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 price dynamics in two secondary markets for Major League Baseball tickets. Controlling for ticket quality, prices decline significantly as a game approaches. The paper examines why this happens in equilibrium, looking at the behavior of both buyers and sellers. It shows that sellers cut prices as a game approaches because their value of holding onto tickets declines as future selling opportunities disappear. This is consistent with theoretical models of dynamic pricing. The decisions of early purchasers, who buy when prices are relatively high, can be rationalized by plausible preferences given the importance of product differentiation in these markets and uncertainty about the availability of particular types of ticket.

[APPENDIX AND TABLES A1-A4 NOT INTENDED FOR PUBLICATION]

1 Introduction

This paper analyzes the dynamics of prices in two online resale (secondary) markets for Major League Baseball (MLB) tickets. A robust stylized fact, which is surprising to many economists, is that average list and transaction prices tend to fall significantly - by 20% or more - in the weeks leading up to a game, with the entire distribution of prices falling as well.

After establishing this stylized fact, I focus on *why* declining prices are the equilibrium outcome in these markets. The observation that prices fall is consistent with the predictions of theoretical

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models of the dynamic pricing of perishable goods (e.g., McAfee and te Velde (2006), Gallego and van Ryzin (1994) and Bitran and Mondschein (1993)). The logic behind declining prices in these models is simple: as the end of the selling horizon approaches the probability that the seller will sell a unit in the future if he does not sell it today tends to fall. This decreases the opportunity cost of a sale and so reduces the optimal price. I estimate structural models of a seller's pricing problem for three different sale formats, and find that sellers cut prices for precisely this reason rather than because of changes in the elasticity of demand.

My work provides the first clear evidence that dynamic pricing models accurately describe seller behavior in perishable goods markets. These models have been widely used in the Operations Research literature to tell managers how they *should* price, but when researchers have looked at airline pricing - the most frequently cited example of this type of pricing problem - they have rejected the "robust prediction" (McAfee and te Velde) that prices should fall as the day of departure approaches (McAfee and te Velde (2006), Escobari and Gan (2007) and Puller et al. (2008)).[1] While the observed pattern of increasing prices can be rationalized for airlines by late-arriving business travellers having less elastic demands, it begs the question of whether there are markets where the theoretical predictions do hold.

The fact that these models do describe pricing behavior in secondary ticket markets is interesting because these markets differ in several respects from airline and hotel markets which are used to motivate the theoretical literature. The canonical dynamic pricing model has a monopolist selling several units of homogenous inventory, whereas secondary ticket markets are characterized by many small sellers, with each seller typically selling a single unit (e.g., a pair of seats) of a differentiated product. In the canonical model buyers arrive stochastically and must either buy at once or exit the market forever. In contrast, consumers in secondary ticket markets may choose to delay purchasing if they expect prices to fall or their value of going to the game to change. On the other hand, some of these features may actually help to explain why I find such strong support for the theory. Gallego and van Ryzin (1994) show that when inventories are large sellers do not lose much by using simpler fixed price policies.[2] In addition, small sellers are unlikely to try to commit to particular pricing policies in order to influence future consumer behavior. In contrast, a large airline, which interacts

[1] In on-going research Gauri et al. (2009) examine pricing by a holiday cruise line. They find that prices fall over time on one route while rising on others. Thomas (2009) finds some price declines for franchised hotels and explains this pattern as resulting from informational asymmetries with centrally-managed units. Zhao and Zheng (2000) show that within a dynamic pricing model expected prices can increase over time if reservation values increase by a sufficiently large amount.

[2] When a seller has multiple units, the optimal price increases in the number of units that have been sold, although the time remaining effect dominates so that expected prices fall over time. McAfee and te Velde (2006) present simulations which show that with many units a rapid fall in expected prices only occurs at the end of the selling horizon.

with many of its customers repeatedly, may want to avoid developing a reputation for cutting prices in order to prevent them from waiting to buy in the future.

The standard theoretical assumption that buyers cannot choose when to purchase is potentially important because it means that sellers will be able to sell some units when they set high prices early on. I calibrate a model of a buyer's utility function to look at whether the early purchase decisions which I observe in secondary ticket markets can be rationalized by plausible preferences, given product differentiation and uncertainty about the future availability and prices of particular types of ticket. This approach is motivated by several recent theoretical papers (Aviv and Pazgal (2008), Liu and van Ryzin (2008), Dasu and Tong (2008), Levin et al. (2008) and Zhou et al. (2006)) which have found that declining prices can still be the equilibrium outcome if future availability is sufficiently uncertain or some consumers have sufficiently strong preferences. I find that plausible preference parameters can rationalize most, but not all, early purchases. I also find that there are patterns in the data which are consistent with the type of sorting suggested by the calibrations. For example, the need to make complementary investments, such as travel arrangements, which may be more expensive if made at the last minute, can rationalize early purchasing. Consistent with this, people buy earlier when they have to travel further to attend a game.

Although it is focused on testing theories of dynamic pricing, the paper also contributes to a recent literature on secondary ticket markets. These markets have evolved rapidly in the last few years and have become increasingly accepted by primary market sellers (Section 2). Forrester Research (2008) estimates that revenues in these markets will grow from $2.6 billion in 2007 to $4.5 billion in 2012, with 70% of these revenues generated from the resale of sports tickets. The existing theoretical (Courty (2000, 2003a,b), Karp and Perloff (2005)) and empirical (Leslie and Sorensen (2007)) literatures analyze how these markets affect welfare using one-shot market clearing models. My paper provides some insights into how the price formation process actually works. The paper is also indirectly related to the literature on the declining price anomaly in sequential auctions (*inter alia* Ashenfelter (1989), Ginsburgh (1998), McAfee and Vincent (1993)). Much of that literature has focused on particular features of the auction mechanism used by an individual seller or auctioneer (e.g., the first buyer gets to choose among the available items). In contrast I look at price declines which occur across several different kinds of mechanism, including fixed prices, in a setting with many different sellers.

The paper is structured as follows. Section 2 briefly describes the relevant institutional background and Section 3 describes my data. Section 4 shows that prices tend to fall as a game approaches. Section 5 describes two alternative explanations for why sellers cut prices over time, and Section 6 quantifies how important each of these explanations actually is. Section 7 examines early purchase decisions. Section 8 concludes.

2 Institutional Background

MLB teams sell tickets in the *primary market* to a combination of fans and professional resellers.[3] These resellers may be legally registered brokers or less formal scalpers. The *secondary market* reallocates tickets. Sellers in the secondary market include fans who do not wish to attend a game and professional resellers. Because few season ticket holders attend all 81 home games, secondary markets for MLB tickets are characterized by a greater proportion of small sellers than similar markets for NFL or concert tickets. In contrast to some concert promoters MLB teams do not hold back tickets to build demand, and there are also only one or two small examples of teams experimenting with dynamic pricing in the primary market.[4]

Trade in the secondary market can take place in several ways, aside from fans trading informally with friends. Fans can list tickets on several online trading sites including Stubhub and EBay. These are the markets I look at in this paper, and they accounted for more than 50% of online secondary ticket market transactions in 2007 (Forrester Research (2008)). Tickets may be listed on these sites simultaneously. Brokers may also use these sites, in addition to posting listings on their own websites and trying to sell them offline. Resellers may also purchase additional tickets on the resale market, and sometimes they also list tickets on behalf of fans in return for a percentage of revenues if the tickets are sold.

Even though several markets compete for listings, Stubhub is able to generate large commissions (charging 15% commission to sellers and 10% commission to buyers in the event of sale). EBay purchased Stubhub in 2007 and, partly motivated by the opportunity to get a share of these revenues, many primary market sellers have endorsed particular secondary markets. For example, Stubhub has been MLB's "Official Fan to Fan Marketplace" since 2008. Traditional problems of counterfeiting have also been reduced (for example, Stubhub guarantees that valid tickets will be provided to anyone buying tickets on its site), and most states have now relaxed legal restrictions on secondary markets.

Tickets to particular games are *differentiated products.* Primary market sellers may have several pricing bands, but differences in quality can be priced more finely in secondary markets. Differenti-

[3] Teams also provide tickets to players and staff, some of which may end up on the secondary market.

[4] The Colorado Rockies have used limited dynamic pricing for certain sections for several years and the San Francisco Giants are experimenting with dynamic pricing for some less expensive seats in 2009.

ation is likely to play an important role in supporting equilibrium outcomes, in at least three ways. First, differentiation will give each seller a degree of market power even when several sellers are listing tickets at the same time. Second, consumers with strong preferences for a particular type of seat may choose to buy early even when prices tend to fall, if they are concerned that the types of ticket that they prefer will not be available if they wait until the last minute. Third, differentiation complicates some strategies which would seek to exploit the price declines. For example, suppose that someone sells a promise to supply a ticket at a high price early on and then fulfills it by buying a ticket at a lower price closer to the game. This will be difficult to execute if buyers want to know exactly which seats they are buying and the short-seller does not know which tickets will be available later on. In practice I observe that listings with missing row information trade at a discount (20%) which is probably large enough to make this type of strategy unprofitable.

3 Data

3.1 Secondary Market Data

I use data from EBay and Stubhub on regular season MLB games in 2007. Three Tampa Bay games played in Orlando and make-ups of rained out games, which are often scheduled at very short notice, are excluded. I do include rained out games as my interest is in price dynamics in the weeks leading up to the game, rather than on the day itself.

3.1.1 Stubhub.com

The Stubhub data contains *list prices*, collected from Stubhub's "buy" page for each game each day from January 6, 2007 to September 30, 2007 using an automated script. From a buyer's perspective, sellers are anonymous but Stubhub guarantees that tickets at least as good as those purchased will be supplied. Sellers list tickets for free, but sellers pay a 15% commission and buyers a 10% commission in the event of a sale. Buyers also pay for FedEx shipping.[5] Tickets can only be listed within 3 days of the game if hard copies are supplied to Stubhub which can pass them to buyers, for a $15 handling charge, at an office close to each stadium.

The data collected includes a listing identification number, the game (e.g., Seattle Mariners at the New York Yankees on May 6), the number of seats available (and if a smaller number of seats can be

[5] In 2007 this cost $11.95 per listing for transactions more than 14 days before the game and $16.95 per transaction thereafter.

purchased), the section and row (e.g., Loge Box 512 row D at Yankee Stadium) and the listed price per seat. The identification number allows for only imperfect tracking of listings over time because sellers may change prices by entering a new listing.[6]

I only use listings in Stubhub's fixed price format (99.5% of listings, auctions accounting for the remainder). I drop a small number of listings (0.4%) in a format which has a linearly declining price as the game approaches. The fact that Stubhub offers this option is informative about how prices tend to change. I also only use listings with non-missing section information (99.7% of the remaining sample), six or fewer seats (91%) and prices which are less than $1,000 per seat (99.9%).

3.1.2 EBay

The EBay data was purchased from EBay's official data reseller, Advanced E-Commerce Research Systems. A seller can list tickets in several different sale formats, including pure auctions (of different durations), pure fixed price formats including a format for sellers with EBay stores, and the hybrid Buy-It-Now (BIN) auction format where a consumer can buy at a fixed price if no auction bids have been placed. Sellers can also use secret reserve prices in auctions, although these are used in less than 3% of cases. Sellers pay a small listing fee and commissions which vary from 1% to 7% depending on the transaction price and the sale format. Buyers pay shipping costs set by the seller. Buyers see a seller's username and current feedback score, and reputations may matter because there is no equivalent of the Stubhub guarantee.

The full dataset contains all event ticket listings from January 1 to September 30, 2007.[7] I use the data on regular season MLB games, but the full dataset is used to impute missing data on feedback scores and zipcodes. For each listing I observe the game, the seller's identity number, the number of seats available, the section and row, the sale format and the relevant prices (only an indicator for a secret reserve), the start date and duration of the listing, the seller's revenues and some of the additional text from the listing provided by the seller. It also indicates whether the listing was highlighted on a search page or contained additional information such as pictures. For all bids, it contains the identity number of the bidder, the level of the bid and an indicator for whether the bid was successful. For all transactions, it contains the buyer and seller identity numbers, feedback scores, shipping costs and (a relatively novel aspect of the data) the zipcodes of the buyer and seller.

[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.

[7] AERS 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.

Section information could not be identified for 0.5% of listings which were dropped. I drop listings with more than six seats, list or transaction prices above $1,000 or shipping costs above $40. These restrictions drop a further 0.7% of the sample.

3.2 Primary Market Data

The secondary market data is complemented by several types of data from the primary market and on team performance. Single game (face value) prices for each section for each game were collected from team websites. Some teams, such as the Boston Red Sox, charge the same prices for all games, whereas others, such as the New York Mets, have several pricing tiers. Face value information is unavailable for the Colorado Rockies and for some season ticket-only sections for other teams. These observations are excluded from specifications where some variables are based on face values.

Team performance may affect demand. Game result data from Retrosheet.org was used to construct performance measures for each team for each day during the season: the number of games back from leading their division (zero if leading), number of games ahead in their division (zero if behind), the number of games back from leading the wild card race (zero if leading) and the number of games ahead in the wild card race (zero if behind). These variables, and interactions with the number of games remaining in the season, are included in all of the specifications below for both teams unless otherwise noted.

Realized attendance data was also collected from Retrosheet. I measure attendance as a proportion of the maximum attendance during the season as this frequently exceeds nominal stadium capacities. Some specifications include controls for a game's expected attendance on a given day. Expected attendance is modeled using a censored normal regression and estimated using Retrosheet data from 2000 to 2007.[8] Specifically, I estimate the model so that I can predict a game's attendance on 22 dates prior to the game (which correspond to the Days to Go dummies included in the specifications below). Explanatory variables are the home and away team form variables on the day in question, and home team, home team*year, home team*month, home team*day of week of the game and dummies for the type of game being played (interleague, within-league but cross-division and within-division).

[8] As the exact attendance can vary even when a game is sold out, I top-code the attendance variable at 0.98 and use that as the censoring point.

3.3 Summary Statistics

Table 1 shows some statistics on the number of listings and average EBay transaction prices by team. Stubhub has more listings than EBay for every team, and the difference in the number of listings available on an average day is even larger because Stubhub listings are available for an average of 16 days compared with 4.5 days for EBay. The teams with the highest attendances tend to have the most listings. This is also true looking across games within individual teams, and this pattern continues right up until the game even though the primary market may have been sold out for months. For example, on average 79 listings are available two days before a Boston Red Sox home game against the New York Yankees (probably the highest demand series in regular season baseball), compared with 31 listings for other Boston home games all of which were also sold out.[9] Average secondary market prices also differ substantially across teams, with Red Sox tickets having the largest secondary market mark-up as a proportion of face value.[10] 87% of EBay listings (86% of transactions) are for two seats. 43% of Stubhub listings are for four seats but 90% of these listings allow someone to purchase only a pair of seats.

[TABLE 1 ABOUT HERE]

Figure 1 shows some features of market dynamics. The average number of listings available on Stubhub peaks 30 days before the game and declines dramatically in the final week. In contrast, the number of listings available on EBay (defined by listings available at fixed prices or auctions ending that day) peaks 6 days before the game. The average number of daily transactions on EBay also peaks close to the game. However, 50% (25%) of transactions occur more than ten days (one month) before the game. Consistent with sellers moving down their residual demand curves, the probability that a listing results in a sale increases as a game approaches for all types of sales mechanism, except single unit auctions for which there is a small decline in the final ten days. The mix of mechanisms used on EBay also changes over time, with a shift towards pure auctions and then hybrid BIN auctions.[11] While this paper does not focus on these changes, they may have a simple explanation which is consistent with declining opportunity costs of sale. Fixed prices may be preferred by buyers, encouraging sellers to use them when selling immediately is not so important. On the

[9] These numbers count tickets available at fixed prices and in auctions ending two days before the game as available.

[10] When commissions are excluded average posted fixed prices on the two sites are very similar relative to face value (99% above face value on Stubhub and 104% on EBay).

[11] Wang (1993) and Zeigler and Lazear (2003) provide theoretical comparisons of auctions and posted prices. Zeithammer and Liu (2006) and Hammond (2008) provide empirical analyses. Hammond's finding that the choice of mechanism is affected by a seller's opportunity cost is consistent with the patterns in my data.

other hand, an auction allows price to be flexible in response to idiosyncratic realizations of demand. This should be attractive to a seller who is very keen to sell because he can sell with high probability by setting a low start price while preserving some possibility of a high price outcome. Figure 1(d) shows that the average quality of both listed and purchased tickets on EBay, as measured by face value and whether the seat is in the front row of a section, remains similar as a game approaches, with a small *increase* in quality in the last few days.

[FIGURE 1 ABOUT HERE]

As noted in the Introduction, the fact that sellers are small may help to support declining prices as the equilibrium outcome. The average HHI measure (based on transactions) in Table 1 is low for all teams, and particularly low for the largest teams. 63% of sellers list only one or two listings on EBay during the entire season, and 90% of sellers have less than 15 listings. 139 sellers have more than 500 listings each, making up approximately 30% of all listings. These are likely to be professional resellers. The buying side of the market is even less concentrated, with 89% of buyers purchasing only one or two listings. 38 buyers purchase more than 100 listings each, and once again, these are likely to be professional traders. The declining price path makes it difficult for a seller to buy and then resell tickets at a profit: in 75% of cases where I observe the same person buying and then selling a set of tickets on EBay they do so at a loss. Most of the profitable trades involve large buyers, who are presumably able to identify listings which are underpriced.

4 Robust Evidence of Price Declines

This section shows that both average prices and the entire distribution of prices tend to fall as a game approaches. The declines are found when looking across listings sold by different sellers and when looking within particular sets of tickets sold by individual sellers. The results are presented in figures. Appendix A contains the coefficient estimates and some additional robustness checks.

Controls for quality. I control for differences in quality across seats and games using detailed fixed effects. A game-section fixed effect groups tickets 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 different sections may have tickets at the same face value (e.g., Loge Boxes 473 to 548 had a face value price of $55). Several variables control for row quality: a linear count for the row number, dummies for the first and second row and dummies for the row not being listed or not being relevant (e.g., open seating bleachers). I also use dummies to control for the number of seats in the listing (and whether fewer seats may be purchased), and whether there is any indication that the seats are behind rather than next to each other (piggy-back), on an aisle or include parking. The fact that *observable* measures of quality do not decline over time provides some additional reassurance that the results are not likely to be driven by trends in unobserved quality. The EBay specifications control for the seller's feedback score using four dummies[12] and include additional dummies for listing characteristics such as whether the listing was highlighted.

The league position variables described in Section 3.2 are used to control for the performance of both teams. I use twenty variables to control for the degree of contemporaneous competition from other listings for the same game.[13] I show that including the form and competition variables actually tends to make the estimated price declines larger and because including the competition variables requires dropping listings without face value information, I only include them where explicitly noted below.

4.1 Average Prices

The following specification is used to estimate the quality-adjusted path of prices

$$p_{it} = D_t\beta_t^D + F_{it}\beta^F + C_{it}\beta^C + Q_{it}\beta^Q + FE + \varepsilon_{it} \quad (1)$$

where p_{it} is the log price per seat of listing i on date t, F are the form controls, C are the competition controls (where applicable), Q are the additional controls for quality and FE are the fixed effects. D contains a set of 22 dummies (Days to Go dummies) for different time periods prior to a game, and it is the coefficients on these dummies which measure the price path. Standard errors are clustered on the game.

Available Tickets on Stubhub [Figure 2]. The first group of regressions estimate the path of average prices for *available* listings on Stubhub. An observation is a listing-day, and as there are over 67 million of these the reported coefficients are based on a 5% random sample of game-sections. The price is measured by the revenue the seller would receive if the ticket was sold.[14] The solid line

[12] The four levels are scores of less than 10, 11-100, 101-1000 and more than 1000.

[13] Separate variables are defined to measure competition from listings for the same or different numbers of seats, and for listings for tickets in the same section or for different sections but with the same face value. For each of these four groups I include a linear count and its square for the number of Stubhub listings and a dummy for any competing listings, the count and its square for the number of listings on EBay.

[14] Results using the price paid by the buyer are very similar except that the change in shipping costs two weeks before the game creates a small non-monotonicity in the price decline.

with open diamonds marks the estimated price path when competition is not controlled for. The corresponding dashed lines mark 95% confidence intervals. Prices are 21% higher one month before the game than they are immediately (0-2 days) before the game, which is roughly $15 per seat given an average list price of $74.48. The line with solid squares shows the price path excluding the form variables, and the line with crosses shows the price path including both competition and form variables. Controlling for competition gives a larger estimated price decline, because prices decline more quickly when the number of competing listings on Stubhub is actually falling. In all three cases the price decline accelerates as the game approaches, which is consistent with simulations of dynamic pricing models (e.g., McAfee and te Velde (2006)).

[FIGURE 2 ABOUT HERE]

Transaction and Listing Prices on EBay [Figure 3]. The line with crosses shows the estimated path of *transaction* prices on EBay, measured by the price per seat paid by the buyer including shipping costs. Transaction prices are 27% higher 40 days before the game than immediately before the game, although the smaller sample size makes the point estimates decline non-monotonically.[15] There is some evidence of a price *increase* more than 60 days before the game. This result is driven by low transaction prices in auctions which only attract a few bidders. This reflects the thin nature of the market more than two months before the game, and it may help to explain the widespread use of fixed prices during that period. This paper will focus on the larger declines which happen closer to the game.

[FIGURE 3 ABOUT HERE]

The lines with solid squares (left axis) and open diamonds (right axis) show the paths of listed fixed and auction start prices respectively. Dummies for the exact type of mechanism used (e.g., store fixed price or a fixed price in a hybrid BIN auction) are included. Each listing is included once, with the Days to Go dummies measuring the posting date for fixed price listings and the scheduled auction end date for auction listings. Fixed prices are 40% higher one month before the game than immediately before the game, with an accelerating decline as the game approaches. Auction start prices fall by even more in the final month, but they are flat or even slightly increasing in the final week before the game.

[15] If competition variables are included prices are estimated to be 28% higher 40 days before the game than immediately before the game and the increase in transaction prices more than 60 days before the game is less pronounced.

Within-Listing/Seller Price Changes [Figure 4]. Theoretical dynamic pricing models describe the problem of an *individual* seller. Figure 4 shows the estimated price path looking at how sellers change prices for individual listings. The open diamonds line (left axis) measures the price path for Stubhub listings, estimated from a regression including listing id fixed effects and using observations from the first day of a listing and all days when the price of a listing is changed.[16] On average, a price set one month before a game is 60% higher than the price set immediately before the game, with an accelerating decline as the game approaches. 89% of observed price changes on Stubhub are price reductions. Time effects also explain quite a large proportion of the within-listing price variation: the within-R^2 when only time dummies are included is 0.44.

[FIGURE 4 ABOUT HERE]

The EBay regressions for fixed and auction start prices include seller id-game-section-row fixed effects. The decline in EBay fixed prices (solid squares, left axis) in the last two months before the game is similar to the decline on Stubhub, although the time dummies alone only explain 20% of the variation. Auction start prices fall even more dramatically. Notably the auction decline continues right up until the game. This suggests that the cross-seller Figure 3 finding that start prices are flat or increasing in the final week reflects a change in the mix of sellers using auctions. This is consistent with the structural results in Section 6.

Robustness Checks. Appendix A presents several robustness checks on the average price results. In particular, it shows that the declines are similar using different price measures, controlling for quality using game-section-row fixed effects and when looking at subsets of the data such as cheap and expensive seats, and high and low demand games.

4.2 Price Distributions

A consumer's decision about when to purchase a ticket is likely to depend on how the entire distribution of prices evolves. In particular, if she believes that prices may increase significantly because the variance of the price distribution increases as a game approaches then early purchases may be rationalized by only a small degree of risk aversion.

I form the quality-adjusted price distribution using the residuals from a game-section fixed effects regression of log prices on listing characteristics (e.g., the row variables). The form and competition

[16] As noted in Section 3.1, some sellers may change prices on Stubhub by creating a new listing which would have a new listing id. Therefore the estimated price declines only apply to the subset of listings and price changes where this does not happen. The results are similar if one tries to link listing ids where this seems likely to have happened.

variables are not included as I would like the estimated price distribution to reflect how these variables also tend to evolve. Figure 5 shows the evolution of the CDFs of the residuals using available listings on Stubhub and transaction prices on EBay. Flatter CDFs reflect more dispersed prices. On both EBay and Stubhub, the variance of the price distribution does increase as the game approaches, but this happens only because the lower percentiles of the price distribution fall significantly and the upper percentiles of the price distribution do not increase. The forces leading to declining prices therefore dominate factors such as changing team performance which should sometimes lead to demand for a particular game increasing.

[FIGURE 5 ABOUT HERE]

5 Theoretical Explanations for Why Sellers Cut Prices

The rest of the paper is concerned with why prices decline in equilibrium. I divide the analysis into two parts. Sections 5 and 6 examine why sellers cut prices given demand which may be changing as the game approaches. Section 7 examines why some buyers are willing to purchase tickets early on given how prices evolve. The behavior of these buyers is important because it makes it profitable for sellers to set high prices early on.

This division is appropriate if and only if each seller ignores how his pricing strategy affects the intertemporal evolution of demand, and each buyer ignores how her purchase decision will affect the evolution of prices in the future. The fact that individual buyers and sellers are small relative to the total size of the market makes this assumption plausible in my setting.

Section 5.1 describes two reasons why sellers may cut prices. Section 6 quantifies their importance. Section 5.2 provides evidence against an alternative explanation, involving seller learning, which is ruled out by assumption in Section 6.

5.1 Why Do Sellers Cut Prices? Falling Opportunity Costs or Changing Demand

Suppose that a risk-neutral seller i has two time periods ($t = 1, 2$) before a game to sell a single listing, by setting fixed prices p_{it}. If the listing is unsold after period 2, he gets a payoff of $\$v_i$, which could reflect the expected value of going to the game himself or selling the ticket outside the stadium. The seller's residual probability of sale function is $Q_{it}(p_{it})$ $\left(\frac{\partial Q_{it}(p_{it})}{\partial p_{it}} < 0\right)$ and it will reflect the search behavior of buyers and competition from other listings. I assume that $Q_{i2}(p_{i2})$ is known in period 1 and does not depend on p_{i1}.[17] Seller i will solve

$$\max_{p_{i1},p_{i2}} p_{i1}Q_{i1}(p_{i1}) + p_{i2}Q_{i2}(p_{i2})(1 - Q_{i1}(p_{i1})) + v_i(1 - Q_{i2}(p_{i2}))(1 - Q_{i1}(p_{i1})) \tag{2}$$

and, assuming that the relevant second-order conditions hold, prices will be

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

$$p_{i1}^* = (p_{i2}^* Q_{i2}(p_{i2}^*) + v_i(1 - Q_{i2}(p_{i2}^*))) - \frac{Q_{i1}(p_{i1}^*)}{\frac{\partial Q_{i1}(p_{i1}^*)}{\partial p_{i1}}} \tag{4}$$

Prices may fall for two reasons. First, reflecting the logic of dynamic pricing models, the opportunity cost of a sale falls over time. The cost in period 2 is v_i whereas in period 1 it is $(p_{i2}^* Q_{i2}(p_{i2}^*) + v_i(1 - Q_{i2}(p_{i2}^*)))$ which is greater than v_i because $p_{i2}^* > v_i$. More generally the first period opportunity cost would also reflect any cost of relisting tickets in the second period. If $Q_{i1}(p_i) \equiv Q_{i2}(p_i)$ then the declining opportunity cost is the only reason why prices fall. Second, the seller may also want to cut prices in period 2 if residual demand becomes more elastic (the opposite of what is believed to happen to airline demand).

The same arguments work if the seller sets start prices for auctions. If $Q_{it}(p_{it})$ $\left(\frac{\partial Q_{it}(p_{it})}{\partial p_{it}} < 0\right)$ is the probability of sale given start price p_{it} and $R_{it}(p_{it})$ $\left(\frac{\partial R_{it}(p_{it})}{\partial p_{it}} > 0\right)$ is the expected revenue in the event of sale then, assuming second-order conditions hold, the chosen start prices will satisfy

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

$$\frac{\partial R_{i1}(p_{i1}^*)}{\partial p_{i1}} Q_{i1}(p_{i1}^*) + \frac{\partial Q_{i1}(p_{i1}^*)}{\partial p_{i1}} [R_{i1}(p_{i1}^*) - (R_{i2}(p_{i2}^*) Q_{i2}(p_{i2}^*) + v_i(1 - Q_{i2}(p_{i2}^*)))] = 0 \tag{6}$$

If $Q_{i1} \equiv Q_{i2}$ and $R_{i1} \equiv R_{i2}$ then start prices will fall only because of declining opportunity costs. On the other hand, changes in the Q or R functions could also cause optimal prices to fall.

5.2 Evidence Against an Explanation with Seller Learning

The empirical analysis in Section 6 assumes that the seller knows the *current* (but not necessarily future) Q and R functions when setting prices. This is a standard assumption, but it rules out an

[17] Q_{i2} might depend on p_{i1} if a high p_{i1} increases the number of potential buyers in period 2, which is possible if a high price causes buyers to wait. I am therefore assuming that each seller is too small for his own first period pricing decision to have more than a negligible effect on his second period demand.

alternative explanation for falling prices, in the spirit of Lazear's (1986) model of clearance sales. In Lazear's model there are two periods, all consumers share the same reservation value and customers arrive stochastically and cannot wait. The seller only knows that a potential customer arrived if a good is sold. A fully informed seller would set the price equal to the reservation value in each period because a lower price cannot increase demand. On the other hand, if the seller only has a prior distribution over the reservation value he will set a high price in the first period, and if there is no sale he will infer that the reservation value was probably lower and cut the price. In a more general model with downward sloping demand learning should also cause prices to fall, at least if the seller only has a single unit to sell, because he would prefer to start off with a high price and cut it if there is no sale, rather than starting off with a low price and finding out that he should probably have set a higher price because the good was sold at once.

The most convincing evidence against learning driving the price declines in my setting comes from comparing the decline in prices for listings posted by experienced and inexperienced sellers. If experienced sellers are more informed about demand then they should have less need to learn and so they should cut prices less than inexperienced sellers. Figure 6 shows the price declines for fixed priced listings on EBay, both with game-section and seller-game-section-row fixed effects, for the quartile of listings posted by sellers with the most listings and the quartile posted by sellers with the least listings. In both cases, the price declines are *larger* for more experienced sellers. The results are similar looking at auction start prices. A theory based on opportunity costs can easily explain this pattern. Professional sellers are likely to have low costs of relisting tickets and so should set high prices early on. On the other hand they are likely to have almost no value to being left with tickets, and so they should set very low prices close to the game.

[FIGURE 6 ABOUT HERE]

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

I quantify the roles of falling opportunity costs and changing demand in causing sellers to cut prices by estimating structural models of the seller's pricing problem for fixed price, single unit auction and hybrid BIN auctions on EBay. To understand the approach, suppose that seller i posts a fixed price listing on day t. I assume that he sets price p_{it} by solving

$$\max_{p_{it}} p_{it}Q_{it}(p_{it}) + o_{it}(1 - Q_{it}(p_{it})) \tag{7}$$

where Q_{it} is the residual probability of sale for the current listing and o_{it} is the opportunity cost of sale at time t. As in the model in Section 5, the seller's opportunity cost will reflect his expectations about how easy it will be to sell an unsold ticket in the future, possibly at different prices, as well as future relisting costs and any value to being left with tickets at the time of the game.

I estimate the Q_{it} function allowing it to vary across four "time periods" (1-10 days, 11-20, 21-40 and more than 41 days) prior to the game.[18] The observed price and the pricing first-order condition allow me to calculate the opportunity cost associated with each listing

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

Consistent with dynamic pricing models, I find that opportunity costs fall significantly as the game approaches. The role of changing demand is isolated by performing a counterfactual experiment. Specifically, I calculate the prices that would be set if residual demand was the same in all four time periods (i.e., eliminating all changes in the level or elasticity of demand and changes in the degree of competition) given estimated opportunity costs. I find that counterfactual prices are generally very close to observed prices, implying that prices decline because of falling opportunity costs. Auction listings can be analyzed in a similar way, allowing for expected revenues in the event of sale to exceed the start price.

Section 6.1 details the empirical specifications. Section 6.2 explains how I deal with the possible endogeneity of prices, resulting from unobserved ticket and listing characteristics. Section 6.3 presents the empirical results. All of the analysis uses EBay data which contains transactions.

6.1 Empirical Specifications

6.1.1 Pure Fixed Price Listings

A fixed price listing can result in either a sale at the stated price, or no sale. I model the residual probability of sale function as a probit where the single index is a linear function of a listing's own

[18] Note that I do not attempt to estimate the underlying valuations of tickets that generate the probability of sale function. Hendricks and Porter (2007) note that this is extremely difficult to do in an environment where buyers may search across multiple listings because people will not bid their values even in a second price auction.

characteristics and price, and the characteristics and prices of competing listings. The dependent variable equals one if the listing was sold within ten days of being posted.[19]

A listing's own price is defined (per seat and including shipping costs) relative to the face value of the ticket.[20] The coefficient on own price is allowed to vary freely across the four time periods, and the intercept is allowed to vary even more flexibly through including the Days to Go dummies (redefined slightly to match the time periods). The listing's own characteristics include home team dummies, home team*face value interactions, home team*expected attendance on the day of listing (calculated using the model described in Section 3), the row variables, number of seat dummies, seller feedback dummies, dummies for additional characteristics (such as highlighting) and dummies for the exact mechanism used (e.g., a store fixed price). I do not include game-section (or similar) fixed effects because the calculation of opportunity costs and counterfactual prices would require consistent estimates of these effects.

Competition variables are based on the number and prices of competing listings defined as those for tickets to the same game, with the same face value and for the same number of seats. Variables based on face values were found to be the most important from several alternative sets of competition variables. I define the competition variables based on tickets available on the day that the listing is posted i.e., when the price is set. The variables are the mean and minimum relative prices of competing listings on EBay, a dummy for whether competing listings are available on EBay, the count and the proportion of competing listings with feedback scores over 100. I include separate variables to measure competition from fixed price and auction listings. I also include the count of the number of competing listings available on Stubhub.

The estimation sample includes single unit, pure fixed price listings for tickets with non-missing face value information which are posted in the last 90 days before the game. The price coefficients are sensitive to outliers with extremely high prices, so I use the 93.2% of fixed price listings where the posted price is less than five times face value.

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

[20] I deduct shipping costs and commission when calculating the opportunity cost and assume that shipping costs would remain the same under the counterfactual. I do not observe shipping costs for listings which do not sell, so I assume that they (a) have the same shipping costs as the average of listings sold by the same seller in the same time period (of the four defined above) before a game and, if this is not available, (b) the average shipping cost of all sellers during that time period. As shipping costs are relatively small (the EBay average is $4 per seat, which remains steady as a game approaches) this imputation should not affect the results too much. The qualitative results are similar if shipping costs are completely ignored.

6.1.2 Pure Auction Listings

Auction listings have the feature that revenues can exceed the start price set by the seller (listings with secret reserve prices are excluded). The probability of sale is modeled using a probit, and the revenue (R_{it}) in the event of a sale is modeled as a left-censored normal regression where realizations below the start price (p_{it}) give the start price as the revenue

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

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

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

$$R_{it} = 0 \text{ if no sale}$$

where both $f()$ and the single index in the probit are linear functions of the same characteristics as in the specification for fixed price listings together with dummies for the duration of the auction. Prices and revenues are per seat and relative to face value. I assume that the residuals in the probit and R functions are uncorrelated so that - once I have dealt with possible endogeneity problems - they can be estimated separately.

The estimation sample consists of single unit auction listings in the last 90 days before the game with non-missing face value information. To deal with the effect of outliers, I use the 96.9% of listings where the start price is less than four times the face value of the ticket and realized revenues are less than six times face value.

6.1.3 Hybrid BIN Auction Listings

BIN listings can result in an auction sale or a sale at the fixed price. I model the probability of each outcome (no sale, auction sale, fixed price sale) using a trinomial logit model, where the auction start price enters the latent variable for the auction sale outcome and the fixed price enters the latent variable for the fixed price sale outcome. I use a censored normal regression, where both prices can matter, to model revenues in the event of an auction sale.

The estimation sample consists of hybrid auction listings made in the last 90 days before the game with non-missing face value information and where the auction start price is below the fixed price.[21] I use the 90.2% of listings with fixed prices less than five times face value, start prices less than four

[21] This excludes 36,248 listings which have a fixed price equal to the start price. This is actually not that uncommon for ticket listings on EBay. Less than 1% of these listings result in an auction sale.

times face value and realized revenues less than six times face value.

6.2 Price Endogeneity and Instruments

Omitted ticket characteristics which increase demand will also affect optimal prices. My models are non-linear so I address endogeneity using a two-step control function approach (e.g., Rivers and Vuong (1988), Wooldridge (2002), p. 472ff) and by defining a set of instruments.[22]

In the case of the probit used for the fixed price model, the approach assumes that the index variable (Q^*_{it}, with a sale if $Q^*_{it} \geq 0$) can be written as

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

where the $\widetilde{X_{it}}$s are exogenous and

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

where the Zs are instruments and u_{it} and v_{it} are mean zero bivariate normal, and $var(u) = 1$. Prices are endogenous if u_{it} and v_{it} are correlated. The control function approach uses the fact that, given normality, $u_{it} = v_{it}\theta_3 + e_{it}$ where e is also normal and independent of $\widetilde{X}$, Z and v. In the first step OLS is used to estimate (11), and the predicted values of the vs are included in the second step estimation of the probit model.[23] For all of my models the coefficients on the $\widehat{v}$s are statistically significant, consistent with an endogeneity problem. I calculate standard errors using a block bootstrap procedure in which games are resampled.

The probit and censored regression models used for the two types of auction listing are estimated using a similar two-step procedure. The trinomial logit, used to determine outcome probabilities for hybrid BIN listings, is more complicated because the residuals are not normally distributed. I follow Wooldridge's (2007) suggestion for a "practical approach" by making the assumption that the latent utility-like variable associated with outcome j can be written as

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

[22] A Full Information Maximum Likelihood approach would be more efficient but it is computationally expensive to implement with many observations and several price interactions. The results using the two-step control function and FIML methods are very similar if I include only a single endogenous variable.

[23] The second step yields scaled estimates of the probit parameters.

where the es are distributed Type I extreme value and the v_{ijt}s come from price equations like (11). Given this ad-hoc assumption the two-step procedure can be used as before.

6.2.1 Instruments

Valid instruments will be factors which affect the seller's price but do not affect potential buyers' valuations. The pricing first-order condition ((8) rearranged) implies that seller characteristics which affect or reflect differences in opportunity costs but which are not associated with ticket or listing quality (conditional on observables which are included in the specification such as the seller's feedback score) are valid instruments. I choose the following variables as instruments, each of which is interacted with dummy variables for the four time periods prior to the game.[24]

- *the distance of the seller's zipcode from the home team's stadium* in the form of dummies for less than 40 km, 40-200 km (the excluded dummy) and more than 200 km. Distant sellers are more likely to be professional sellers for whom it will be cheap to relist tickets if they do not sell and so they should have high opportunity costs a long time before the game. On the other hand, distant sellers are more likely to be dependent on online sales and are unlikely to attend games themselves, and so they may cut prices aggressively as the game approaches;

- *the proportion of the seller's unsold listings which are relisted on EBay* calculated based on listings for other tickets in the same time period.[25] A high relisting rate could reflect either low costs of relisting (high opportunity costs) or limited ability to sell tickets elsewhere (low opportunity costs);

- *the proportion of the seller's listings during the same time period (for other tickets) which are in fixed price and hybrid BIN auction formats.* As suggested in Section 3.3, sellers who are very keen to sell (low opportunity costs) may be more likely to use listings with an auction component;

- (for the hybrid BIN specification only) *the average fixed and auction start prices (relative to face value) set by the seller during the same time period in other hybrid BIN listings.* A seller

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

[25] 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.

who prefers to make a particular type of sale, which may reflect their costs of monitoring a listing, should systematically set relative prices which make that type of sale more likely. These instruments are useful in providing variation in the two prices set for the same listing.

[TABLE 2 ABOUT HERE]

Table 2 reports the coefficients on the instruments when prices are regressed on the instruments and the exogenous variables. The instruments are jointly significant for every sale format. For fixed price listings distant sellers set higher prices early on and, as expected, they cut prices more aggressively as the game approaches. There is a smaller price-cutting effect close to the game for distant pure auction sellers. Sellers who use a lot of fixed price listings tend to set higher prices in every format with the premium disappearing before the game, consistent with fixed price users having high opportunity costs of sale when there is a long time until the game. Among sellers using fixed price listings, a high relisting rate is associated with lower prices consistent with these sellers being those with fewer outside opportunities, whereas the pattern is reversed for auction listings. This difference is consistent with sellers with different opportunity costs sorting into different mechanisms.

6.3 Second Stage Results, Implied Opportunity Costs and Counterfactuals

I now report the results for each of the models. The results support the hypothesis that declining opportunity costs are the main driver of the observed price declines, with the exception of one time period for the pure auction model.

6.3.1 Fixed Price Listings

The own price and competition coefficients from the estimated residual probability of sale function are shown in the upper section of Table 3. The lower section shows the mean implied elasticities $\left(\frac{\partial Q(p)}{\partial p}\frac{p}{Q(p)}\right)$ at observed prices in each time period. As expected, controlling for endogeneity makes the estimated demand function more elastic. The slope of residual demand with respect to a listing's own price is similar across time periods while the (unreported) Days to Go coefficients indicate that the level of demand increases significantly about 45 days before the game and again with around one week to go. The signs of the coefficients on the competition variables are generally sensible: the demand for a listing increases when it faces fewer or more expensive close competitors.

[TABLE 3 ABOUT HERE]

Figure 7(a) shows the evolution of the implied opportunity costs as a game approaches based on the specification in column (2). The distribution shifts to the left as the game approaches, showing that opportunity costs of sale are falling, and the estimates are precise enough to reject that the distributions are the same (to avoid clutter the 95% confidence intervals are only shown for the first time period).

[FIGURE 7 ABOUT HERE]

The role of changing residual demand is evaluated by calculating counterfactual prices i.e., what prices would have been set if residual demand was the same in every period. I operationalize this using the implied opportunity costs for each listing, the estimated demand curve 11 to 14 days before the game and the average level of competition 11-20 days before the game. If counterfactual prices are flat across time periods, then we can infer that changing demand explains all of the decline in prices. On the other hand, if counterfactual prices are either close to observed prices or decline more than observed prices then we can infer that declining opportunity costs explain all of the price decline. Table 4(a) shows that mean and median counterfactual prices are very similar to those observed for fixed price listings, implying that fixed prices only fall because of declining opportunity costs.

[TABLE 4 ABOUT HERE]

Robustness Checks. I now consider three potential issues with the results. The first two issues are particular issues for fixed price listings which are used more frequently by larger sellers and sellers who may be listing their tickets on multiple sites.

1. Sellers with multiple listings. The calculations of opportunity costs and counterfactual prices assume that the seller is only trying to sell a single listing. However, some sellers have multiple listings for similar tickets posted at the same time and multi-product concerns may affect their pricing behavior. Table 4(b) shows that counterfactual prices remain close to observed prices when I restrict attention to sellers who have no other EBay postings for tickets to the same game with the same face value.[26]

2. Sellers listing on multiple sites. The calculations also assume that the tickets are only listed on EBay. To understand why this may matter, suppose that a listing is simultaneously posted

[26] To be precise, I drop 49,981 (out of 109,296) listings where the seller has another listing posted within ten days of the listing date. The decline in average prices for this single-unit seller group is smaller than for all fixed price listings. However, the within seller-game-section-row declines are similar.

on two symmetric sites, with the same $Q_{it}(p_{it})$ functions, at the same prices. The new expression for the seller's opportunity cost (the cost of sale on *either* site) would be

$$o_{it} = p_{it} + \frac{Q_{it}(p_{it})\,(2 - Q_{it}(p_{it}))}{\frac{\partial Q_{it}}{\partial p_{it}}\,(2 - 2Q_{it}(p_{it}))} < p_{it} + \frac{Q_{it}(p_{it})}{\frac{\partial Q_{it}}{\partial p_{it}}} \tag{13}$$

so ignoring cross-listing will lead to opportunity costs being overestimated. If the amount of cross-listing falls over time then this could lead me to erroneously conclude that opportunity costs are falling.

I can use the Stubhub data to get a sense of the amount of cross-listing (recall that Stubhub is the largest secondary market site for sports tickets). I define an EBay listing as being *possibly cross-listed* if there is a listing on Stubhub for seats for the same game, section and row at any time while the listing is posted. The percentage of possibly cross-listed fixed price listings is almost constant at between 47.6% and 47.8% for the first three time periods, falling to 30.1% in the final period.[27] Therefore changes in the extent of cross-listing cannot explain why I estimate that opportunity costs are declining before the final time period.

I can also calculate opportunity costs and counterfactual prices using only listings which are not possibly cross-listed on Stubhub. Median opportunity costs for these listings are 116% of face value more than 41 days before the game, falling to 86%, 52% and 12% as the game approaches. Table 4(c) shows that counterfactual prices remain very similar to observed prices for this subset of listings.

3. Explaining negative opportunity costs. A significant proportion of the implied opportunity costs from the baseline model are negative. This is inconsistent with profit-maximization if sellers can freely dispose of unsold tickets.

One approach to this issue is to check whether the key qualitative results are robust to using a demand specification based on log rather than relative prices. The log specification makes demand very sensitive to price at low prices, making low prices easier to rationalize. With this specification, opportunity costs are estimated to fall (Figure 7(b)) as the game approaches but only 2% of the implied costs are negative (6% in the final time period). Table 4(d) shows that counterfactual prices fall by a similar amount to observed prices for this specification.[28]

An alternative approach is to explain why sellers set prices below the revenue-maximizing level. A plausible explanation is that some sellers only try to recoup what they paid for a ticket, which

[27] Only 20% of EBay auction listings are defined as being possibly cross-listed using this criterion.

[28] I have also estimated log(price) specifications for single unit and BIN auctions listings. For these formats, the log specification results in a signficant number of observed prices (up to 20%) not satisfying the second-order conditions for profit maximization. I therefore focus on the relative price results throughout.

for season ticket holders will typically be slightly less than face value. In a decreasing number of states there are also laws which restrict the mark-up which can be charged, and while these laws are widely ignored they may constrain some sellers.[29] Figure 8 shows the distributions of prices (relative to face value) separately for listings with positive and negative implied opportunity costs. Some of the listings with negative opportunity costs have prices so low that it would be hard for any model to rationalize, but 54% of these listings have prices within $10 of the face value, compared with 21% of listings with positive implied opportunity costs. This is consistent with non-profit maximizing motives affecting pricing for some sellers.

[FIGURE 8 ABOUT HERE]

6.3.2 Pure Auction Listings

Table 5 shows selected coefficients, median opportunity costs and counterfactual prices for the pure auction listing model. An increase in the start price reduces the probability of sale and increases expected revenues in the event of sale - on average, a $1 increase in the start price increases these revenues by $0.51. The 1-10 day own price interaction in the conditional revenue model implies that expected revenues become *less* sensitive to the start price immediately before the game, providing a 'changing demand' explanation for why sellers set low prices immediately before the game. While there is no intuitive explanation for why this is the case, and the result for hybrid BIN auction revenues is different, it has a significant effect on the rest of the results.

[TABLE 5 ABOUT HERE]

Implied opportunity costs fall through the first three time periods but then increase in the final time period before the game. A pattern where opportunity costs do not fall in the final period would be consistent with the fact that average auction start prices remain close to constant in the final week (Figure 3) as the mix of sellers using auctions changes. The increase reflects the change in the elasticity of expected revenues in the event of sale. Counterfactual prices decline almost as much as observed prices through the first three time periods, consistent with declining opportunity costs being the main reason that prices fall. On the other hand, counterfactual prices increase in the final time period, reflecting the increase in implied opportunity costs.

[29] For example, in North Carolina an in-state seller cannot receive revenue of more than $3 above face value (plus fees) for an in-state event.

6.3.3 Hybrid BIN Listings

Table 6 shows the results for the BIN model. The first part of the table shows the own price coefficients from the two models. A higher fixed price reduces the probability of a fixed price sale and increases the expected revenue in the event of an auction sale. The latter effect is sensible because at a higher fixed price buyers with high valuations will be less inclined to buy at the fixed price and more inclined to enter the auction. A higher auction start price raises expected revenues from an auction sale, and, unlike the pure auction model, there is no evidence for a smaller effect in the final time period.[30]

[TABLE 6 ABOUT HERE]

The table shows median opportunity costs implied by the auction start price and counterfactual auction start prices (taking the fixed price as given). Opportunity costs fall monotonically as the game approaches, consistent with dynamic pricing models. Counterfactual prices decline by almost as much as observed prices, indicating that falling opportunity costs, rather than changes in the Q and R functions, explain the vast majority of the decline in prices.

I can also calculate the opportunity costs implied by the chosen fixed price. Unfortunately because an increase in the fixed price is estimated to raise both the probability of an auction sale and expected revenues from an auction sale, almost all of the implied opportunity costs are negative and significantly below the level implied by auction start prices. This is a sign of misspecification, and it may reflect the ad hoc assumption made to deal with endogeneity in the trinomial logit model. However, the median opportunity costs implied by the estimates still fall significantly from -18% of face value in the first time period to -111%, -192% and -226% as the game approaches.

7 Rationalizing Early Purchases

Most theoretical dynamic pricing models assume that consumers cannot strategically decide when to purchase. This assumption matters because it guarantees that a firm will have some demand if it sets high prices early on and it is unrealistic because consumers do have the option to wait. In this section I calibrate a model of buyer utility to examine whether the early purchasing which I observe in the data can be explained by plausible preference parameters, given forward-looking behavior and how prices and availability evolve. I take a calibration approach because the *estimation* of a dynamic

[30] Note that a higher auction start price increases expected revenues even in the first time period (when the coefficient for how the start price enters the mean of the distribution is not significantly different from zero) because of the censoring effect.

search model with product differentiation, heterogenous consumers and a dynamically evolving set of available products and prices is beyond the current literature.

I define early purchases as those taking place more than 10 days before a game and I only use data from EBay where I observe transactions. I find that most, but not all, of these purchases can be rationalized by plausible ticket valuations, search cost and substitution patterns between different types of seat. The parameters seem particularly plausible given that they only need to apply to the *subset of people who choose to purchase early* rather than the population as a whole.

I keep the analysis simple by modeling an early purchaser as facing a binary choice: she can either buy a particular set of tickets early (which is what she actually does) or she can wait, return to the market five days before the game and take a utility-maximizing choice about whether and what to buy given the set of tickets available then. Returning five days before the game should be optimal if the buyer can only return to the market once because it is when availability is maximized (Figure 1(a)) and prices are close to their lowest level. The buyer's observed choice implies that her payoff from buying early is greater than her expected payoff from waiting. I describe an early purchase as being *rationalized* if, for particular values of the parameters, the associated inequality holds.

The next sub-section describes the calibration framework. Section 7.2 describes a baseline set of assumptions. Section 7.3 describes the results under these assumptions and under an alternative assumption about substitution. Section 7.4 provides some supporting evidence which is consistent with the results of the calibration.

7.1 A Model of Buyer Decision Making with Uncertain Future Prices and Availability, Search Costs and Risk Aversion

There are two periods $t = 1, 2$. Consumer i can either purchase a given set of tickets in period 1, giving her utility v_{i1} at price p_1, or wait until period 2. Waiting entails a return to market cost s_i, and when she returns she will make a utility-maximizing choice about which (if any) ticket to purchase. From her perspective in period 1, the surplus $v_{2i} - p_2$ from buying a ticket in period 2 has density $f_{2i}(.)$, and it will be equal to zero if no tickets are available. Assuming risk-neutrality her decision to purchase early implies that

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

The incentive to purchase early will increase with $v_{1i} - p_1$ and s_i and it will also rise if f_2 becomes less favorable. The analysis can be extended to allow for a constant absolute risk aversion (CARA) utility function.[31] I test whether this inequality holds for purchases made more than 10 days before a game for particular values of v_{1i}, v_{2i}, s_i, risk aversion and estimates of expected future ticket availability and prices.

7.2 Baseline Assumptions

I make the following baseline assumptions on preferences, return to market costs and the consumer's willingness to substitute between different types of listing if she waits.

1. *Net surplus from tickets purchased* ($v_{1i} - p_1$). I consider values of \$10, \$25, \$50 and \$75 per seat. p_1 is observed so each value of $v_{1i} - p_1$ implies a value for v_{1i}.

2. *Return to market costs* (s_i). These costs may reflect the time involved in additional search or extra costs from making arrangements which are complementary to going to the game (travel plans, finding baby sitters etc.) at the last minute. I allow s_i to take on values of \$0 or \$25 per seat.

3. *Risk aversion.* I assume either risk-neutrality or a CARA coefficient of 0.05.[32]

4. *Valuation of tickets in period 2* (v_{2i}). I make several assumptions about how the consumer would substitute between tickets five days before the game. I always assume that she would only substitute to listings for the same game with at least as many seats and would get no value from any additional seats. For the baseline case I go further by assuming that (i) she would only substitute to listings which are weakly better than those purchased (where better is defined by the tickets having the same or greater face value, with a better row if the face value is the same, and the feedback score of the seller being at least as high)[33]; and, (ii) these listings would only give her the same utility per seat (v_{1i}) as the tickets she actually purchased.

[31] For example with a CARA coefficient of α_i ($\alpha_i > 0$) the consumer's utility if she buys in the first period is $-\frac{1}{\alpha_i}\exp(-\alpha_i(v_{1i} - p_1))$. I have also looked at the effect of allowing the consumer to experience a fixed loss in utility if she gets a worse deal by waiting than the one which was available in the first period (loss aversion, Rabin (2000)). For most valuations which I consider, a loss cost of \$25 produced similar results to a CARA parameter of 0.05.

[32] A CARA coefficient of 0.05 implies that the person is indifferent to taking a gamble where she can win \$10 or lose \$10 with a probability of winning of 0.62.

[33] A justification for the better ticket assumption is that, once she has identified a particular quality of ticket, a consumer may suffer some fixed utility loss to trading down to a lower quality item. I implement the feedback criterion using the four feedback score categories defined in Section 4.

5. *Mechanisms which the consumer would buy from in period 2.* I assume that in period 2 the consumer would only buy tickets available at fixed prices, including at a fixed price in a hybrid BIN listing. This avoids the need to model the price that the consumer would expect to pay if she entered an auction and it is plausible if the buyer wants to avoid the uncertainty associated with bidding in an auction.

Assumptions 4 and 5 imply that a consumer who waits will buy the cheapest available better listing or not purchase at all. With risk-neutrality this implies that her expected payoff from waiting is $-s_i + q_i \int_0^{v_{1i}} (v_{1i} - p_2) g_{2pi}(p_2) dp_2$, where q_i is the probability that any better listing will be available at a fixed price and $g_{2pi}(p_2)$ is the pdf of the price per seat of the cheapest available better listing given the characteristics of the listing purchased in the first period.

q_i and g_{2pi} are estimated from the data. For all listings with non-missing face values which are ever purchased I identify whether at least one better listing was available at a fixed price at midnight five days before the game and, if so, what was the lowest price among these listings. Availability of a better listing (q_i) is modeled using a probit. The explanatory variables include game characteristics (home team dummies, home team*expected attendance, day of game), ticket characteristics (home team*log(face value), home team*(log(face value))^2, row variables and number of seat dummies) and listing characteristics (seller feedback score dummies).

The lowest price per seat of an available better listing is modeled as a draw from a two-parameter gamma distribution

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

X_0 contains all of the variables included in the probit model, while X_1 contains the number of seat dummies, the row variables, and log(face value) and expected attendance variables without team interactions. This specification, estimated using maximum likelihood, matches the first and second moments of the price distribution more closely than several alternatives. The coefficients from these models show a sensible pattern (Table A4 reports selected coefficients). Better listings are more likely to be available five days before the game for lower quality seats, and less likely to be available for listings with more than two seats. The lowest price tends to increase with quality: a \$1 increase in face value increases the average predicted lowest price by \$0.66 per seat all else equal. Higher expected attendances increase both availability and prices (a 10 percentage point increase in expected attendance raises the predicted lowest price by \$7.50 per seat).

7.3 Results

The upper section of Table 7 shows the percentage of early purchases (for tickets with non-missing face values) for which inequality (14) holds for different values of the parameters. The table shows separate results for all early purchases (139,762 observations) and purchases of three or more seats (18,322). Substitute listings are less likely to be available for this second group, so it is easier to rationalize early purchasing. For example, if buyers are risk-neutral with no return to market costs and they get \$10 of surplus per seat then 76% of purchases of three or more seats are rationalized compared with only 46% of all purchases (41% of one or two seat purchases). Risk aversion and return to market costs increase the percentage rationalized significantly.

[TABLE 7 ABOUT HERE]

The results can also be broken down by other listing characteristics. In particular, one might expect that the better ticket assumption would make it easier to rationalize the early purchase of seats with higher face values. However, it turns out that the percentages are pretty similar for cheap and expensive seats. Indeed with risk-neutrality, no return to market costs and \$25 surplus per seat, a slightly *higher* percentage of early purchases of listings with face values under \$40 are rationalized (57%) than those with face values over \$40 (55%). This makes the observed pattern that the average face value of purchased listings tends to increase on EBay immediately before the game (Figure 1(d)) less surprising.

7.3.1 Results Under An Alternative Assumption About Substitution

The better ticket assumption imposes severe restrictions on a consumer's valuation of different types of seat: she is assumed to get no utility from buying worse seats (whatever their price) and is assumed to get no additional utility from buying better seats. These restrictions make it easier to rationalize early purchasing, and while people who choose to purchase early are likely to have stronger preferences than most fans, they are almost certainly too strong.[34] The lower section of Table 7 reports the results under the alternative assumption that the buyer would consider substituting to any tickets for the same game (with at least as many seats) and that her value would vary dollar-for-dollar with the face value of the ticket. If the buyer was to wait she would choose the tickets with the cheapest price

[34] An analysis of people bidding in auctions who had already submitted unsuccessful bids in earlier auctions for tickets to the same game shows that 68% of them bid for tickets with the same or greater face value and 74% of them bid for tickets with the same or higher feedback score.

relative to face value or not purchase at all.[35] If people buy seats which are particularly good matches for their preferences then this assumption will make it too difficult to rationalize early purchasing.

The percentage of purchases which are rationalized falls for all values of the parameters. The majority of purchases of more than three seats are rationalized if buyers have either high valuations or significant return to market costs or if they are risk-averse. On the other hand, rationalization of the majority of one or two seat purchases requires all of these factors to be at work. If this combination is considered implausible, even for the subset of people who choose to purchase early, then rationalizing these purchases requires some stronger restrictions on how buyers substitute between tickets.

7.4 Supporting Evidence: Who Buys Early?

The calibration results prompt the question of which types of seat tend to be bought early and which types of buyer tend to purchase early. I investigate this using the four specifications shown in Table 8. An observation is the purchase of a listing with non-missing face value information and the dependent variable is the number of days prior to the game that the purchase took place. The explanatory variables include two types of buyer characteristics: the experience of the buyer (measured by how many MLB listings they purchase in the entire 2007 season) and the distance of the buyer's zipcode from the stadium of the home team. If early purchasing happens because buyers are unaware of price declines, then we might expect to see less experienced buyers purchasing earlier. Most distant buyers are likely to have to make larger complementary investments to attend a game (travel arrangements etc.) so if these are important we should expect more distant buyers to purchase earlier. Listing characteristics include the number of seats, the row variables, face value and (where relevant) dummies for the home team, the day of week of the game and the month of the game, and the expected attendance 90 days before the game.

[TABLE 8 ABOUT HERE]

The column (1) coefficients show that more distant buyers purchase earlier. All else equal someone living in New York is predicted to buy a ticket for a Boston Red Sox home game seven days earlier than someone living next to Fenway Park, which is a substantial difference given that 50% of purchases happen within 10 days of the game. Four or six seat purchases tend to be made earlier than purchases of one or two seats, consistent with it being less likely that substitutes for these listings will be available

[35] To implement this assumption I model the cheapest price available relative to face value (i.e., price − face value) using a normal distribution rather than a gamma distribution.

close to the game. However, purchases of three or five seats (2% of transactions) are made closer to the game: one can speculate that this is because they are bought by people who want an even number of seats and discard the additional seat.[36] First and second row seats tend to be purchased earlier than seats further back (for example, a front row seat is predicted to be purchased 1.7 days earlier than a row 20 seat). Tickets for high demand games are also purchased earlier, although this may reflect the secondary market becoming active when the primary market sells out, which should happen earlier for these games.

More experienced buyers tend to purchase earlier. This suggests that early purchasing is not being done only by people who are unaware of the price declines. One might think that this finding comes from the fact that professional traders buy tickets early in order to resell them. The remaining columns therefore exclude buyers who I ever observe trying to sell more than one listing on EBay (I cannot rule out the possibility that they sell them elsewhere). The experience coefficients become slightly smaller but the basic pattern remains.

The specification in column (3) includes game fixed effects to control more thoroughly for factors which vary across games. The coefficients on buyer experience and ticket characteristics are similar to those in columns (1) and (2). The specification in column (4) includes buyer-zipcode fixed effects.[37] The distance coefficients are now identified by people who purchase tickets for more than one team and have to travel different distances to attend games. The coefficients predict that someone living next to Yankee Stadium will buy tickets 5.3 days earlier if she is going to a game in Boston rather than a game at Yankee Stadium, all else equal. This provides strong evidence that complementary investments are one of the main drivers of early purchasing.

8 Conclusion

This paper has examined a striking feature of prices in online resale markets for MLB tickets: they tend to fall significantly as a game approaches. The falling price pattern exists for both posted and transaction prices and it holds across different trading mechanisms. Consistent with theoretical models of dynamic pricing for perishable goods, sellers cut prices as a game approaches because their value of holding onto tickets declines as their future selling opportunities disappear. My finding that these theoretical models accurately describe the behavior of ticket sellers, who do not typically employ

[36] An alternative explanation would be that these listings become more available close to the game: however, on average, the mix of listings with different numbers of seats remains fairly constant as the game approaches, although the number of six seat listings does decline in the last few days.

[37] Using buyer-zipcode fixed effects allows for the possibility that some people move during the sample.

complex revenue management systems, contrasts with the results of previous attempts to test these models using data from the airline industry.

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

Two questions seem ripe for further analysis. First, why are pricing patterns in this market different from those observed in airline markets and possibly markets for other perishable goods including hotel rooms and (based on discussions with advertising executives) spots on radio and television stations? A possible demand-side explanation is that, in contrast to what happens in resale markets for MLB tickets, demand becomes more inelastic over time as the mix of potential buyers changes. An alternative, and perhaps more intriguing, supply-side explanation is that market concentration and repeated interaction between the same buyers and sellers provides incentives for sellers to commit or build reputations for not reducing their prices. I have heard this type of argument made by people selling spots for radio stations.

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

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

[9] Coase, Ronald H. (1972), "Durability and Monopoly", *Journal of Law and Economics*, 15(1),143-149

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

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

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

[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] Gauri, Dinesh K., Mingyu Joo and Kenneth C. Wilbur (2009), “Multiproduct Pricing, Advertising, and Capacity on the High Seas: A Structural Model of Cruise Supply and Demand”, mimeo, University of Southern California

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

[25] Hammond, Robert (2008), “A Structural Model of Competing Sellers: Auctions and Posted Prices”, mimeo, North Carolina State University

[26] Hendricks, Ken and Robert H. Porter (2007), "An Empirical Perspective on Auctions" in the *Handbook of Industrial Organization*, volume 3, edited by M. Armstrong and R. Porter, Elsevier

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

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

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

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

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

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

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

[34] 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

[35] Puller, Steven L., Anirban Sengupta and Steven N. Wiggins (2008), "Testing Theories of Scarcity Pricing and Price Dispersion in the Airline Industry", mimeo, Texas A&M

[36] Rabin, Matthew (2000), "Risk Aversion and Expected-Utility Theory: A Calibration Theorem", *Econometrica*, 68(5), 1281-1292

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

[38] Thomas, Catherine (2009), "Organizational Form, Information Asymmetry and Market Prices", mimeo, Columbia University

[39] 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

[40] Wang, Ruqu (1993), "Auctions versus Posted-Price Selling", *American Economic Review*, 83(4), 838-851

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

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

[43] Ziegler, Alexander and Edward P. Lazear (2003), "The Dominance of Retail Stores", NBER Working Paper No. 9795

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

[45] Zeithammer, Robert and Pengxuan Liu (2006), "When is Auctioning Preferred to Posting a Fixed Selling Price?", mimeo, UCLA

[46] Zhao, Wen and Yu-Sheng Zheng (2000), "Optimal Dynamic Pricing for Perishable Assets with Nonhomogenous Demand", *Management Science*, 46(3), 375-388

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

A Coefficient Estimates for Average Price Declines and Additional Robustness Checks

Table A1 reports the coefficients shown in Figures 2, 3 and 4. I now discuss some additional robustness checks on the regressions shown in columns (1) (Stubhub listings) and (4) (EBay transactions) of Table A1, with the coefficients appearing in Tables A2 and A3. In all cases I continue to find significant price declines, although there is some variation across the datasets in whether a particular robustness check makes the decline larger or smaller.

Alternative Price Measures. The regressions in columns (1) use per-seat list prices (Stubhub) and revenues (EBay) divided by the face value of the ticket as the dependent variable. Listings with missing face value information are dropped. EBay transaction prices fall by 40% of face value in the month before the game.

Game-Section-Row Fixed Effects. The Table A1 specifications implicitly assume that the row number affects the value of a seat in the same way across games and sections. I relax this assumption by including game-section-row fixed effects in the column (2) specifications, although now identification of the price declines comes only from those game-section-rows where I observe multiple listings. The estimated price declines are very similar to Table A1 for both datasets.

Cheap and Expensive Seats. Seats for MLB games are differentiated products, with face value providing a rough proxy for quality. Face values in the data vary from \$5 to \$312, with 25^{th} and 75^{th} percentiles of \$19 and \$45. Columns (3) and (4) report the results using only tickets with face values of less than \$20 and more than \$45 (plus tickets in premium season-ticket only sections) respectively. On Stubhub the proportional price declines are very similar for cheap and expensive seats, but on EBay they are larger for cheaper seats.

High and Low Demand Games. Section 3 explained how I use several years of attendance data and team form variables to model a game's expected attendance. Columns (5) to (8) show estimated price paths when I divide games into four groups based on expected attendance 90 days before the game. On EBay the size of the price decline does not vary in a systematic way with expected attendance, but on Stubhub prices fall more for lower demand games.

Overlap of listings between EBay and Stubhub. Some sellers post listings on both sites. I identify a Stubhub listing as being *possibly cross-listed* on EBay if there is a listing on EBay for the same game, section and row at some point while the listing is on Stubhub. A similar criterion is used to identify *possibly cross-listed* EBay listings. Based on these criteria, 7% of Stubhub listings are possibly cross-listed on EBay and 33% of EBay listings are possibly cross-listed on Stubhub, although these numbers should overstate the amount of cross-listing. The regressions in column (9) show that the price declines are slightly smaller for listings which are not possibly cross-listed.

[APPENDIX TABLES A1-A4]

Table 1: Summary Statistics

	Mean Attendance in 2007 (%)	Number of Stubhub Listings	Number of EBay Listings	Number of EBay Transactions	Mean Seller Revenue (EBay) $ Per Seat	Mean Seller Revenue (EBay) As Propn of Face Value	EBay Seller HHI Based on Transactions
Arizona Diamondbacks	0.57	91,758	4,883	2,246	37.84	1.06	186
Atlanta Braves	0.63	150,956	15,913	8,124	37.34	1.03	260
Baltimore Orioles	0.55	146,770	17,159	6,889	56.72	1.64	83
Boston Red Sox	0.99	342,658	65,016	35,907	97.85	2.86	39
Chicago White Sox	0.85	257,272	33,701	15,440	37.38	1.05	150
Chicago Cubs	0.96	485,003	52,508	25,755	61.25	2.07	13
Cincinnatti Reds	0.59	32,426	16,882	7,968	36.41	1.65	151
Cleveland Indians	0.68	57,438	15,306	7,879	35.91	1.36	218
Colorado Rockies	0.59	33,714	3,484	1,815	41.61	N/A	226
Detroit Tigers	0.85	227,020	36,595	17,276	36.30	1.68	97
Florida Marlins	0.40	8,134	1,673	859	31.39	0.84	666
Houston Astros	0.85	100,240	10,225	5,650	43.56	1.51	82
Kansas City Royals	0.48	19,928	4,702	2,237	37.36	1.73	223
Los Angeles Angels	0.94	238,824	34,485	16,605	34.23	1.41	54
Los Angeles Dodgers	0.85	216,623	43,382	21,730	33.92	0.89	121
Milwaukee Brewers	0.78	27,650	14,743	8,845	30.47	1.24	202
Minnesota Twins	0.59	23,173	3,170	1,523	31.67	1.10	297
New York Mets	0.84	201,669	30,964	13,051	46.07	1.26	52
New York Yankees	0.96	579,124	103,569	41,192	48.41	1.44	26
Oakland Athletics	0.68	37,773	4,343	1,845	41.37	1.11	109
Philadelphia Phillies	0.85	92,735	11,323	5,993	54.14	1.57	66
Pittsburgh Pirates	0.58	20,992	2,871	1,972	27.17	1.26	286
San Diego Padres	0.77	82,755	11,399	5,078	50.57	1.49	166
San Francisco Giants	0.91	334,489	28,349	12,744	41.53	1.13	45
Seattle Mariners	0.71	62,792	5,423	2,883	47.49	1.43	156
St Louis Cardinals	0.95	260,886	42,521	19,418	44.62	1.31	48
Tampa Bay Devil Rays	0.45	14,445	2,518	1,245	46.12	1.12	298
Texas Rangers	0.58	47,675	12,035	5,261	31.03	0.92	227
Toronto Blue Jays	0.58	19,606	2,161	698	37.59	0.85	862
Washington Nationals	0.60	117,399	5,914	2,251	30.51	0.73	204
Totals		4,331,927	637,217	298,128			

Notes: listings may be available for multiple days. Revenues relative to face value calculated based on seats with non-missing face values (single game prices). Attendance measured as % of maximum attendance during year.

Table 2: Regressions of EBay Prices on Instruments

Listing Sample	Pure Fixed Price	Pure Auction	Hybrid BIN Listings	
Price (relative to face value)	Fixed Price	Auction Start	Auction Start	Fixed Price
Seller Within 40 km	-0.0284	0.0191	-0.0327*	-0.0335
	(0.024)	(0.028)	(0.020)	(0.023)
* 1-10 Days Prior to Game	0.0503*	0.020	0.029	0.0252
	(0.030)	(0.029)	(0.021)	(0.025)
* 11-20 Days Prior to Game	0.028	-0.017	0.0359	0.0324
	(0.028)	(0.028)	(0.023)	(0.029)
* 21-40 Days Prior to Game	-0.0208	-0.018	0.0038	0.0347
	(0.028)	(0.028)	(0.022)	(0.028)
Seller More than 200 km	0.158***	-0.048**	-0.0372*	-0.0311
	(0.023)	(0.022)	(0.020)	(0.023)
* 1-10 Days Prior to Game	-0.218***	-0.050**	-0.00622	-0.0281
	(0.030)	(0.023)	(0.020)	(0.024)
* 11-20 Days Prior to Game	-0.130***	-0.039	-0.0152	0.0151
	(0.026)	(0.024)	(0.021)	(0.026)
* 21-40 Days Prior to Game	-0.0652**	0.008	-0.0388*	-0.0269
	(0.027)	(0.023)	(0.022)	(0.025)
Proportion of Seller's Unsold Listings	-0.115***	-0.051*	0.139***	0.0687**
During Time Period Relisted on Market 2	(0.034)	(0.030)	(0.025)	(0.032)
* 1-10 Days Prior to Game	-0.0873*	0.283***	-0.173***	-0.168***
	(0.051)	(0.033)	(0.029)	(0.038)
* 11-20 Days Prior to Game	-0.147**	0.145***	-0.122***	-0.126***
	(0.063)	(0.035)	(0.031)	(0.042)
* 21-40 Days Prior to Game	-0.434***	0.257***	-0.0428	-0.0719*
	(0.050)	(0.038)	(0.034)	(0.042)
Proportion of Seller's Other Listings	-0.0922	0.230***	0.153***	0.155***
in Hybrid BIN Format	(0.057)	(0.052)	(0.034)	(0.039)
* 1-10 Days Prior to Game	0.155**	-0.041	-0.0483	-0.114***
	(0.068)	(0.056)	(0.035)	(0.042)
* 11-20 Days Prior to Game	0.254***	-0.003	-0.0437	-0.0247
	(0.072)	(0.055)	(0.038)	(0.043)
* 21-40 Days Prior to Game	0.0908	-0.046	-0.00307	-0.0481
	(0.071)	(0.056)	(0.040)	(0.048)
Proportion of Seller's Other Listings	0.140***	0.473***	0.123***	0.219***
in Pure Fixed Price Formats	(0.040)	(0.048)	(0.044)	(0.052)
* 1-10 Days Prior to Game	-0.227***	-0.590***	-0.0973**	-0.237***
	(0.047)	(0.055)	(0.048)	(0.060)
* 11-20 Days Prior to Game	0.0291	-0.476***	-0.137**	-0.147**
	(0.052)	(0.055)	(0.056)	(0.071)
* 21-40 Days Prior to Game	0.0106	-0.361***	-0.0205	-0.03
	(0.054)	(0.061)	(0.054)	(0.061)
Average Relative Fixed Price in	-	-	-0.203***	0.391***
other Hybrid BIN Listings			(0.012)	(0.014)
* 1-10 Days Prior to Game	-	-	0.0687***	0.0443***
			(0.013)	(0.017)
* 11-20 Days Prior to Game	-	-	0.0904***	0.0202
			(0.021)	(0.023)
* 21-40 Days Prior to Game	-	-	0.0701***	-0.0653*
			(0.016)	(0.035)
Average Relative Start Price	-	-	0.600***	-0.127***
in other Hybrid BIN Listings			(0.014)	(0.016)
* 1-10 Days Prior to Game	-	-	0.0522***	0.0781***
			(0.019)	(0.021)
* 11-20 Days Prior to Game	-	-	0.00242	0.0427*
			(0.024)	(0.025)
* 21-40 Days Prior to Game	-	-	-0.0439**	0.0834**
			(0.022)	(0.036)
Observations	109,296	182,558	115,603	115,603
F-statistic on the instruments	15.71	47.96	235.23	75.96

Notes: Specifications also include competition variables, number of seat dummies, seller feedback score dummies, ticket and listing characteristics, row quality controls, home team dummies, home team*face value interactions, home team*game expected attendance interactions, form variables, game day of week dummies, and Days to Go dummies and dummies for sellers with 1 and less than 10 listings. Auction specification also includes dummies for duration of the auction. Robust standard errors in parentheses clustered on the game. ***,** and * denote significance at 1%, 5% and 10% levels.

Table 3: Fixed Price Probability of Sale Model

	(1) Probit Model	(2) Probit Model With Control Function
<u>Own Price Coefficients</u>		
Relative Fixed Price	-0.200	-1.153***
	(0.015)	(0.104)
1-10 Days Prior to Game*Relative Price	0.066***	-0.005
	(0.017)	(0.028)
11-20 Days Prior to Game*Relative Price	0.061***	0.002
	(0.017)	(0.029)
21-40 Days Prior to Game*Relative Price	0.034*	-0.029
	(0.018)	(0.027)
<u>Competition Coefficients (EBay)</u>		
Mean Relative Price for Fixed Price Listings	0.093***	0.329***
	(0.012)	(0.033)
Mean Relative Start Price for Auction Listings	0.027*	0.104***
	(0.014)	(0.023)
Minimum Relative Price for Fixed Price Listings	-0.003	0.062***
	(0.011)	(0.019)
Minimum Relative Price for Auction Listings	-0.042***	-0.104***
	(0.014)	(0.022)
Dummy Variable for No Competing	0.269***	0.872***
Fixed Price Listings	(0.028)	(0.029)
Dummy Variable for No Competing	-0.094***	-0.180**
Auction Listings	(0.023)	(0.078)
Number of Competing Fixed Price Listings	-0.006**	-0.0187***
	(0.003)	(0.004)
Proportion of Competing Fixed Price Listings with	-0.058	0.030
Seller Feedback Scores Above 100	(0.039)	(0.053)
Number of Competing Auction Listings	0.001	0.006*
	(0.002)	(0.003)
Proportion of Competing Auction Listings with	-0.015	-0.096***
Seller Feedback Scores Above 100	(0.023)	(0.028)
<u>Competition Coefficients (Stubhub)</u>		
Number of Stubhub Listings/100	-0.011	0.058***
	(0.011)	(0.017)
<u>Mean Probability of Sale Elasticities at Observed Prices</u>		
1-10 Days Prior to Game	-0.196	-1.701
11-20 Days Prior to Game	-0.291	-2.413
21-40 Days Prior to Game	-0.465	-3.331
More than 41 Days Prior to Game	-0.753	-4.374
Number of observations	109,296	109,296

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

Table 4: Comparison of Observed and Counterfactual Prices for the Fixed Price Model

Counterfactuals remove the effects of changing demand by using the demand parameters for 11-14 days prior to game and the average value of the competition variables 11-20 days before the game. Standard errors in parentheses calculated using a block bootstrap (resampling games) with 200 repetitions.

(a) Baseline Relative Price Specification

	Days Prior to Game			
	41 plus	**21-40**	**11-20**	**1-10**
Observed				
Mean Price $	69.44	65.81	60.93	53.58
Median Price $	58.50	54.20	49.50	40.63
Counterfactual:				
Mean Price $	72.30	68.27	62.04	53.98
	(2.22)	(2.41)	(2.37)	(2.00)
Median Price $	61.05	56.01	50.40	41.80
	(2.05)	(2.14)	(2.08)	(1.63)

(b) Single Unit Sellers Only

	41 plus	**21-40**	**11-20**	**1-10**
Observed				
Mean Price $	66.26	66.04	62.68	54.01
Median Price $	54.61	54.09	50.92	41.50
Counterfactual:				
Mean Price $	68.35	68.00	63.92	54.49
	(2.20)	(2.51)	(2.51)	(2.06)
Median Price $	56.43	56.05	52.00	42.75
	(1.84)	(2.18)	(2.19)	(1.71)

(c) Listings Only on EBay

	41 plus	**21-40**	**11-20**	**1-10**
Observed				
Mean Price $	72.00	68.41	61.78	54.22
Median Price $	60.00	53.50	47.78	40.00
Counterfactual:				
Mean Price $	75.16	70.85	63.22	54.75
	(2.53)	(2.63)	(2.46)	(2.01)
Median Price $	63.80	56.00	48.93	40.95
	(2.10)	(2.29)	(2.01)	(1.62)

(d) Log Price Specification

	41 plus	**21-40**	**11-20**	**1-10**
Observed				
Mean Price $	69.44	65.81	60.93	53.58
Median Price $	58.50	54.20	49.50	40.63
Counterfactual:				
Mean Price $	71.26	66.55	60.74	52.59
	(0.89)	(0.82)	(0.37)	(0.48)
Median Price $	61.67	57.08	51.77	42.87
	(0.88)	(0.80)	(0.45)	(0.38)

Table 5: Single Unit Auction Listing Model

	(1) Probability of Sale Probit Estimated with Control Function	(2) Revenue Function Estimated with Control Function
Standard Deviation	-	0.850***
		(0.017)
Own Price Coefficients		
Relative Fixed Price	-1.223***	0.346***
	(0.087)	(0.055)
1-10 Days Prior to Game*Relative Price	-0.267***	-0.182***
	(0.062)	(0.051)
11-20 Days Prior to Game*Relative Price	-0.256***	-0.006
	(0.059)	(0.048)
21-40 Days Prior to Game*Relative Price	-0.290***	-0.016
	(0.058)	(0.043)
Competition Coefficients (EBay)		
Mean Relative Price for Fixed Price Listings	0.225***	0.203***
	(0.014)	(0.019)
Mean Relative Start Price for Auction Listings	0.156***	0.198***
	(0.016)	(0.017)
Minimum Relative Price for Fixed Price Listings	0.066***	0.132***
	(0.014)	(0.019)
Minimum Relative Price for Auction Listings	-0.110***	-0.175***
	(0.018)	(0.014)
Dummy Variable for No Competing	0.565***	0.790***
Fixed Price Listings	(0.031)	(0.040)
Dummy Variable for No Competing	0.042***	-0.056***
Auction Listings	(0.021)	(0.018)
Number of Competing Fixed Price Listings	-0.090***	-0.122***
	(0.021)	(0.023)
Proportion of Competing Fixed Price Listings with	-0.010***	-0.001
Seller Feedback Scores Above 100	(0.024)	(0.020)
Number of Competing Auction Listings	0.033	0.099***
	(0.023)	(0.028)
Proportion of Competing Auction Listings with	-0.059*	-0.148***
Seller Feedback Scores Above 100	(0.033)	(0.031)
Competition Coefficients (Stubhub)		
Number of Stubhub Listings/100	0.000	-0.015
	(0.014)	(0.016)
Number of observations	187,801	122,823

Median Implied Opportunity Costs (Relative to Face Value)	
More than 41 Days Prior to Game	0.52 (0.09)
21-40 Days Prior to Game	0.36 (0.09)
11-20 Days Prior to Game	0.09 (0.09)
1-10 Days Prior to Game	0.44 (0.08)

Counterfactual	Observed Prices $s		Counterfactual Prices $s	
	Mean	Median	Mean	Median
More than 41 Days Prior to Game	31.14	23.32	28.39	20.40
			(1.08)	(1.07)
21-40 Days Prior to Game	25.91	14.87	25.38	13.80
			(0.71)	(0.78)
11-20 Days Prior to Game	21.59	11.95	21.39	11.40
			(0.20)	(0.28)
1-10 Days Prior to Game	20.95	11.50	24.48	15.60
			(1.05)	(1.21)

Notes: see notes to Table 3. Specifications also include dummies for length of auction.

Table 6: Hybrid BIN Listing Model

	(1) Probability of Sale With Control Function to Address Own and Competitor Price Endogeneity (Trinomial Logit)		(2) Revenue Function With Control Function to Address Own and Competitor Price Endogeneity (Censored Normal)	
Standard Deviation	-		0.535***	
			(0.007)	
<u>Own Price Coefficients</u>				
Relative Auction Start	-1.861***		0.00324	
	(0.055)		(0.028)	
1-10 Days Prior to Game*Relative Start Price	-0.069		0.213***	
	(0.068)		(0.034)	
11-20 Days Prior to Game*Relative Start Price	-0.271***		0.175***	
	(0.067)		(0.035)	
21-40 Days Prior to Game*Relative Start Price	-0.142*		0.123***	
	(0.080)		(0.037)	
Relative Fixed Price	-0.967***		0.659***	
	(0.062)		(0.023)	
1-10 Days Prior to Game*Relative Fixed Price	0.215***		-0.159***	
	(0.059)		(0.022)	
11-20 Days Prior to Game*Relative Fixed Price	0.123**		-0.142***	
	(0.056)		(0.021)	
21-40 Days Prior to Game*Relative Fixed Price	0.059		-0.0579***	
	(0.060)		(0.023)	
Observations	115,603		37,696	
Median Implied Opportunity Costs (Relative to Face Value)				
More than 41 Days Prior to Game		0.97 (0.03)		
21-40 Days Prior to Game		0.70 (0.04)		
11-20 Days Prior to Game		0.33 (0.03)		
1-10 Days Prior to Game		0.20 (0.03)		
Counterfactual Prices	<u>Observed Prices $s</u>		<u>Counterfactual Prices $s</u>	
	Mean	Median	Mean	Median
More than 41 Days Prior to Game	48.51	40.94	44.61	38.22
			(1.84)	(1.79)
21-40 Days Prior to Game	42.15	33.80	38.12	30.00
			(1.36)	(1.22)
11-20 Days Prior to Game	34.51	26.99	33.93	25.92
			(0.32)	(0.29)
1-10 Days Prior to Game	31.36	23.76	33.63	25.74
			(0.96)	(1.22)

<u>Notes:</u> see notes to Table 3. Specifications also include competition variables.

Table 7: Rationalizing Observed Early Purchase Decisions

table shows proportion of purchases made more than 10 days before the game which can be rationalized for different assumptions and values of the parameters.

	Number of Seats	All	All	All	All	≥3	≥3	≥3	≥3
		Net Surplus Given By Tickets Purchased							
Search/Return to Market Cost	**CARA Coefficient**	**$10**	**$25**	**$50**	**$75**	**$10**	**$25**	**$50**	**$75**
Baseline Assumption: buyer would only consider substituting to better tickets, all tickets valued same as those purchased									
$0	Risk Neutral	46%	57%	62%	65%	76%	86%	90%	92%
$25	Risk Neutral	80%	81%	83%	83%	95%	96%	97%	97%
$0	0.05	58%	74%	84%	89%	87%	96%	99%	100%
$25	0.05	90%	92%	95%	97%	99%	99%	100%	100%
Alternative Assumption: buyer would consider substituting to any seats for same game, valuation varies with face value									
$0	Risk Neutral	3%	8%	15%	18%	21%	47%	63%	67%
$25	Risk Neutral	35%	43%	47%	48%	73%	77%	78%	79%
$0	0.05	17%	36%	47%	51%	64%	76%	82%	85%
$25	0.05	64%	67%	69%	70%	83%	85%	87%	89%

Table 8: Timing of Purchases

dependent variable is the number of days prior to the game that a purchase is made

	(1)	(2)	(3)	(4)
Sample	All Transactions with Non-Missing Face Value and Zip	Same As (1) But Exclude Buyers Who Sell More Than 1 Listing	Same As (1) But Exclude Buyers Who Sell More Than 1 Listing	Same As (1) But Exclude Buyers Who Sell More Than 1 Listing
<u>Distance of Buyer's Zipcode from Stadium</u>				
Distance (km)	0.0079***	0.0069***	0.0068***	0.0105***
	(0.0009)	(0.0008)	(0.0008)	(0.0010)
Distance^2/1000	-0.0010***	-0.0008***	-0.0008***	-0.0018***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Distance Less than 40 km	-4.9333***	-4.6432***	-4.5261***	-2.2545***
	(0.3838)	(0.3035)	(0.3025)	(0.6748)
<u>Buyer Experience (Number of Listings Bought in 2007)</u>				
2 to 10	4.1977***	2.9633***	3.2882***	-
	(0.2514)	(0.2549)	(0.2566)	
11 to 20	11.5834***	8.3178***	8.8251***	-
	(1.0073)	(1.1682)	(1.1631)	
21 or more	11.3433***	7.5111***	8.2459***	-
	(1.5933)	(2.8742)	(2.9061)	
<u>Number of Seats (One excluded)</u>				
Two	1.2360	0.4099	0.6584	-2.3007**
	(0.8426)	(0.8719)	(0.8743)	(1.0570)
Three	-3.3837***	-3.6664***	-2.9904***	-4.9802***
	(0.9256)	(0.9589)	(0.9596)	(1.3226)
Four	2.7276***	1.4996	1.8091**	-0.6827
	(0.8894)	(0.9123)	(0.9129)	(1.1026)
Five	-2.9374***	-2.3935**	-1.4516	-3.7903*
	(1.1032)	(1.1521)	(1.1426)	(2.0041)
Six	16.1375***	13.3788***	13.5146***	8.1645***
	(1.6651)	(1.4836)	(1.4647)	(1.6527)
<u>Face Value</u>				
Face Value ($)	-0.0396***	-0.0315***	-0.0279***	-0.0272***
	(0.0029)	(0.0026)	(0.0026)	(0.0032)
<u>Row Variables</u>				
First Row Dummy	3.0718***	2.6618***	2.8994***	1.4038***
	(0.3404)	(0.3096)	(0.3073)	(0.3381)
Second Row Dummy	2.7581***	2.3395***	2.4248***	1.0811***
	(0.3366)	(0.3021)	(0.3018)	(0.3613)
Number of Row	0.0666***	0.0805***	0.0626***	0.0394***
	(0.0163)	(0.0148)	(0.0147)	(0.0182)
<u>Game Variables</u>				
Expected Attendance 90 Days Prior to Game (% of capacity)	0.2483***	0.2238***	-	0.1579***
	(0.0128)	(0.0111)		(0.0126)
Home Team Dummies	Y	Y	N	Y
Day of Week of Game Dummies	Y	Y	N	Y
Month of Game Dummies	Y	Y	N	Y
Game FEs	N	N	Y	N
Buyer Zipcode FEs	N	N	N	Y
Number of Observations	286,706	245,829	245,829	245,829
R-squared	0.08	0.07	0.10	0.83

<u>Notes</u>: Standard errors in parentheses. In columns (1)-(3) standard errors are clustered on the buyer. In column (4) they are clustered on the buyer-zipcode. ***,** and * denote significance at the 1, 5 and 10% levels.

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

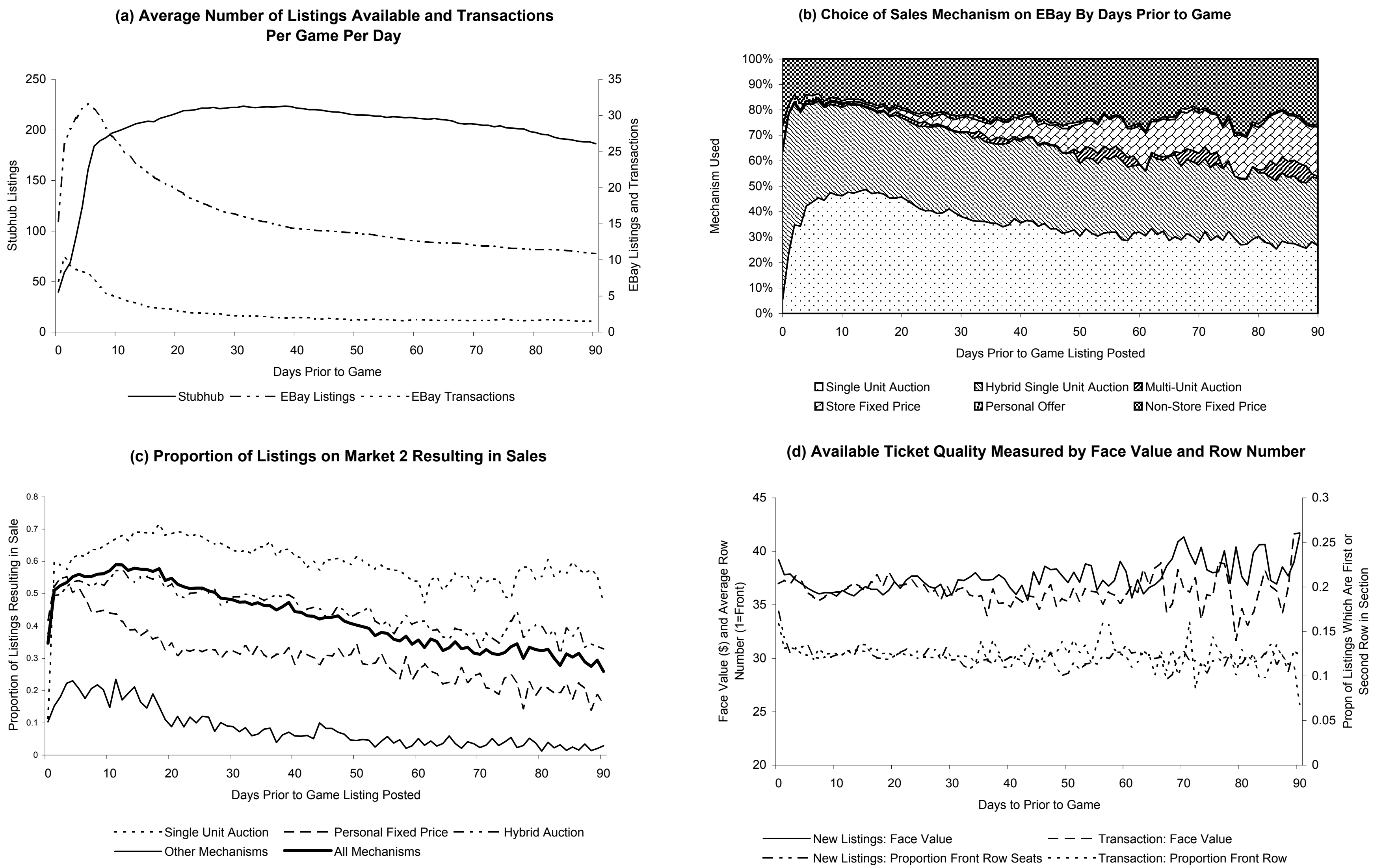


Figure 2: Path of Average Listed Prices of Available Tickets on Stubhub

Solid line with crosses: controlling for form and competition. Solid line with squares: controlling for neither form nor competition. Solid line with open diamonds: controlling for form only. Dashed lines: 95% confidence intervals (based on standard errors clustered on the game). For coefficients see Table A1.

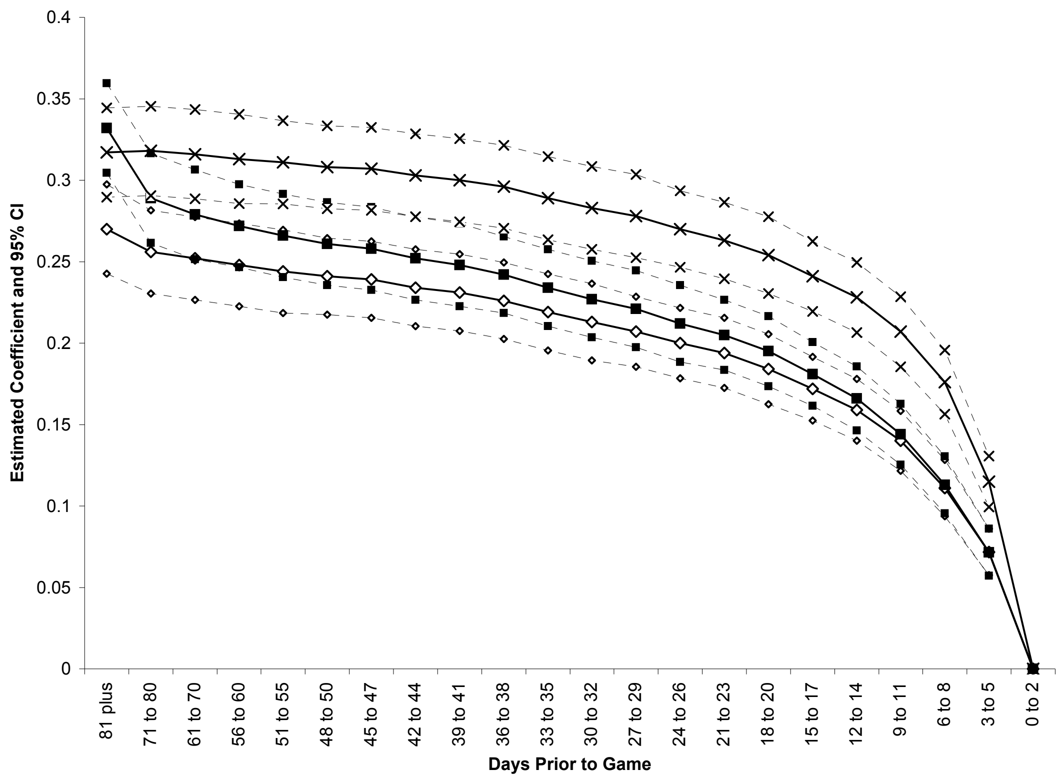


Figure 3: Path of Average Prices on EBay

Solid line with crosses: buyer prices for transactions. Solid line with squares: listed fixed prices. Solid line with open diamonds (right axis): auction start prices. Dashed lines: 95% confidence intervals (based on standard errors clustered on the game). For coefficients see Table A1.

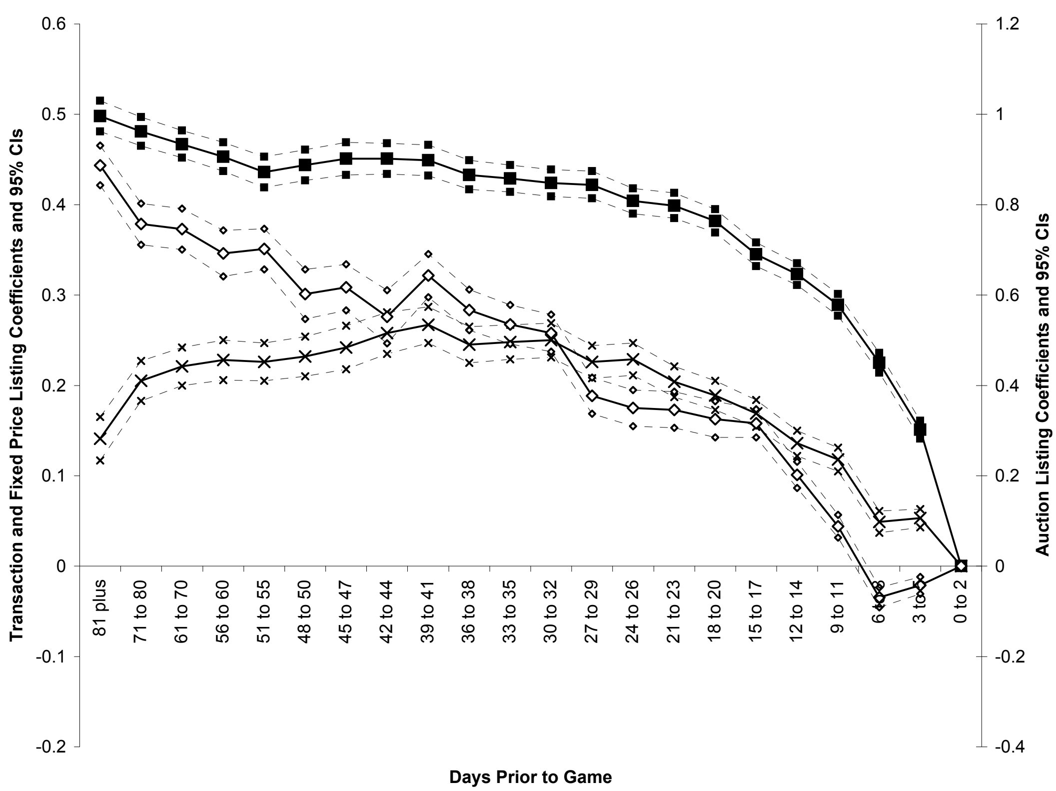


Figure 4: Within-Listing Price Changes for EBay and Stubhub

Solid line with crosses (right axis): EBay auction start prices (seller-game-section-row fixed effects). Solid line with squares: EBay fixed prices (seller-game-section-row fixed effects). Solid line with diamonds: Stubhub fixed prices (listing id fixed effects). Dashed lines: 95% confidence intervals (based on standard errors clustered on the game).

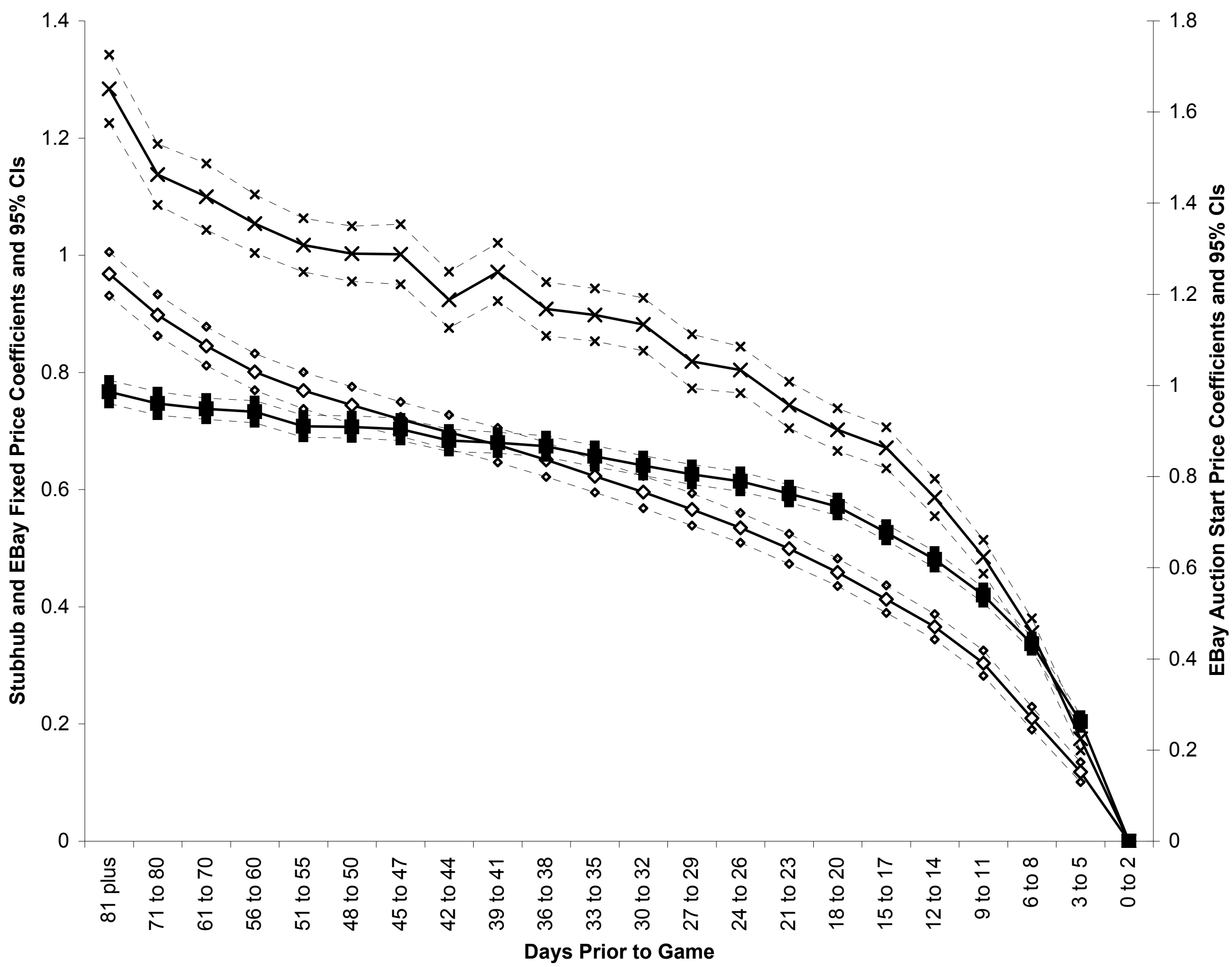


Figure 5: Evolution of the Price Distribution

CDFs of the residuals from a regression of log(price) on listing characteristics

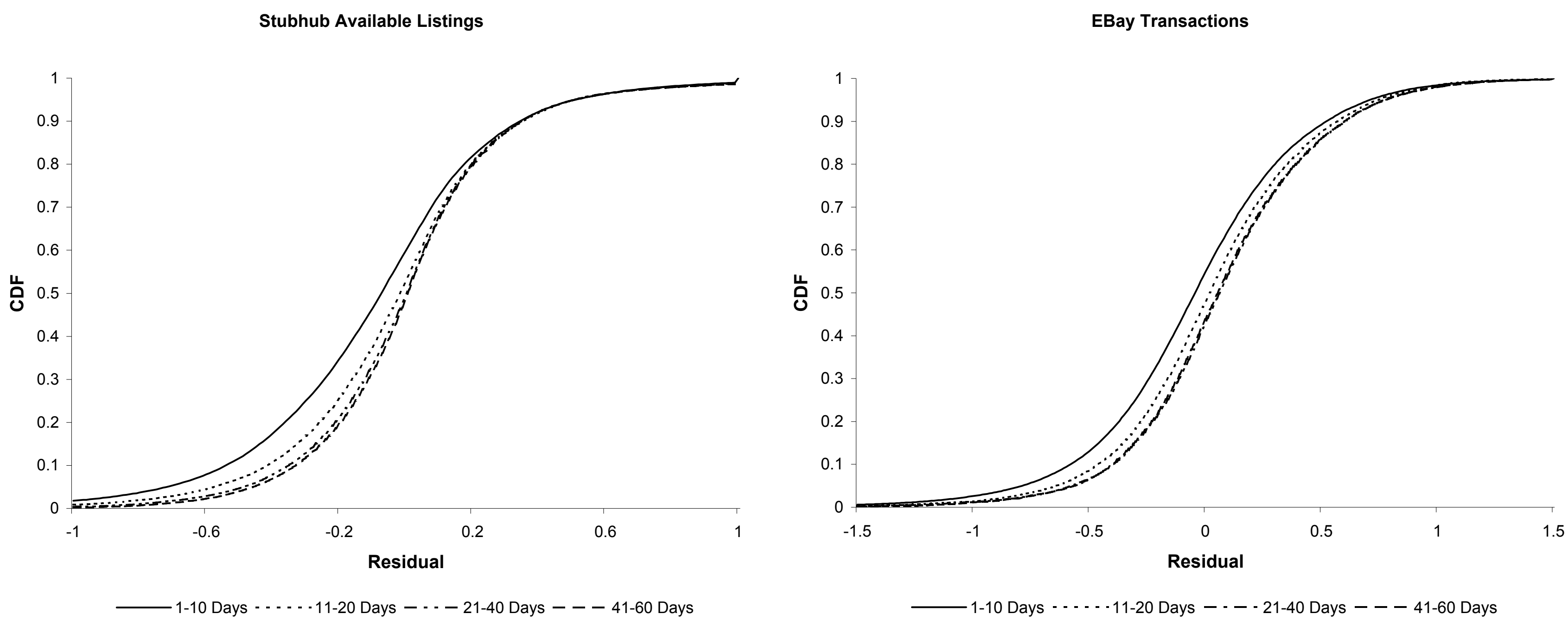
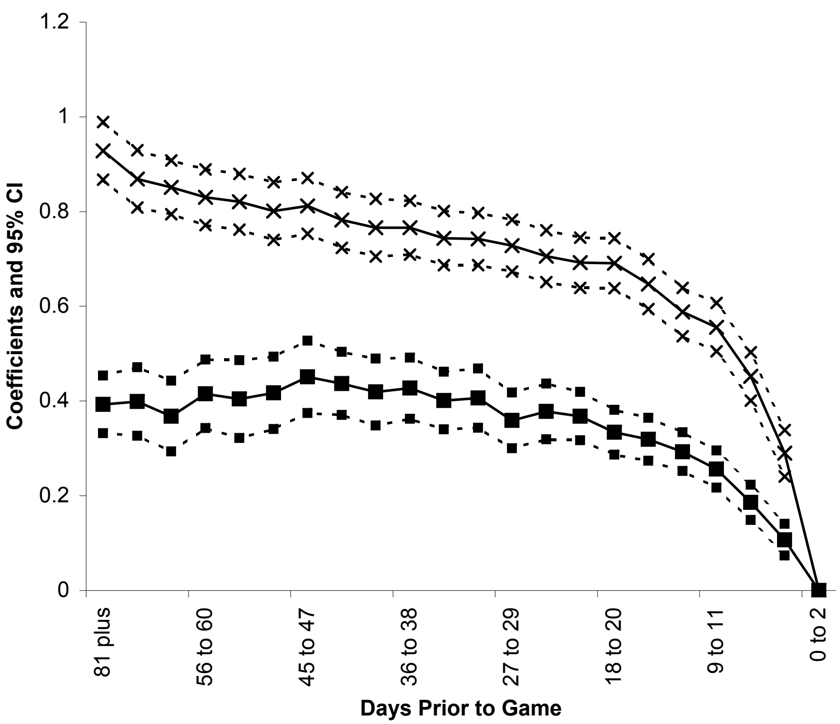


Figure 6: Comparison of Price Declines for Experienced and Inexperienced Sellers (EBay)

Solid line with squares: quartile of fixed price listings sold by the least experienced sellers (N=98,322). Solid line with crosses: quartile of fixed price listings sold by most experienced sellers (N=97,777). Dashed lines: 95% confidence intervals (based on stnadard errors clustered on the game).

Game-Section Fixed Effects



Seller-Game-Section-Row Fixed Effects

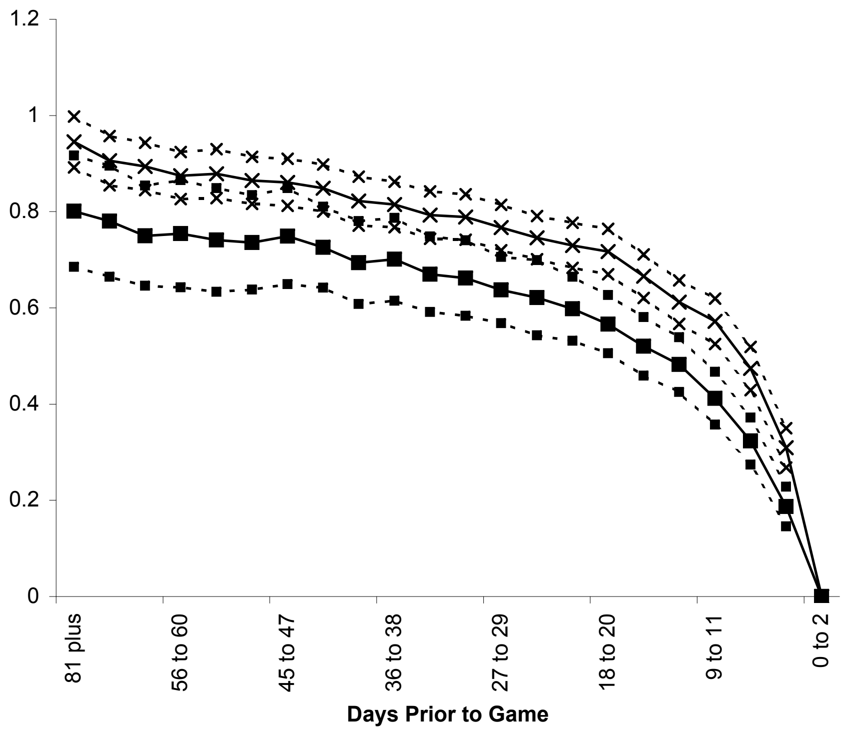
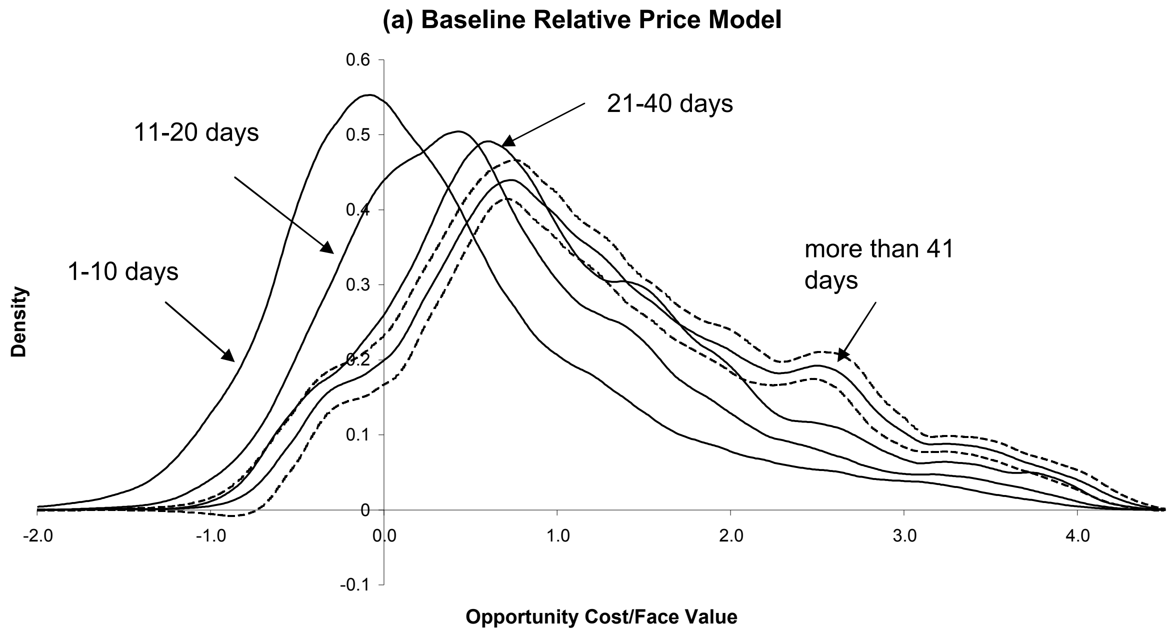


Figure 7: Opportunity Costs Implied by Fixed Price Listing Models

Dashed line shows 95% confidence interval (based on standard errors clustered on the game using a block bootstrap with 200 repetitions) for the first time period in the relative price model



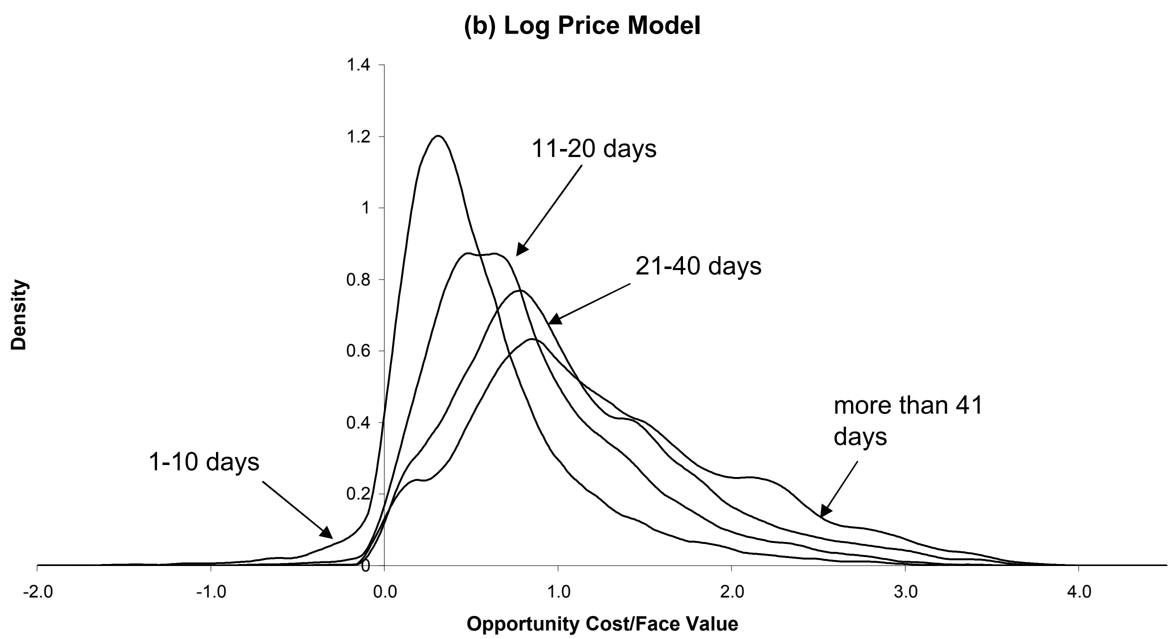
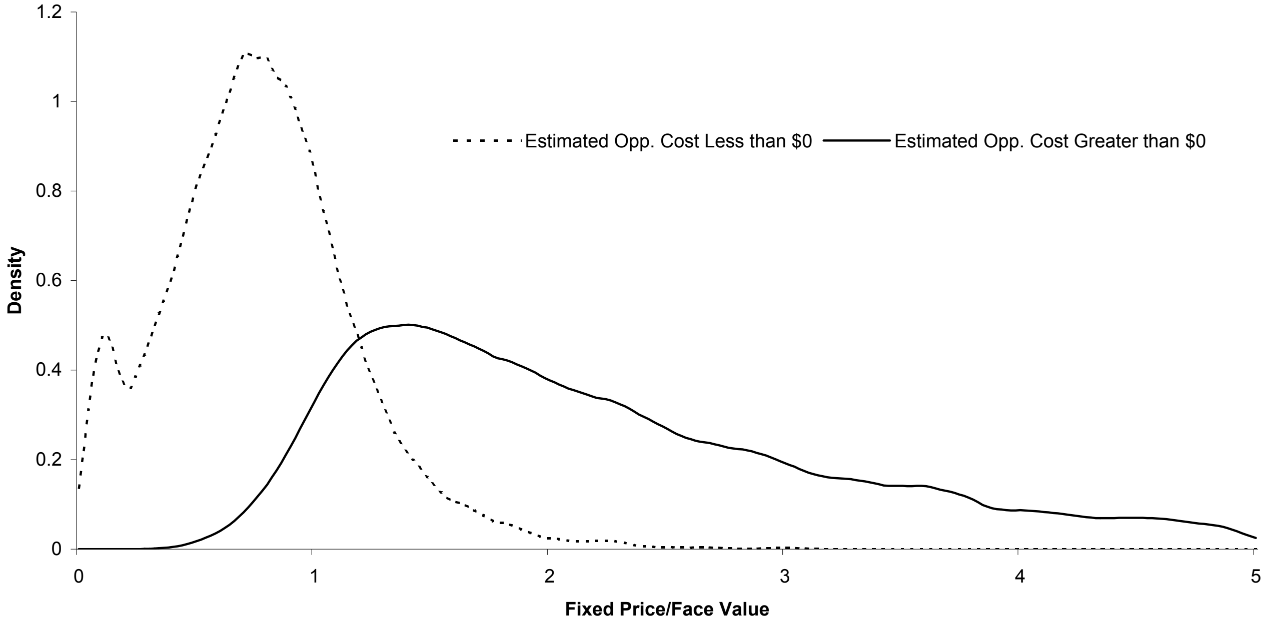


Figure 8: Distribution of Listed Prices for Fixed Price Listings with Positive and Negative Implied Opportunity Costs



Appendix
Tables

Table A1: Coefficients for Regressions Described in Section 4

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Available Stubhub Listings	Available Stubhub Listings	Available Stubhub Listings	EBay Transactions	EBay Fixed Price Listings	EBay Auction Listings	Stubhub Listings	EBay Fixed Price Listings	EBay Fixed Price Listings
Definition of Time Dummies	Date Available	Date Available	Date Available	Purchase Date	Listing Date	Auction End Date	Listing or Price Change Date	Listing Date	Auction End Date
Price Variable	Log(Seller)	Log(Seller)	Log(Seller)	Log(Buyer)	Log(List)	Log(Start)	Log(Seller)	Log(List)	Log(List)
<u>Days to Go Dummies</u>									
3 to 5	0.0718***	0.0716***	0.115***	0.0531***	0.134***	-0.0426**	0.118***	0.195***	0.225***
	(0.007)	(0.007)	(0.008)	(0.010)	(0.009)	(0.019)	(0.009)	(0.011)	(0.026)
6 to 8	0.111***	0.113***	0.176***	0.0490***	0.199***	-0.0690***	0.210***	0.325***	0.458***
	(0.009)	(0.009)	(0.010)	(0.012)	(0.011)	(0.022)	(0.010)	(0.012)	(0.031)
9 to 11	0.140***	0.144***	0.207***	0.118***	0.264***	0.0882***	0.304***	0.408***	0.624***
	(0.009)	(0.010)	(0.011)	(0.013)	(0.011)	(0.025)	(0.011)	(0.012)	(0.037)
12 to 14	0.159***	0.166***	0.228***	0.136***	0.301***	0.202***	0.366***	0.470***	0.754***
	(0.010)	(0.010)	(0.011)	(0.014)	(0.012)	(0.029)	(0.011)	(0.014)	(0.041)
15 to 17	0.172***	0.181***	0.241***	0.169***	0.325***	0.316***	0.413***	0.519***	0.863***
	(0.010)	(0.010)	(0.011)	(0.015)	(0.013)	(0.031)	(0.012)	(0.014)	(0.045)
18 to 20	0.184***	0.195***	0.254***	0.189***	0.363***	0.325***	0.459***	0.564***	0.903***
	(0.011)	(0.011)	(0.012)	(0.016)	(0.013)	(0.040)	(0.012)	(0.014)	(0.047)
21 to 23	0.194***	0.205***	0.263***	0.204***	0.380***	0.346***	0.499***	0.585***	0.957***
	(0.011)	(0.011)	(0.012)	(0.017)	(0.013)	(0.040)	(0.013)	(0.015)	(0.051)
24 to 26	0.200***	0.212***	0.270***	0.229***	0.384***	0.350***	0.535***	0.607***	1.034***
	(0.011)	(0.012)	(0.012)	(0.018)	(0.014)	(0.040)	(0.013)	(0.017)	(0.051)
27 to 29	0.207***	0.221***	0.278***	0.226***	0.403***	0.377***	0.566***	0.621***	1.053***
	(0.011)	(0.012)	(0.013)	(0.018)	(0.015)	(0.040)	(0.014)	(0.016)	(0.059)
30 to 32	0.213***	0.227***	0.283***	0.250***	0.410***	0.516***	0.596***	0.638***	1.134***
	(0.012)	(0.012)	(0.013)	(0.019)	(0.015)	(0.041)	(0.014)	(0.016)	(0.058)
33 to 35	0.219***	0.234***	0.289***	0.248***	0.413***	0.535***	0.623***	0.654***	1.155***
	(0.012)	(0.012)	(0.013)	(0.019)	(0.015)	(0.043)	(0.014)	(0.017)	(0.058)
36 to 38	0.226***	0.242***	0.296***	0.245***	0.419***	0.567***	0.651***	0.670***	1.168***
	(0.012)	(0.012)	(0.013)	(0.020)	(0.015)	(0.045)	(0.015)	(0.017)	(0.059)
39 to 41	0.231***	0.248***	0.300***	0.267***	0.437***	0.643***	0.676***	0.677***	1.249***
	(0.012)	(0.013)	(0.013)	(0.020)	(0.016)	(0.048)	(0.015)	(0.017)	(0.064)
42 to 44	0.234***	0.252***	0.303***	0.258***	0.437***	0.552***	0.698***	0.681***	1.188***
	(0.012)	(0.013)	(0.013)	(0.023)	(0.017)	(0.059)	(0.015)	(0.018)	(0.062)
45 to 47	0.239***	0.258***	0.307***	0.242***	0.437***	0.617***	0.720***	0.701***	1.288***
	(0.012)	(0.013)	(0.013)	(0.024)	(0.017)	(0.051)	(0.015)	(0.018)	(0.066)
48 to 50	0.241***	0.261***	0.308***	0.232***	0.433***	0.602***	0.744***	0.704***	1.289***
	(0.012)	(0.013)	(0.013)	(0.022)	(0.017)	(0.055)	(0.016)	(0.018)	(0.061)
51 to 55	0.244***	0.266***	0.311***	0.226***	0.427***	0.702***	0.769***	0.707***	1.308***
	(0.013)	(0.013)	(0.013)	(0.021)	(0.017)	(0.045)	(0.016)	(0.018)	(0.059)
56 to 60	0.248***	0.272***	0.313***	0.228***	0.443***	0.692***	0.801***	0.731***	1.355***
	(0.013)	(0.013)	(0.014)	(0.022)	(0.017)	(0.051)	(0.016)	(0.018)	(0.064)
61 to 70	0.252***	0.279***	0.316***	0.221***	0.460***	0.746***	0.845***	0.738***	1.414***
	(0.013)	(0.014)	(0.014)	(0.021)	(0.015)	(0.045)	(0.017)	(0.017)	(0.073)
71 to 80	0.256***	0.289***	0.318***	0.205***	0.473***	0.757***	0.898***	0.747***	1.463***
	(0.013)	(0.014)	(0.014)	(0.022)	(0.016)	(0.046)	(0.018)	(0.019)	(0.067)
81 plus	0.270***	0.332***	0.317***	0.141***	0.515***	0.887***	0.968***	0.778***	1.651***
	(0.014)	(0.014)	(0.014)	(0.024)	(0.017)	(0.044)	(0.019)	(0.020)	(0.075)
<u>Row Variables</u>									
First Row	0.104***	0.103***	0.101***	0.174***	0.149***	0.237***	-	-	-
	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)	(0.024)			
Second Row	0.057***	0.057***	0.059***	0.00575	-0.00204	0.00508	-	-	-
	(0.008)	(0.008)	(0.025)	(0.009)	(0.009)	(0.025)			
Number of Row	-0.014***	-0.014***	-0.014***	-0.00639***	-0.00373***	-0.00322**	-	-	-
(lower=better)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.002)			
No Row Listed	-0.425***	-0.427***	-0.423***	-0.196***	-0.211***	-0.0908**	-	-	-
	(0.018)	(0.018)	(0.018)	(0.011)	(0.013)	(0.037)			
Fixed Effects	GS	GS	GS	GS	GS	GS	Listing Id	SGSR	SGSR
Team Form controls	Y	N	Y	Y	Y	Y	Y	Y	Y
F-test stat, p-value	27.05, 0.000	-	19.22, 0.000	20.9,0.000	25.71, 0.000	5.74, 0.000	12.15, 0.000	16.95, 0.000	2.3, 0.002
Competition controls	N	N	Y	N	N	N	N	N	N
F-test stat, p-value	-	-	47.60, 0.000	-	-	-	-	-	-
Mechanism Type controls	NA	NA	NA	NA	Y	Y	NA	Y	Y
Observations	3,356,081	3,356,081	3,294,733	300,431	391,050	450,514	2,230,223	391,050	450,514
R-squared	0.83	0.83	0.83	0.84	0.83	0.57	0.97	0.96	0.95

<u>Notes:</u> all specifications also include dummies for the number of seats in the listing (1-6) and dummies for ticket characteristics (e.g., piggy back seats). EBay regressions also include controls for seller feedback (four dummies) and additional characteristics (e.g., pictures and whether the seller has a store). Robust standard errors clustered on the game. ***,** and * denote significance at the 1, 5 and 10% levels.
Fixed Effects: GS=Game-Section, SGSR=Seller-Game-Section-Row

Table A2: Robustness Checks Using List Prices on Stubhub

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Robustness Check	Available Stubhub Listings	Available Stubhub Listings GSR FEs	Available Stubhub Listings Cheap ≤$20	Available Stubhub Listings Expensive ≥$45	Available Stubhub Listings Exp Att >95%	Available Stubhub Listings Exp Att ≤95%,>85%	Available Stubhub Listings Exp Att ≤85%, >75%	Available Stubhub Listings Exp Att ≤75%	Available Stubhub Listings No Overlap
Definition of Time Dummies	Date Available	Date Available	Date Available	Date Available	Date Available	Date Available	Date Available	Date Available	Date Available
Price Variable	Price/Face	Log(Seller)	Log(Seller)	Log(Seller)	Log(Seller)	Log(Seller)	Log(Seller)	Log(Seller)	Log(Seller)
<u>Days to Go Dummies</u>									
3 to 5	0.0800***	0.0943***	0.0706***	0.0725***	0.0362**	0.0644***	0.0694***	0.110***	0.0764***
	(0.014)	(0.007)	(0.019)	(0.007)	(0.015)	(0.012)	(0.019)	(0.011)	(0.008)
6 to 8	0.131***	0.145***	0.108***	0.114***	0.0632***	0.105***	0.115***	0.161***	0.117***
	(0.017)	(0.008)	(0.021)	(0.009)	(0.018)	(0.015)	(0.022)	(0.014)	(0.009)
9 to 11	0.172***	0.180***	0.137***	0.142***	0.0822***	0.132***	0.145***	0.198***	0.145***
	(0.019)	(0.009)	(0.022)	(0.009)	(0.018)	(0.016)	(0.024)	(0.015)	(0.010)
12 to 14	0.201***	0.203***	0.158***	0.161***	0.0963***	0.151***	0.161***	0.226***	0.161***
	(0.019)	(0.009)	(0.023)	(0.010)	(0.020)	(0.017)	(0.025)	(0.015)	(0.010)
15 to 17	0.219***	0.221***	0.174***	0.173***	0.0988***	0.163***	0.174***	0.249***	0.173***
	(0.020)	(0.010)	(0.024)	(0.010)	(0.020)	(0.017)	(0.027)	(0.016)	(0.010)
18 to 20	0.236***	0.235***	0.186***	0.185***	0.106***	0.174***	0.188***	0.263***	0.184***
	(0.021)	(0.010)	(0.025)	(0.010)	(0.021)	(0.018)	(0.029)	(0.016)	(0.011)
21 to 23	0.251***	0.247***	0.192***	0.195***	0.108***	0.185***	0.196***	0.276***	0.192***
	(0.022)	(0.010)	(0.026)	(0.011)	(0.021)	(0.018)	(0.031)	(0.016)	(0.011)
24 to 26	0.261***	0.257***	0.196***	0.200***	0.108***	0.192***	0.200***	0.287***	0.198***
	(0.022)	(0.011)	(0.027)	(0.011)	(0.021)	(0.019)	(0.032)	(0.016)	(0.011)
27 to 29	0.274***	0.266***	0.208***	0.207***	0.114***	0.197***	0.208***	0.295***	0.205***
	(0.023)	(0.011)	(0.027)	(0.011)	(0.022)	(0.019)	(0.032)	(0.016)	(0.011)
30 to 32	0.282***	0.273***	0.214***	0.212***	0.118***	0.200***	0.215***	0.304***	0.210***
	(0.023)	(0.011)	(0.027)	(0.011)	(0.022)	(0.019)	(0.032)	(0.017)	(0.012)
33 to 35	0.291***	0.281***	0.221***	0.218***	0.119***	0.207***	0.225***	0.310***	0.215***
	(0.023)	(0.011)	(0.027)	(0.011)	(0.022)	(0.020)	(0.032)	(0.017)	(0.012)
36 to 38	0.303***	0.289***	0.228***	0.223***	0.121***	0.216***	0.234***	0.319***	0.222***
	(0.023)	(0.011)	(0.028)	(0.011)	(0.023)	(0.020)	(0.032)	(0.017)	(0.012)
39 to 41	0.313***	0.295***	0.234***	0.227***	0.123***	0.220***	0.240***	0.327***	0.227***
	(0.024)	(0.011)	(0.028)	(0.011)	(0.023)	(0.020)	(0.033)	(0.017)	(0.012)
42 to 44	0.320***	0.300***	0.237***	0.229***	0.126***	0.222***	0.244***	0.328***	0.229***
	(0.024)	(0.012)	(0.028)	(0.012)	(0.024)	(0.020)	(0.033)	(0.018)	(0.012)
45 to 47	0.331***	0.305***	0.246***	0.232***	0.131***	0.225***	0.250***	0.333***	0.235***
	(0.025)	(0.012)	(0.028)	(0.012)	(0.024)	(0.021)	(0.033)	(0.018)	(0.012)
48 to 50	0.332***	0.309***	0.250***	0.234***	0.130***	0.230***	0.255***	0.336***	0.238***
	(0.025)	(0.012)	(0.029)	(0.012)	(0.024)	(0.021)	(0.033)	(0.018)	(0.012)
51 to 55	0.336***	0.314***	0.257***	0.238***	0.135***	0.234***	0.257***	0.340***	0.241***
	(0.025)	(0.012)	(0.029)	(0.012)	(0.025)	(0.021)	(0.034)	(0.018)	(0.013)
56 to 60	0.346***	0.320***	0.263***	0.240***	0.137***	0.235***	0.260***	0.344***	0.243***
	(0.026)	(0.012)	(0.029)	(0.012)	(0.025)	(0.022)	(0.034)	(0.018)	(0.013)
61 to 70	0.354***	0.327***	0.263***	0.243***	0.139***	0.239***	0.265***	0.349***	0.247***
	(0.026)	(0.012)	(0.030)	(0.013)	(0.026)	(0.022)	(0.035)	(0.018)	(0.013)
71 to 80	0.361***	0.336***	0.270***	0.247***	0.138***	0.245***	0.272***	0.358***	0.252***
	(0.027)	(0.013)	(0.030)	(0.013)	(0.026)	(0.023)	(0.035)	(0.019)	(0.013)
81 plus	0.388***	0.357***	0.291***	0.262***	0.145***	0.258***	0.296***	0.372***	0.267***
	(0.029)	(0.013)	(0.030)	(0.014)	(0.028)	(0.025)	(0.034)	(0.020)	(0.014)
<u>Row Variables</u>									
First Row	0.212***	-	0.114***	0.0641***	0.0533***	0.111***	0.128***	0.105***	0.0897***
	(0.029)		(0.026)	(0.012)	(0.017)	(0.019)	(0.024)	(0.017)	(0.010)
Second Row	0.119***	-	0.0292	0.0599***	0.0275**	0.0557***	0.0769***	0.0657***	0.0562***
	(0.024)		(0.022)	(0.010)	(0.013)	(0.016)	(0.022)	(0.015)	(0.009)
Number of Row	-0.0289***	-	-0.0155***	-0.0139***	-0.0141***	-0.0140***	-0.0144***	-0.0157***	-0.0139***
(lower=better)	(0.002)		(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
No Row Listed	-0.871***	-	-0.271*	-0.455***	-0.451***	-0.368***	-0.378***	-0.519***	-0.422***
	(0.055)		(0.140)	(0.026)	(0.036)	(0.030)	(0.040)	(0.033)	(0.020)
Fixed Effects	GS	GSR	GS	GS	GS	GS	GS	GS	GS
Team Form controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
F-test stat, p-value	16.78, 0.000	34.87, 0.000	7.63, 0.000	17.67, 0.000	12.44, 0.000	14.355, 0.000	9.01, 0.000	10.03, 0.000	15.57,0.000
Observations	3,294,733	3,356,081	843,865	1,107,116	828,083	1,012,934	659,756	855,308	2,313,056
R-squared	0.56	0.92	0.60	0.83	0.88	0.81	0.78	0.83	0.86

<u>Notes:</u> see Table A1. Expensive seat regression also includes listings for premium season-ticket only sections with no single game face values.

Table A3: Robustness Checks Using Transactions Price on EBay

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Robustness Check	EBay Transactions	EBay Transactions GSR FEs	EBay Transactions Cheap ≤$20	EBay Transactions Expensive ≥$45	EBay Transactions Exp Att >95%	EBay Transactions Exp Att ≤95%,>85%	EBay Transactions Exp Att ≤85%, >75%	EBay Transactions Exp Att ≤75%	EBay Transactions No Overlap
Definition of Time Dummies	Purchase Date	Purchase Date	Purchase Date	Purchase Date	Purchase Date	Purchase Date	Purchase Date	Purchase Date	Purchase Date
Price Variable	Price/Face	Log(Buyer)	Log(Buyer)	Log(Buyer)	Log(Buyer)	Log(Buyer)	Log(Buyer)	Log(Buyer)	Log(Buyer)
Days to Go Dummies									
3 to 5	0.0473**	0.0471**	0.0293**	0.0517***	0.0561***	0.0329*	0.0458*	0.0890***	0.0490***
	(0.019)	(0.021)	(0.015)	(0.015)	(0.016)	(0.019)	(0.026)	(0.021)	(0.013)
6 to 8	0.0517**	0.0623***	0.0139	0.0724***	0.0722***	0.025	0.0147	0.0802***	0.0548***
	(0.024)	(0.023)	(0.017)	(0.018)	(0.019)	(0.022)	(0.031)	(0.023)	(0.014)
9 to 11	0.167***	0.122***	0.108***	0.124***	0.154***	0.106***	0.0641*	0.120***	0.114***
	(0.026)	(0.026)	(0.019)	(0.019)	(0.020)	(0.026)	(0.034)	(0.026)	(0.016)
12 to 14	0.187***	0.146***	0.121***	0.148***	0.148***	0.127***	0.0835**	0.171***	0.134***
	(0.028)	(0.027)	(0.020)	(0.021)	(0.021)	(0.028)	(0.039)	(0.027)	(0.016)
15 to 17	0.257***	0.177***	0.164***	0.149***	0.185***	0.176***	0.102**	0.194***	0.156***
	(0.032)	(0.029)	(0.023)	(0.023)	(0.025)	(0.030)	(0.040)	(0.028)	(0.018)
18 to 20	0.311***	0.207***	0.202***	0.153***	0.181***	0.172***	0.171***	0.246***	0.167***
	(0.044)	(0.029)	(0.025)	(0.024)	(0.024)	(0.032)	(0.040)	(0.032)	(0.019)
21 to 23	0.319***	0.228***	0.214***	0.189***	0.193***	0.200***	0.186***	0.239***	0.172***
	(0.044)	(0.032)	(0.026)	(0.028)	(0.027)	(0.034)	(0.045)	(0.033)	(0.021)
24 to 26	0.418***	0.221***	0.248***	0.225***	0.228***	0.222***	0.157***	0.286***	0.212***
	(0.063)	(0.034)	(0.028)	(0.029)	(0.028)	(0.034)	(0.053)	(0.039)	(0.023)
27 to 29	0.406***	0.225***	0.236***	0.210***	0.196***	0.239***	0.186***	0.273***	0.195***
	(0.059)	(0.034)	(0.028)	(0.028)	(0.026)	(0.039)	(0.052)	(0.037)	(0.022)
30 to 32	0.402***	0.240***	0.282***	0.206***	0.225***	0.260***	0.233***	0.283***	0.228***
	(0.060)	(0.035)	(0.028)	(0.032)	(0.028)	(0.042)	(0.045)	(0.040)	(0.024)
33 to 35	0.414***	0.255***	0.283***	0.234***	0.224***	0.237***	0.252***	0.298***	0.217***
	(0.052)	(0.038)	(0.028)	(0.034)	(0.031)	(0.037)	(0.054)	(0.042)	(0.025)
36 to 38	0.387***	0.246***	0.251***	0.217***	0.220***	0.273***	0.201***	0.276***	0.210***
	(0.054)	(0.040)	(0.031)	(0.034)	(0.030)	(0.041)	(0.057)	(0.042)	(0.025)
39 to 41	0.411***	0.267***	0.301***	0.236***	0.233***	0.286***	0.247***	0.319***	0.242***
	(0.049)	(0.036)	(0.030)	(0.032)	(0.029)	(0.037)	(0.064)	(0.042)	(0.025)
42 to 44	0.394***	0.270***	0.267***	0.212***	0.214***	0.272***	0.246***	0.325***	0.239***
	(0.057)	(0.040)	(0.035)	(0.034)	(0.030)	(0.049)	(0.065)	(0.048)	(0.027)
45 to 47	0.393***	0.248***	0.252***	0.213***	0.223***	0.269***	0.185***	0.270***	0.194***
	(0.065)	(0.044)	(0.037)	(0.038)	(0.032)	(0.056)	(0.064)	(0.045)	(0.030)
48 to 50	0.400***	0.227***	0.281***	0.168***	0.220***	0.225***	0.163***	0.307***	0.197***
	(0.059)	(0.043)	(0.035)	(0.037)	(0.033)	(0.045)	(0.056)	(0.045)	(0.027)
51 to 55	0.378***	0.225***	0.260***	0.204***	0.192***	0.234***	0.175***	0.307***	0.190***
	(0.060)	(0.039)	(0.030)	(0.040)	(0.031)	(0.042)	(0.068)	(0.047)	(0.027)
56 to 60	0.341***	0.239***	0.231***	0.258***	0.202***	0.241***	0.160**	0.297***	0.211***
	(0.062)	(0.040)	(0.034)	(0.033)	(0.037)	(0.040)	(0.066)	(0.043)	(0.027)
61 to 70	0.334***	0.218***	0.249***	0.231***	0.205***	0.224***	0.160***	0.275***	0.208***
	(0.057)	(0.039)	(0.030)	(0.033)	(0.031)	(0.043)	(0.055)	(0.045)	(0.025)
71 to 80	0.305***	0.210***	0.214***	0.240***	0.173***	0.231***	0.230***	0.213***	0.172***
	(0.059)	(0.041)	(0.032)	(0.033)	(0.033)	(0.042)	(0.055)	(0.056)	(0.027)
81 plus	0.144*	0.155***	0.168***	0.171***	0.118***	0.148***	0.0994	0.210***	0.131***
	(0.076)	(0.045)	(0.033)	(0.030)	(0.037)	(0.044)	(0.062)	(0.055)	(0.028)
Row Variables									
First Row	0.326***	-	0.214***	0.0855***	0.134***	0.159***	0.150***	0.233***	0.148***
	(0.022)		(0.013)	(0.015)	(0.014)	(0.015)	(0.021)	(0.020)	(0.012)
Second Row	0.0327**	-	-0.0012	-0.0350**	0.0289**	-0.0236	-0.0440*	0.0351*	0.0121
	(0.015)		(0.013)	(0.018)	(0.011)	(0.017)	(0.025)	(0.020)	(0.012)
Number of Row	-0.00972***	-	-0.00628***	-0.00592***	-0.00443***	-0.00775***	-0.00831***	-0.00905***	-0.00581***
(lower=better)	(0.001)		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
No Row Listed	-0.310***	-	-0.100***	-0.193***	-0.152***	-0.221***	-0.259***	-0.240***	-0.181***
	(0.028)		(0.026)	(0.022)	(0.015)	(0.021)	(0.031)	(0.031)	(0.015)
Fixed Effects	GS	GSR	GS	GS	GS	GS	GS	GS	GS
Team Form controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
F-test p-value	10.97,0.000	5.68,0.000	13.64,0.000	8.17,0.000	13.38,0.000	9.09,0.000	4.35,0.000	3.33,0.000	15.57,0.000
Competition controls	N	N	N	N	N	N	N	N	N
F-test p-value									
Observations	300,431	290,410	89,317	102,544	92,543	86,276	48,126	73,486	215,627
R-squared	0.96	0.75	0.77	0.83	0.80	0.80	0.82	0.87	0.86

Notes: see Table A2.

Table A4: Models for Ticket Availability and Expected Prices Five Days Prior to Game

under assumption that only better tickets available in fixed price listings are considered substitutes

	Probit Model for Ticket Availability	Gamma Model for Prices of Available Tickets: Shape Parameters	Gamma Model for Prices of Available Tickets: Scale Parameters
Monday	0.0977***	0.090***	-
	(0.017)	(0.005)	
Tuesday	0.273***	-0.031***	-
	(0.017)	(0.005)	
Wednesday	0.322***	-0.072***	-
	(0.017)	(0.005)	
Thursday	-0.117***	0.009*	-
	(0.017)	(0.005)	
Friday	-0.0539***	0.043***	-
	(0.014)	(0.004)	
Saturday	-0.181***	0.070***	-
	(0.013)	(0.004)	
Feedback 10-100	-0.0581**	-0.012**	-
	(0.027)	(0.006)	
Feedback 100-1000	-0.258***	0.022***	-
	(0.026)	(0.006)	
Feedback Greater Than 100	-0.987***	0.262***	-
	(0.026)	(0.006)	
Two Seats	0.0311	0.283***	-0.989***
	(0.048)	(0.027)	(0.031)
Three Seats	-1.538***	0.309***	-0.469***
	(0.053)	(0.037)	(0.041)
Four Seats	-1.649***	0.338***	-0.685***
	(0.049)	(0.029)	(0.033)
Five Seats	-2.564***	0.621***	-0.935***
	(0.066)	(0.072)	(0.079)
Six Seats	-2.781***	0.318***	-0.782***
	(0.060)	(0.067)	(0.075)
Front Row	-0.105***	0.003	0.000
	(0.014)	(0.009)	(0.010)
Second Row	-0.0873***	0.021**	-0.009
	(0.015)	(0.010)	(0.012)
Row Number	0.0223***	0.000	-0.008***
	(0.001)	(0.000)	(0.001)
Row N/A	0.775***	0.096***	-0.444***
	(0.059)	(0.023)	(0.024)
No Row Listed	0.763***	-0.122***	-0.130***
	(0.019)	(0.011)	(0.012)

	Probit Model for Ticket Availability	Gamma Model for Prices of Available Tickets: Shape Parameters	Gamma Model for Prices of Available Tickets: Scale Parameters
Main Effects (Arizona Diamondbacks)			
Constant	-4.545***	0.048	3.121***
	(0.870)	(0.357)	(0.070)
Log(Face Value)	2.265***	-0.525***	0.040
	(0.490)	(0.215)	(0.038)
Log(Face Value)^2	-0.451***	0.101***	0.081***
	(0.071)	(0.033)	(0.006)
Expected Attendance	5.138***	1.397***	-0.164***
	(0.340)	(0.132)	(0.014)
Interaction Effects for Selected Teams (not reported for other teams)			
Boston Red Sox Interactions			
Constant	0.976	0.105	-
	(0.980)	(0.366)	
Log(Face Value)	0.678	-0.920***	-
	(0.530)	(0.219)	
Log(Face Value)^2	-0.087	0.108***	-
	(0.076)	(0.033)	
Expected Attendance	-3.227***	1.648***	-
	(0.370)	(0.133)	
Chicago Cubs Interactions			
Constant	-6.555***	-0.470	-
	(1.180)	(0.411)	
Log(Face Value)	2.816***	-0.671***	-
	(0.680)	(0.249)	
Log(Face Value)^2	-0.534***	0.147***	-
	(0.099)	(0.038)	
Expected Attendance	2.297***	0.837***	-
	(0.430)	(0.142)	
Average Availiability Data, Predicted	0.87,0.87		
Average Prices Data, Predicted	-	50.87, 50.95	
Std Deviation Prices Data, Predicted	-	60.50, 54.04	
Log-Likelihood	-60,133.3	-1,163,032	
Number of Observations	289,784	254,720	

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