228	-1120320.5	
Number of Observations	289,784	255,885	

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

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